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ABSTRACT

This paper explores the behavior of daily, international portfolio flows into and out of 46 countries from 1994 through 1998. Our data are from State Street Bank & Trust and encompass over 3 million trades by client institutions. We find a number of interesting facts. First, we detect regional factors within the flows. Second, the flows are strongly persistent -- the persistence decays only slowly over time. Third, flows are strongly influenced by past returns, so that investor trend-following is apparent. Fourth, we find that inflows have forecasting power for future emerging market returns, but not for developed country returns. Fifth, we find the sensitivity of local stock prices to foreign inflows to be positive and determine that transitory inflows impact future returns negatively. Finally, we examine and reject that the positive covariance of returns and inflows is associated with an information disadvantage on the part of international investors.

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I. Introduction

How do international portfolio flows behave? Do flows affect asset and currency returns? Are emerging market stock prices and exchange rates particularly vulnerable to such flows? These questions have been of perennial interest to investors, economists, and policy makers for as long as capital has crossed borders. They are posed with greater urgency during times of financial upheaval (e.g. the 1997–1998 Asian and 1994–1995 Mexican currency crises.) Frequently, the answers to these questions cast international investors in a poor light. It is argued that foreign outflows lead to prices that overreact and to contagion. An opposing view—espoused most often by economists—is that trading is merely the process by which information is incorporated into asset prices. International investors do not create or exacerbate crises; their trading behavior simply reflects their assessment of underlying fundamentals.

While there are plenty of strongly held views, there is surprisingly little information on the behavior of international portfolio flows and their relationship with local currency and asset returns. Indeed, what little information there is on aggregate investor purchases in major capital markets comes from quarterly, or at best monthly, data. For example, Tesar and Werner (1993, 1995), Bohn and Tesar (1996), and Brennan and Cao (1997) examine estimates of aggregate international portfolio flows. They find evidence of positive, contemporaneous correlation between inflows and returns. But the low frequency of previously available data is a severe limitation given the poor statistical precision it permits. Partly as a result of this, little has thus far been said about international flows (e.g., is there herding or trend-following), or about the effects international flows have on local asset returns.[2]

In this paper, we exploit a new and potentially superior source of flow data to help answer these questions. The data come from State Street Bank & Trust, one of the world's largest custodian banks. Custodians keep detailed records of worldwide securities holdings, trades, and transaction settlements. State Street's clients are predominantly large institutional investment pools from developed countries, including pensions, endowments, mutual funds and governments. They can be thought of as a large sample of sophisticated international investors. State Street's aggregated, international, settlement data provide us with net and gross international trades on a daily basis, by country, from mid-1994 through mid-1998. We are therefore able to track daily purchases into, and sales out of, 46 countries.

Of course, every transaction can be viewed from the perspective of the buyer or the seller and this makes the behavior of *any* flow data inherently ambiguous. A randomly selected subsample of buys or sells, is, by definition, uncorrelated with similarly obtained subsamples as well as with returns. So portfolio flows in general, and our flows in particular, are interesting only to the extent they identify a group which differs from other investors. For us, large institutional investors domiciled outside of the "local" market are that group. An inflow into the "local" market is defined as any purchase by one of these investors which settles in local currency.[3] This is useful because the profile of these transactions corresponds closely to the generic definition of cross-border flows. Such flows are often thought to respond to similar information (and misinformation), and as already mentioned, to give rise to contagion and excessive volatility in local-market asset prices.

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[2] An important exception to this is Choe, Kho, and Stulz (1998), which examines all trades on the Korean stock market from late 1996 through 1997.

[3] Typically, local-market securities settle in local currency. The most commonplace exceptions are depository receipts which trade and settle in a currency different than the underlying shares. For more details, see the discussion in Section III below.

We put the flow data to work in a number of ways. First, we examine the behavior of flows across countries. We find that there is a small, but significant, correlation in contemporaneous cross-country flows, and that this correlation is larger within regions. Using factor analysis, we then identify a regional factor that summarizes regional flows across countries. The factor explains roughly 40% of flow variation within the region. It also helps remove much individual-country noise.

Second, we characterize the flow data by their persistence. Standard market microstructure models predict that traders with private information reach their desired positions slowly, in order to reduce transaction costs.[4] Thus, the order flow of informed traders will be positively autocorrelated. Furthermore, in models in which informed investors are prevented from borrowing, transactions are (on average) less autocorrelated than uninformed transactions.[5] Empirically, we find substantial evidence that flows are persistent. We also find that gross outflows are more persistent than gross inflows.

Third, we examine the covariance of equity and currency returns with cross-border flows. A major disadvantage of previous studies that use quarterly or monthly data is that they cannot be precise about whether measured covariance is truly contemporaneous. The daily data allow us far greater precision in determining contemporaneous versus non-contemporaneous components of quarterly covariance. We decompose the covariance of quarterly flows and quarterly returns into three components: a) covariance of flows and lagged returns; b) the covariance of contemporaneous flows and returns; and c) the covariance of flows and future returns.

Here we find statistically positive contemporaneous covariance between (net) inflows and both dollar equity returns excess currency returns.[6] The data also reveal strong evidence of correlation between net inflows and lagged equity and currency returns, with the sign generally positive. This is evidence that international investors are "trend chasers." Indeed, trend chasing—interpreted to mean that an increase in today's returns leads to an increase in future flows, without holding current and past inflows constant —seems to explain 60-85 percent of the quarterly covariance between emerging market inflows and returns. The flows are also correlated with future equity and currency returns in emerging markets. The predictability of future currency and equity returns explains between 20 and 40 percent of the covariance of quarterly returns and flows. International investors therefore appear to act on valuable private information on emerging markets.

Interestingly, the data provide no support for the hypothesis that flows into developed countries contain private information. To the contrary, in developed countries we find price pressure or overreaction of price to flow to be the dominant effect: today's inflows predict prices will ease over time. Thus, developed markets appear to have both greater liquidity and greater informational efficiency than emerging markets.

While these findings are themselves provocative, we ask the data to go further. The third component of our investigation re-examines the predictability issue using the full bivariate behavior of returns and flows. This is a worthwhile exercise because the finding that returns predict future inflows may follow from the fact that returns are correlated with *current* inflows and, as noted above, inflows are persistent. In other words, in a world in which flows are autocorrelated and current flows move current prices,

[4] See, for example, Kyle (1985) who derives transaction costs that are quadratic in instantaneous order flow.

[5] See, for example, Perold (1998).

[6] This finding is reminiscent of studies of order flow in other markets. See Warther (1995).

returns will predict flows. Trend-chasing behavior may be more stringently defined as predictability of future inflows *over and above* that implied by past inflows.

Similarly, we show that market indexes—particularly those of emerging markets—react sluggishly to news in that they display high-frequency positive autocorrelation. Given the sluggishness of market indexes, the covariance between contemporaneous inflows and returns suggests that inflows will predict returns. A more stringent test of whether investors are acting on superior information would therefore be to ask whether inflows predict returns *over and above* any predictability generated by past returns.

In the bi-variate VAR we find that returns do help in predicting flows over and above the predictability of past flows. So the "trend–chasing" characteristic of the data meets the more stringent test. Past flows also remain important for predicting future flows once lagged returns are included. However, the statistical significance of lagged returns falls considerably. On the prediction of returns, we are unable to detect statistically that flows have incremental forecasting value over and above lagged returns, although the correlation between flows and returns tends to reduce the power of our tests.

By using the data alone, we can verify association, but not causality. To understand the implications of a specific causal structure, we lay out a simple structural model of flows and returns. In this model, inflows are driven by past flows and past returns, while returns are driven by current and past flows. This model seems reasonably realistic; for example, it endogenizes the commonly-observed autocorrelation properties of index returns. Using the model, we can trace out the dynamic impact on prices and portfolio holdings of exogenous shocks to inflows and returns.

Our main finding here is that the impact of exogenous flows on returns is strongly significant. Furthermore, we find that if the exogenous flow is transitory, prices tend to decline once the inflow recedes. In other words, an exogenous shock to flows appears to generate expectations of additional future flows. The current price increase seems to recognize this, increasing by more in anticipation of further future flows. If the future inflows do not materialize, then prices decline. No actual net outflow is required.

Finally, our data have interesting implications for the recent crisis in Asia. Although we find that international investors appear to have incremental information in Asia generally, we find no evidence that they were more informed than their counterparties during the crisis; indeed, they appear to be marginally less well-informed. In addition, while international investors show signs of trend chasing during the full sample, returns are negative predictors of future inflows during the Asian crisis. Taken together these facts suggest that, during the crisis, the cross-Asian correlation of international inflows is much higher in daily data than would be revealed by looking at lower horizon aggregations.

The rest of the paper is organized as follows. Section II provides a brief summary of related literature. Section III discusses the data in more detail and provides summary statistics and variance ratios of flows. Section IV examines the correlation of returns and flows. It begins by distinguishing several hypotheses of interest, then presents covariance ratios used to test these hypotheses. Our bivariate, vector auto-regressions are then presented in Section IV. Section V concludes.

II. Related Literature

There are two main areas of work on which this paper builds. The closest is the small literature focused on international portfolio flows: Tesar and Werner (1993, 1995); Bohn and Tesar (1996); and Brennan and Cao (1997). These papers document positive contemporaneous correlations between inflows and dollar stock returns. There is mixed evidence of correlation between inflows and developed country exchange rates in Brennan and Cao (1997). Because their papers use quarterly data, there is little consistent evidence of non-contemporaneous correlations.

Brennan and Cao (1997) argue that the contemporaneous correlation between inflows and returns may be attributable to international investors updating their forecasts by more than locals in response to public information about local markets. If international investors' priors are more diffuse than those of locals, i.e., if they have a "cumulative informational disadvantage", then positive information releases will cause asset holdings to be reallocated toward international investors. Brennan and Cao favor this hypothesis because it may also help explain home bias in investor portfolios around the world.[7]

A second explanation for the correlation between inflows and local-market returns is that of shocks to international demand that are unrelated to information. For example, shocks to the risk tolerance of international investors (relative to the risk tolerance of local-market investors) will increase local-stock prices and result in a reallocation of local-market stocks toward international investors. Similarly, exogenous shocks to international investor wealth will generate re-balancing demands that can simultaneously affect ownership patterns and prices.

Shocks to international investor demand suggest that we should observe positive correlation across country inflows. The Brennan and Cao story does not suggest large common components in cross-country flows. The regional component of individual-country flows is best thought of as a supranational or global shock. It seems unrealistic to assume that international investors are at an information disadvantage relative to local market investors with respect to such global shocks. Common shocks to investor demand would more naturally explain regional components in portfolio flows across countries.

Indeed, by identifying the regional factor in flows we can determine whether the remaining idiosyncratic components account for the contemporaneous correlation of returns and flows. If, once the regional factor of flows is removed, there is no remaining contemporaneous correlation between returns and inflows, it suggests that international demand shocks, not shocks to information, better explain the correlation.

Do flows move prices too much, so that they predict returns negatively, or too little, so that they predict returns positively? Here the evidence from international flows is scarce. Clark and Berko (1996) examine Mexico during the late 1980s through the crisis in 1993. They find that unexpected inflows of 1% of the market's capitalization drive prices up by 13%. In spite of the large effect, there is no evidence of non-contemporaneous correlation: the price change is permanent and there is no further predictability.

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[7] Frankel and Schmukler (1996) provide evidence that local market investors have informational advantages over foreign investors during times of crisis. They look at Mexican closed end funds at the time of the crisis and find that changes in net asset values tend to Granger cause changes in fund prices on the NYSE. The implication is that trading by locals in the underlying shares led to informed price changes that were incorporated only afterward in international prices.

There is, of course, a much larger empirical literature examining how the composition of investors impacts prices.[8] Warther (1995) investigates aggregate monthly inflows into mutual funds and the impact they have on stock and bond prices. He finds unexpected inflows (i.e., the shock to inflows beyond that predicted by past inflows) are correlated with contemporaneous returns, but that expected inflows are not. His data suggest that a 1% increase in mutual fund equity assets results in a 5.7% increase in stock prices. He also finds no evidence that such price increases are transitory. A second strand of literature looks at inflows into US mutual funds. Here again there is little evidence of non-contemporaneous correlation between flows and returns.

Finally, there is considerable evidence in other markets that investor flows drive prices. For example, Froot and O'Connell (1997) study catastrophe risk prices and find that fluctuations in investor demand, given the supply of insurable risks, drives prices away from estimates of fair value. Gompers and Lerner (1997) provide similar evidence for private equity. It is worth noting that even if overshooting of prices in response to flows is present, such effects are difficult to discern in short time series samples such as the one used in this paper.

[8] See Stulz (1997) for an excellent revue of these and the international flow issues.

III. Data

a. Flow data

Our flow data differ in a number of respects from those used in previous studies. The data are derived from (and are proprietary to) State Street Bank & Trust (SSB). SSB is the largest US master trust custodian bank, the largest US mutual fund custodian (with nearly 40% of the industry's funds under custody), and one of the world's largest global custodians. It has over $4.0 trillion of assets under custody. SSB records all transactions in the securities they hold in custody.[9] From this database we distinguish cross-border transactions by the currency in which the transactions are settled. For example, transactions that are settled in Thai baht encompass purchases and sales of Thai equities and baht-denominated debt by SSB clients. To produce our data, SSB has extracted all transactions that settle in baht, and removed from them any transactions initiated by Thai investors. Our measure of cross-border flows is therefore that of transactions by non-local SSB clients in local securities.

The data identify daily cross-border flows for 46 countries—18 developed countries and 28 emerging markets.[10] There are over $845 billion in equity purchases and sales. The data separately track daily purchases and sales of both equities and local-currency debt. For each country we have the dollar value of these four measures plus the number of transactions each day. The data begin on August 1, 1994 and continue through May 15, 1998.

Since these data use the market of settlement as a reference point, they differ in a number of ways from data used in previous studies.[11] Other work uses data from the US Treasury, which reports equity and debt purchases by US entities with non-US entities on a quarterly basis. In addition to the higher frequency of our data, the Treasury data may also miss or misreport the transactions of foreign-based firms or intermediaries trading on behalf of US investors. Consider, for example, a US mutual fund family that has received a deposit into one of its international stock funds.[12] If this fund purchases foreign equity directly, then the purchase is reflected in the Treasury accounts. But if the mutual fund transfers the deposit to its affiliate in London, which in turn executes the equity transactions, then the Treasury data will miss the equity purchase. Furthermore, the data may also misidentify the country receiving the inflow. In this example, the inflow from the Treasury's perspective is into the UK, even if the ultimate shares are purchased in other countries.

Our data, improve on this, but also are not perfect. A US mutual fund will show up as the investor in the securities ultimately purchased. If the securities happened to be, say, Thai stocks, then the data will record a US inflow into Thailand. But clearly, if the mutual fund is a "Thai equity" fund, and if the

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[9] OTC derivative contracts are bilateral agreements, and are not processed by a multilateral settlement agency. As a result, records on these contracts may be incomplete in these data.

[10] We divide the 46 countries into 5 regions exhaustively. These are: Latin America (Mexico, Venezuela, Columbia, Peru, Brazil, Argentina, Chile); East Asia (Korea, Hong Kong, Taiwan, Philippines, Indonesia, Singapore, Malaysia, Thailand, Pakistan, India); Emerging Europe (Turkey, Greece, Portugal, Hungary, Czech Republic, Poland); Other Emerging (South Africa, Zimbabwe, Morocco, Egypt, Israel,); and Developed Countries (Spain, Italy, France, Switzerland, Austria, Germany, Netherlands, Belgium, U.K. , Ireland, Denmark, Norway, Sweden, Finland, New Zealand, Australia, Japan, Canada). Other regional groups include World (all regions); All Emerging Markets (Latin America, East Asia, Emerging Europe, and Other Emerging); and All Developed Markets. See Table A-1 in the Appendix.

[11] See Tesar and Werner (1993, 1994), Bohn and Werner (1996), and Brennan and Cao (1997).

[12] See Levich, 1994.

purchase came from deposit made by a Thai resident into that fund, then our data would miss the round-trip nature of the cross-border flow. One can regain some meaning by emphasizing that the investment decision is guided by the investment manager rather than the ultimate beneficiary (if there is distinction between the two). But clearly, any data on cross-border flows will have flaws.[13]

It is also worth noting the consequences of the fact that we observe settlement date rather than trade date. Since the price for trades is set on trade date, we approximate trade date using the settlement date and the settlement conventions of each country.[14] Occasionally trades may settle in more or less time than normal. This adds measurement error to our dating of trades. We try to allow for this by using longer intervals (every-other-day, weekly, etc.) in addition to daily intervals. Our interpretation of the results is that trade-date measurement error cannot explain our findings.

To scale the flows, denoted by $F_{i,t}$, we divide by local market capitalization[15], $M_{i,t}$, so scaled flows are denoted by $f_{i,t} = F_{i,t} / M_{i,t}$. While we observe separate variables for purchases of local equity, sales of local equity, purchases of local-debt, and sales of local debt, we focus primarily on net equity transactions, i.e., purchases less sales.

b. Equity data

We chose broad, well-known equity indices from each country. For instance, many of the indices used to calculate equity returns are the same ones listed in the "Financial Indicators" and "Emerging Market Indicators" sections of the *Economist* magazine. A complete list of the equity indices used is given in Appendix 1.

c. Currency data

We collect daily, currency prices (against the US$) from Datastream. Specifically we use the WM/Reuters time series.

d. Interest rate data

In order to calculate excess currency returns, we collected interest rates from a number of sources. For developed markets we used euro-currency deposit rates from Datastream. For emerging markets the task is far more challenging. These rates are compiled from a number of sources including Bridge Information Systems, DRI, and the International Monetary Fund.

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[13] ADRs are problematic for both SSB and US Treasury data. A purchase by a US resident of an ADR from a local-country investor is a true cross border flow. The US treasury will miss such transactions unless the broker/dealer is from the local market. The SSB data will miss such transactions because they settle in dollars. Of course, net purchases of ADRs lead to transactions in which some intermediary purchases shares in the local market and leaves them with the depository as ADRs. The SSB data will record this as a cross-border flow only if the intermediary is a State Street client, which is unlikely.

[14] In future work, we hope to obtain trade dates from State Street as well.

[15] The market capitalization data are from the International Finance Corporation.

IV. The Behavior of Portfolio Flows

a. Descriptive statistics

Table 1 provides general information about the data. Total transactions (buys plus sells) come to over \$845 billion—\$854 million per day—from over 3.2 million transactions during the sample period. The largest number of these cross-border transactions took place in Japan and the UK followed by Hong Kong and France. While there are 72 transactions on average per day per country, some countries, such as Zimbabwe and Morocco, average one or fewer transactions per day.

Overall, the transactions account for a net average daily inflow of \$130 million into our 46 countries, \$30 million of which went into emerging markets (predominantly Latin America and East Asia), and \$100 million of which went into developed countries. The average trade size ranges between about \$100,000 (Venezuela, Peru, and Turkey) to about \$500,000 (Switzerland and the Netherlands). The standard deviation of trade size is very large for Brazil, for which we have a small number of very large transactions. But for most countries, the average trade size and standard deviation of average daily trade size are a few hundred thousand dollars. We did not exclude or censor any data in our analysis.

b. Factor analysis and the cross-correlation of flows

We begin by looking at the correlation matrix of the daily flows. A "heat map" of the correlations efficiently summarizes over 1,000 correlation coefficients[16] and is shown in Figure 1. It is evident from the figure that the flow correlations are on average slightly positive. They are more positive within some regions, particularly Asia and somewhat positive in Latin America and Developed Countries. The data reject the hypothesis that the cross-correlations are zero. Average correlation coefficients for the world and regions are shown at the bottom of Figure 1. Note how the flow correlations are larger in Asia, and how they have risen in Asia and elsewhere during the Asian crisis period. It is useful to compare Figure 1 with similar heat maps of dollar stock and currency return correlations. These are shown in Figures 2 and 3, respectively. The regional character of stock returns is evident in Figure 2, but this is less so for the currency returns in Figure 3.

As stated in the introduction, it is natural to think of international trades as embodying a regional component, due to shocks to regional information, preferences, or wealth, and a local-market component, associated with local-market information or liquidity. In what follows, we attempt to decompose flows into these components, and to examine the properties of each component separately. In particular, we assume that the flows of each country can be decomposed as:

$$f_{i,t} = \mu_i^f + \beta_i f_t^R + \varepsilon_{i,t}, \tag{1}$$

where μ_i^f is a country-specific mean flow, f_t^R a regional factor, β_i is country i's loading on the regional factor, and $\varepsilon_{i,t}$ is the country-specific portion of time-t flows. The simplest and most natural null hypothesis is that flows are cross-sectionally and serially uncorrelated—i.e., that the regional component f_t^R is zero and the local-market component $\varepsilon_{i,t}$ is uncorrelated over time. This null is implied if the data are drawn from a random selection of buyers and sellers in each country and over time. It is also implied if local information shocks drive portfolio flows. Since local information shocks

[16] The usual estimate for the standard deviation of the correlation coefficient, assuming the variables are normally distributed is $(1-\rho^2)/\sqrt{T-3}$, which in our data is on average 0.034.

can be thought of as orthogonal to regional shocks, then the flows which result from local shocks should be uncorrelated as well.

To effect this decomposition, we first estimate f_t^R using factor analysis (see, Johnson and Wichern (1992) for an example). Specifically, we assume that the correlation matrix of country flows illustrated in Figure 1 can be written as

$$\mathbf{C} = \Lambda \cdot \Lambda' + \Psi , \tag{2}$$

where Λ is a vector of factor loadings, and Ψ is a diagonal matrix containing country-specific variances. From the spectral decomposition of $\mathbf{C}$, we estimate Λ by $\sqrt{\lambda_1}\mathbf{e}_1$, where λ_1 is the largest eigenvalue of $\mathbf{C}$, and $\boldsymbol{e}_1$ is the corresponding eigenvector. The regional factor f_t^R is then recovered as the factor score:

$$f_t^R = (1/\lambda_1)\Lambda'\mathbf{f}_t , \tag{3}$$

where $\mathbf{f}_t$ is the vector of country flows at time t.[17]

Figure 4 provides an example of this regional factor. It shows cumulated inflows into all emerging market countries from August 1994 to May 1998. The factor accounts for net purchases equal to about 1.4% of emerging-market capitalization over the sample. The usefulness of the regional factor measure can be gauged by contrasting its behavior with that of equal- and market capitalization-weighted averages of the flows, which are also shown in Figure 4. For example, very large inflows into Brazil are recorded in the data over a short period in July 1997. These are reflected in a large jump in both the equal- and market capitalization-weighted averages. By contrast, the regional factor exhibits a much smaller jump. The reason is that inflows into Brazil are relatively uncorrelated with other inflows into emerging markets. Accordingly, Brazil receives a relatively small weight in the linear combination f_t^R, and the surge of assets into Brazil has a relatively small impact on the curve.

This property of the regional factor renders it a useful measure of co-movement in flows. The factor does a good job of identifying the Mexican crisis (December 1994–April 1995) and the East Asian crisis (July 1997–January 1998). Both episodes are clearly associated with a strong attenuation of emerging market inflows. It appears that foreign investors held fast during the Mexican crisis, and actually slightly withdrew assets in the midst of the Asian crisis. During the intervening period, these investors increased their exposures to emerging market equities by almost 1% of market capitalization.

As to the long-debated relationship between flows and prices, Figure 5 provides a visually striking piece of evidence. The figure demonstrates that the de-trended regional factor and emerging market equity prices move together at low frequencies. (We later test their tendency to move together at higher frequencies.) The co-movement could, of course, be attributed to either overreaction, information shocks, or demand shocks.

However, it is worth noting that the co-movement is not likely to be attributed to the Brennan and Cao information hypothesis. They stress international investors are at an informational disadvantage vis-à-vis local investors, i.e., that international investors may face a disadvantage in knowing as much about local

[17] Note that we apply the weights to the actual flow data, not to the standardized data.

shocks. But Figures 4 and 5 depict *common* or regional components of flows across these countries. This component clearly moves (strongly) with returns.

Having estimated f_t^R, we project $f_{i,t}$ onto it to generate the orthogonal decomposition shown in (1). The country-specific (or idiosyncratic) component for a given country is just the residual from this regression. To gain a sense of the importance of the factor for regional and country flows, we report the R^2 from the regressions. For each region, Table 2 shows the fraction of total regional variation that is explained by the regional factor, as well as an average across countries of country flows explained by the regional factor. Notice that for local regions such as Latin America, East Asia, and Emerging Europe, the regional factor explains about 20% of the variation of flows for countries within the region.

The factor analysis is used throughout the paper. Because of the large number of countries in the sample, we find is efficient to run tests on regions. In order to aggregate country data to the regional level we use one of the following weighting schemes: i) equal weighting, ii) market cap weighting, or iii) factor weighting.

$$X = \sum_{i=1}^{N_R} \omega_i x_i$$

Where N_R is the number of countries in the region and ω_i is country i's weight. The relevant weights for the market cap weighting and factor weighting are given in Appendix I. Generally, we run tests with all three weighting schemes, but only report one result. The choice of the weighting scheme is not found to drive our results.

c. The persistence of order flow

We next examine the persistence of order flow, using variance ratio statistics as a measure. This statistic compares the variance of daily flows with the variance of flows measured over k = 2, 5, 20, and 60 day intervals. The statistic is given by:

$$VR_i^k = \frac{\sum_{t=k}^{T}\left[\sum_{s=0}^{k-1}\left(f_{i,t-s} - \overline{f}_i\right)\right]^2}{k\sum_{t=1}^{T}\left(f_{i,t} - \overline{f}_i\right)^2} \cdot \left[\frac{T-1}{(T-k-1)(1-\frac{k}{T})}\right] \tag{4}$$

where the last term is a degrees of freedom adjustment. Because of the large number of countries, we report variance ratios only for our designated regions. The statistic reported for each region is a the variance ratios of the factor weighted flow.[18]

Table 3 reports variance ratios of equity trades. The data are arranged in three panels, top, middle, and bottom, showing net flows (buys minus sells), inflows (buys), and outflows (sells), respectively. Heteroskedasticity-consistent standard errors are reported beneath the point estimates.

Several facts come out of the data. First, the flows are very persistent. All of the variance ratios are statistically greater than one. Second, regional flows are persistent at low frequencies as well as at high

[18] We calculated variance ratios using alternative weighting schemes (i.e., equal, market capitalization, etc.) and found broadly similar results to those reported below. We also calculated the variance ratios on a country by country basis. Again, we found very persistent flows, similar to the ones reported.

frequencies. The evidence for this is that the variance ratio statistics increase strongly with horizon. High frequency persistence alone would lead to a leveling off of variance ratios as horizon increases. The finding of low-frequency persistence is important because it implies that our results are not an artifact of dating problems associated with time zone differences or imprecision about trade (vs. settlement) date. Such problems might significantly distort the daily autocorrelation of flows, but they would have only a minor effect on the variance ratios for the 20- and 60-day aggregation values.

Again, it is useful to benchmark these results against similar variance ratios for asset market returns. These are shown in Table 4 for the regions, with countries weighted equally.[19] As previous work has shown, equity market returns generally reveal evidence of high frequency persistence. This is particularly the case in the emerging markets. This is not the case in developed countries today, which show no persistence.[20] As for the currencies, there is not much evidence of high frequency persistence except in East Asia. And in developed countries, there is no statistical evidence of persistence at any horizon. However, the emerging markets show strong persistence in the excess currency returns at longer horizons. This may be a result of the role of governments in setting local exchange rate and interest rate policies.

[19] We also computed market-capitalization weighted variance ratios. As expected, these were on average closer to one and less statistically significant. But equity index returns remained statistically persistent for the emerging countries, and even somewhat so for developed countries.

[20] See Lo and MacKinlay (1990), Froot and Perold (1994), Boudoukh, Richardson, and Whitelaw (1994) for a discussion of the factors behind positive index autocorrelation.

V. The Interaction Between Flows and Returns

In this section we explore the bivariate behavior of flows and returns. Are flows and returns correlated? Do flows forecast returns and vice versa? We begin our exploration by looking at the unconditional covariance between the two data series at various horizons. We then examine their conditional covariances within a vector autoregression framework.

a. The covariance of flows and returns

As described in the introduction, it is known from prior studies that the quarterly covariance of cross-border inflows and equity returns is positive. For example:

$$\operatorname{cov}[r_{i,t}(k), f_{i,t}(k)] > 0 \qquad k \cong 60 \text{ trading days} \tag{5}$$

where $r_{i,t}(k)$ is the k-period return on equity, and $f_{i,t}(k)$ is cumulative sum of daily flows from $t\text{-}k\text{+}1$ to t.[21] Note however that the covariance between k-period returns and flows can be broken down into a series of daily cross-covariances. We can think of the quarterly covariance as being comprised of three components: (a) the covariance between current flows and past returns; (b) the contemporaneous covariance between daily flows and returns, and (c) the covariance between current flows and future returns (or past flows and current returns.) Specifically:

$$\operatorname{cov}\left[r_{i,t}(k), f_{i,t}(k)\right] = \underbrace{\sum_{s=1}^{k-1}(k-s)\cdot\operatorname{cov}\left[r_{i,t-s}, f_{i,t}\right]}_{\text{Component (a)}} + \underbrace{k\cdot\operatorname{cov}\left[r_{i,t}, f_{i,t}\right]}_{\text{Component (b)}} + \underbrace{\sum_{s=1}^{k-1}(k-s)\cdot\operatorname{cov}\left[r_{i,t+k}, f_{i,t}\right]}_{\text{Component (c)}} \tag{6}$$

It is of interest to know which of these components drives quarterly covariance. If (a) turns out to be the largest fraction of quarterly covariance, we can hypothesize that there is trend-chasing behavior driving managers' investment decisions. If (c) is large we might believe that future returns can be predicted on the basis of current flows.

The high frequency of our data allows us to calculate these components separately. However, we would still like to make statistical inferences. In order to achieve this goal simply, we divide the quarterly covariance by k times the daily variance of the flows and in doing so estimate the following "covariance ratio" statistic (or CVR):

$$CVR_i^{\,k} = \frac{\operatorname{cov}\left[r_{i,t}(k), f_{i,t}(k)\right]}{k\cdot\operatorname{var}\left[f_{i,t}\right]} = \frac{\sum_{t=k}^{T}\left[\sum_{s=0}^{k-1}\left(r_{i,t-s}-\overline{r_i}\right)\right]\cdot\left[\sum_{s=0}^{k-1}\left(f_{i,t-s}-\overline{f_i}\right)\right]}{k\sum_{t=1}^{T}\left(f_{i,t}-\overline{f_i}\right)^2} \tag{7}$$

This is reminiscent of the variance ratio statistic used earlier. However, notice that the denominator is not k times the covariance between daily flows and returns, but rather k times the variance of flows. The

[21] Here we define k=1 to be the contemporaneous covariance between flows and returns.

statistic can therefore be thought of as the coefficient from a regression of k-period returns on k-period flows. From the covariance decomposition in (6) it follows directly that:

$$CVR_i^k = \underbrace{\sum_{s=1}^{k-1} \left(1 - \tfrac{s}{k}\right) \cdot \beta(r_{i,t-s}, f_{i,t})}_{\text{Component (a)}} + \underbrace{\beta(r_{i,t}, f_{i,t})}_{\text{Component (b)}} + \underbrace{\sum_{s=1}^{k-1} \left(1 - \tfrac{s}{k}\right) \cdot \beta(r_{i,t+s}, f_{i,t})}_{\text{Component (c)}} \tag{8}$$

where $\beta(r_{i,s}, f_{i,t})$ is the coefficient from a regression of daily returns at time s on daily flows at time t. The formulation of CVR(k) in (8) allows us to easily decompose quarterly covariance and make statistical inference.

Table 5 presents the decomposition of the quarterly covariance of flows and equity returns at the regional level. The first column reports the actual *CVR*-statistic with k set equal to 60 (quarterly decomposition.) For the purposes of inference, the variance of the *CVR*-statistic and its components is estimated from the heteroscedasticity-consistent variances of the daily β estimates.

The first point to note about the tables is that they show clearly the benefit of using daily data instead of monthly or quarterly data. As we can see from Table 5, Panel B, contemporaneous covariance, accounts for *at most* 13% of measured quarterly covariance. We can see that only a third of the quarterly covariance between flows and equity returns can be attributed to the window period from -5 days to +5 days.

Table 5 also shows the decomposition of the lag and lead effects. For both developed markets and emerging markets, it is clear that most of the *CVR*-statistic is due to component (a). As mentioned earlier, the size and significance of component (a) tell a simple story of investor "trend chasing" behavior. In other words, positive local stock market returns result in future local inflows.

For the world overall, there is little predictability of future returns from current flows. However, the world-wide data obscure an important difference between developed and emerging markets. If we concentrate on developed markets only, Table 5 shows evidence that flows predict future equity returns *negatively*. This is particularly true at longer horizons. Such a finding might be evidence of overreaction or price pressure. Emerging markets, on the other hand, indicate that flows predict equity returns *positively*, and seem to do so at short as well as long horizons. Over most time horizons the coefficients are statistically positive.[22] Once again the covariance grows over time, so that an inflow today is associated with a tendency toward positive emerging market returns over many days into the future. This is consistent with the view that international investors may have better marginal information than locals have in emerging markets.[23]

These findings seem inconsistent with the Brennan and Cao view that the positive covariance between emerging market returns and inflow is attributable to international investors' information disadvantage. If local, not global, information shocks drive emerging market returns, then we would not expect to see a large, regional flow component, nor would we expect it to covary strongly with returns, as the top panel

[22] Emerging Europe and Other Emerging are the exceptions here. They behaves differently in a number of contexts, and show the lowest level of flows in Table 1.

[23] Further disaggregation of net trades into buys and sells reveals that essentially all of the predictability of emerging market returns appears to be coming from *outflows*, not inflows.

of Table 5 suggests it does. Moreover, the use of the regional factor (of flows) appears to suggest international investors have a marginal informational *advantage*.

Pursuing this line of thinking one step further, we investigate the covariances of *idiosyncratic* (country specific) portion of flows from equation (1). This is the portion of flows that the Brennan and Cao local-information story emphasizes. Table 6 shows that country specific flows differ from regional factors in several important ways. First, the country-specific flows affect prices less than the regional factor does. Estimated *CVR*s are smaller and less statistically significant than those reported in Tables 5. Second, with a few exceptions, country-specific flows seem unrelated to past returns. Third, idiosyncratic flows have only modest predictive power—positive or negative—for future returns. Overall, the results suggest that idiosyncratic flows behave according to our simplest null hypothesis: that flows are relatively uncorrelated with each other and with returns. This is directly at odds with the Brennan and Cao story, which implies a strong correlation between idiosyncratic flows and local returns.

Tables 7 and 8 are analogous to Tables 5 and 6, except that they focuses on excess currency (not equity) returns. Table 7 results are similar to Table 5 in that flows predict currency returns in emerging markets, but not in developed markets.

b. Vector autoregressions

While the covariance results tell us broadly about predictability, we can learn more about the structure of flows and returns from a vector autoregression. Specifically, we ask two questions: i) do returns predict flows over and above the predictions of lagged flows?; and ii) do flows predict returns over and above the predictions of lagged returns?

One way to address these questions is to consider a simple structural model of flows and returns. Our structural model assumes the following. First, the decision to buy more of a country's equity depends on past inflows and past returns. Past inflows matter because they are correlated with the disparity between price and value, as perceived by investors. This assumes that there is information about future value in informed investors trades. Past returns enter because some investors are not informed and cannot observe inflows. These investors therefore rely on past returns as a proxy for information.

Second, the price set by market makers is a function of current and past inflows. Current inflows positively affect prices because current inflows may contain information about value. However, lagged inflows may also matter. With current inflows given, the larger are past inflows, the more prices have *already* risen. If the past price increase already impounded all of the information into prices, then past order flow should have no further impact on returns and the coefficient on lagged flows should be zero. However, order flow may increase prices temporarily due to transient price pressure. In such a case, prices rise with current inflows, but then decline when the inflow stops. Past inflows will therefore have a negative impact on current returns. Alternatively, if the inflow contains enough information, future prices may continue to rise (as others learn that information) even after the inflow has stopped. In this case, past inflows will have a positive impact on current returns.

This model can be summarized in the following way:

$$\begin{bmatrix} f_t \\ r_t \end{bmatrix} = \begin{bmatrix} \alpha_f \\ \alpha_r \end{bmatrix} + \begin{bmatrix} a\lambda^f(L) & b\lambda^r(L) \\ c\lambda^f(L) & 0 \end{bmatrix} \cdot \begin{bmatrix} f_{t-1} \\ r_{t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ ef_t \end{bmatrix} + \begin{bmatrix} \varepsilon_t^f \\ \varepsilon_t^r \end{bmatrix} \tag{9}$$

where $\lambda^f(L)$ and $\lambda^r(L)$ represent distributed lag operators on lagged flows and returns:

$$\lambda^f(L)f_{t-1} = \sum_{s=1}^{32} \left(\lambda^r\right)^{s-1} f_{t-s} \quad \text{and} \quad \lambda^r(L)r_{t-1} = \sum_{s=1}^{32} \left(\lambda^r\right)^{s-1} r_{t-s} \tag{10}$$

and λ^f and λ^r are decay coefficients to be estimated. ε^f and ε^r represent are the unexpected inflow and shocks to returns; *a* and *b* are respective persistence and trend following parameters for order flow, *e* describes the price impact of unexpected order flow on return, and *c* represents the extent to which price pressure offsets the information content of inflows. Our structural model can be thought of as a restricted (and over identified) version of the following reduced form model:

$$\begin{bmatrix} f_t \\ r_t \end{bmatrix} = \begin{bmatrix} \alpha_f \\ \alpha_r \end{bmatrix} + \begin{bmatrix} \pi_{11}\lambda^f(L) & \pi_{12}\lambda^r(L) \\ \pi_{21}\lambda^f(L) & \pi_{22}\lambda^r(L) \end{bmatrix} \cdot \begin{bmatrix} f_{t-1} \\ r_{t-1} \end{bmatrix} + \begin{bmatrix} u_t^f \\ u_t^r \end{bmatrix}, \tag{11}$$

where the distributed lag is the same as in the structural model. Parameters π_{11} and π_{21} show the incremental predictability of lagged flows for future flows and returns, respectively. Similarly, π_{12} and π_{22} show the incremental predictability of lagged returns for future flows and returns.

The structural model (9) can be recovered from the reduced form model (11) by using the following restrictions:

$$\begin{bmatrix} a & b \\ c & e \end{bmatrix} = \begin{bmatrix} \pi_{11} & \pi_{12} \\ \pi_{21} - \dfrac{\pi_{11}\pi_{22}}{\pi_{12}} & \dfrac{\pi_{22}}{\pi_{12}} \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} u_t^f \\ u_t^r \end{bmatrix} = \begin{bmatrix} \varepsilon_{i,t}^f \\ e\varepsilon_{i,t}^f + \varepsilon_{i,t}^r \end{bmatrix}. \tag{12}$$

We estimate equation (11) using nonlinear least squares equation-by-equation (i.e., without taking account of any correlation between the residuals, u^f and u^r. The results from equation (11) are presented in Table 10. Most of the π coefficients are positive and, for most regions, statistically so. For all countries combined, a 1 basis point increase in today's cross-border holdings is associated with a 0.36 basis point increase in tomorrow's cross-border holdings, and with a 3.50 basis point increase in tomorrow's return. For emerging markets, this latter number is more than four times as large. Similarly, for the world as a whole, a 1 percent increase in today's returns is associated with a 0.02 basis point inflow (relative to market capitalization) and a 4 basis point increase in future returns. For emerging markets, many of these coefficients are statistically greater than zero. The only exception is π_{21}, the incremental impact of flows on future returns. The same basic pattern applies across most regions.

Table 9 reports our estimates of the structural parameters, *a, b, c, e.* Note that the magnitude of coefficient *e* is affected by the fraction of true inflows that are captured by our data. If State Street clients' share of total inflow into developed countries is half of their share into emerging markets, then we would expect the developed countries' coefficient to be twice as large. In any case, our estimates of *e* are positive and statistically significant. The estimate for the world suggests that a positive shock to inflows equal to 1 basis point of capitalization results in a contemporaneous increase in prices of 68 basis points.[24] The corresponding coefficient for developed countries is 90 basis points. Of course, if these State Street's clients account for a fifth of total inflows, then the semi-elasticity is one fifth as big. Even so, this would still be a larger sensitivity to prices than has been previously estimated for flows into US mutual funds.

[24] Note that all countries can simultaneous receive inflows from foreigners, provided that domestics everywhere are behind the corresponding outflows.

The estimates of c are universally negative, with all but one being statistically significant at the 5% level. Note that a negative estimate of c (combined with the positive coefficient e) suggests that temporary inflows result in a temporary price increases. However, this does not mean that inflows forecast returns negatively—inflows are strongly persistent as we have seen, so that it is unlikely that inflows today will subside fully tomorrow. Thus, the information content in inflows—which we have seen to be positive in emerging markets—is a result of fact the current inflows predict future inflows, and future inflows drive up future prices.

This story has interesting implications for crises—such as Mexico and Southeast Asia—in emerging markets. Much debate has focused on whether international investors sold at the beginning or in the midst of the crises. While we have already shown that net sales are small, our last results suggest that prices fall when international inflows subside. Prices, which were rationally high in expectation of further inflows, appear not to be sustainable once the inflows cease. Thus, our estimates of c and e suggest how a fall in emerging market inflows can be associated with price declines.

Given the parameter estimates in Table 9, what is the cumulated impact over time of flows and returns if there is an unexpected shock to flows? Panel B of Table 9 answers this question. It shows the cumulative change in flows and returns over the next 32 days after current flows are shocked by 1 basis point. Cumulated flows increase by 1 to 2 basis points (beyond the initial shock) over that time. Returns, however, increase by a much larger multiple. A 1 basis point shock to flows (i.e., a 1 basis point unexpected inflow) results in a 50 to 400 basis point increase in emerging market returns. Measured in this way, the impact of flows on prices is very large indeed. If State Street's share of the market is even 10%, these numbers represent semi-elasticities of between 5 and 40.

VI. Conclusions

We have used a new source of high frequency data on international portfolio flows to learn about how inflows behave and how they interact with returns. Our findings can be summarized as follows:

1. International portfolio inflows are slightly positively correlated across countries, and are more strongly correlated within regions. The correlation of flows in most regions, and particularly within Asia, rises strongly during the Asian crisis subsample, but not during the Mexican crisis subsample.
2. Inflows and outflows are highly persistent. The persistence is complex in the sense that a shock to inflows today is associated with slightly greater inflows over a long period of time.
3. There is very strong trend following in international inflows. The majority of the co-movement of flows and returns at quarterly or monthly intervals is actually due to returns predicting future flows.
4. There is also some ability for international inflows to forecast returns. In emerging markets, inflows predict on average to positive future returns. The majority of price increases do not occur over a short period of time, such as a few days. Rather prices seem to rise subsequent to inflows for a month or two. The limited time sample of our data prevents us from saying more about such low frequency predictability.
5. In developed markets, inflows do not forecast positive returns. At longer horizons, returns are negative and even statistically so.
6. Transitory inflows lead to partially transitory price increases.
7. The forecasting power of inflows for future returns occurs because current inflows predict future inflows, and future inflows drive up prices.
8. We find little support for the Brennan and Cao hypothesis that emerging market inflows are the result of a cumulative informational disadvantage on the part of international investors about local country conditions. The common factor of inflows within a region seems to positively predict prices and to move contemporaneously with prices. On the other hand, the country-specific factor of flows has little price impact and predicts future returns poorly.
9. Our explanation for the co-movement of returns and flows is that flows contain information about future value. Emerging market prices do not fully appreciate the implication of an increase in inflow for future value, so cross-border trades tend to be "informed". However, price pressure in these markets is substantial, so that a cessation of inflow can reduce emerging market prices. This hypothesis is unable to explain the home bias in international portfolio allocations, but it better fits the facts of flows and returns.

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Table 1

Descriptive Statistics

Cross-border flows from August 1, 1994 to May 15, 1998 representing 990 trading days. The data are derived from (and are proprietary to) State Street Bank & Trust. Daily flows are converted to US$ at the daily exchange rate. Market capitalization weighting is used to calculate the average fraction of buy-sell per day within a region.

Region	Total Equity Buy+Sell (US$ mm)	Total Equity Transactions Buy+Sell (#)	Average Net Equity Buy-Sell Per Day (US$ 000)	Standard Deviation Net Equity Buy-Sell Per Day (US$ 000)	Fraction of Market Capitaliza. Buy-Sell Per Day (bp)	Average Trade Size Buys Only (US$)	Trade Size Standard Deviation Buys Only (US$)
World	845,477	3,273,074	129,866	196,699	0.114	213,066	376,597
All Developed Countries	677,187	2,348,937	99,844	155,819	0.114	270,678	305,605
All Emerging Markets	168,291	924,137	30,022	103,814	0.115	171,210	415,757
Latin America	33,152	129,477	10,912	96,590	0.174	172,779	727,465
East Asia	112,329	661,049	12,483	33,184	0.097	186,337	215,440
Emerging Europe	11,762	76,168	2,144	7,497	0.230	147,514	183,540
Other Emerging	11,048	57,443	4,483	8,020	0.090	171,438	355,813
Australia	28,541	155,097	3,590	13,267	0.126	204,918	136,232
Austria	4,104	23,270	714	4,488	0.215	205,684	344,132
Belgium	4,637	23,421	567	5,523	0.050	222,865	512,391
Canada	19,798	96,735	2,951	35,570	0.067	185,545	293,568
Denmark	5,623	23,145	1,070	4,492	0.150	283,201	276,501
Finland	9,499	37,837	1,544	8,451	0.204	251,876	282,267
France	65,797	192,737	11,478	70,144	0.200	271,499	511,457
Germany	65,989	162,977	8,925	38,358	0.124	372,273	336,734
Ireland	1,908	4,711	589	2,401	0.408	252,406	286,096
Italy	27,985	101,597	4,115	19,861	0.177	225,927	235,143
Japan	178,671	772,749	27,769	65,391	0.080	246,834	156,377
Netherlands	38,000	38,467	4,114	20,183	0.100	467,394	254,158
New Zealand	3,896	25,908	295	4,034	0.088	164,878	162,381
Norway	7,085	13,598	731	4,868	0.169	212,303	169,052
Spain	18,544	65,080	714	11,320	0.034	270,503	282,019
Sweden	32,529	90,152	3,278	16,835	0.181	359,336	250,166
Switzerland	45,316	93,950	5,906	30,555	0.142	457,225	367,692
U.K.	119,265	427,506	21,493	44,760	0.134	263,439	108,504
Argentina	2,095	15,218	220	1,863	0.024	137,148	111,815
Brazil	21,701	57,042	9,570	96,453	0.325	353,988	1,605,136
Chile	152	1,365	114	446	0.016	111,236	100,137
Columbia	468	3,696	57	654	0.044	117,303	100,207
Mexico	7,786	42,569	985	4,715	0.091	171,831	112,631
Peru	697	6,606	-49	698	-0.044	91,739	91,018
Venezuela	253	2,981	14	425	0.017	98,471	123,735
Hong Kong	45,775	211,783	2,528	20,784	0.085	205,965	87,378
Indonesia	7,476	61,736	1,245	3,740	0.195	132,430	78,362
Korea	6,792	33,876	1,856	7,739	0.186	239,344	258,275
Malaysia	20,720	145,081	1,979	10,631	0.093	154,953	119,331
Philippines	5,045	45,667	1,479	3,044	0.253	135,138	99,099
Singapore	15,348	90,714	1,454	7,549	0.112	179,506	106,482
Taiwan	2,025	6,491	469	3,305	0.021	389,942	603,642
Thailand	9,148	65,701	1,473	4,663	0.175	150,029	86,139
Czech Republic	934	5,584	261	1,615	0.369	159,893	244,253
Greece	2,110	14,599	369	3,353	0.185	135,235	156,635
Hungary	785	5,280	114	1,061	0.403	161,904	232,551
Poland	939	8,227	210	1,173	0.402	113,729	103,329
Portugal	4,581	21,014	806	5,758	0.337	209,543	198,076
Turkey	2,412	21,464	384	1,980	0.138	106,805	111,021
Egypt	485	3,618	283	993	0.210	128,911	169,962
India	1,672	9,236	507	2,260	0.036	192,686	213,185
Israel	653	5,507	344	1,044	0.084	121,446	119,219
Morocco	141	1,071	25	350	0.038	132,051	184,752
Pakistan	448	1,922	251	843	0.239	233,801	533,114
South Africa	7,517	35,698	3,051	7,243	0.109	218,688	586,175
Zimbabwe	132	391	22	316	0.106	140,738	243,737

Table 2
Principal Components

This table shows the percentage of total flow variation that is explained by the common factor in each region. Column (a) gives the R-squared from a regression of the market cap-weighted average of all flows within a region on the common factor for that region. Column (b) gives the simple average of the R-squared statistics from regressions of individual country flows on the regional common factor.

Region	(a) R^2 from Regional Regression	(b) Average R^2 from Region
World	0.4686	0.0541
All Developed Countries	0.4853	0.1005
All Emerging Markets	0.2171	0.0685
Latin America	0.2567	0.1755
East Asia	0.7895	0.2159
Emerging Europe	0.5374	0.1878
Other Emerging	0.0031	0.1279

Table 3

Variance Ratio Statistics from Flows

Table 3 shows the variance ratio statistic at lags of 2 through 60 days (sixty days is approximately three months of trading.) Portfolio flows are formed using the common factor from each region. Similar results are found using equal and market cap weighting to form the regional portfolios. The variance ratio statistics use overlapping intervals and are corrected for bias in the variance estimators. Standard errors are asymptotic and heteroscedasticity-consistent

Panel A: Net Flows (Buys - Sales)

Region		VR(2)	VR(5)	VR(20)	VR(60)
World	VR stat	1.522	2.607	6.094	10.095
	s.e.	*(0.05)*	*(0.09)*	*(0.19)*	*(0.32)*
All Developed Markets		1.361	2.179	4.474	7.060
		(0.04)	*(0.09)*	*(0.18)*	*(0.30)*
All Emerging Markets		1.483	2.433	5.385	10.052
		(0.05)	*(0.10)*	*(0.20)*	*(0.34)*
Latin America		1.361	2.125	4.082	7.149
		(0.07)	*(0.14)*	*(0.24)*	*(0.35)*
East Asia		1.452	2.311	4.764	8.172
		(0.06)	*(0.11)*	*(0.23)*	*(0.39)*
Emerging Europe		1.204	1.828	4.186	9.623
		(0.04)	*(0.10)*	*(0.19)*	*(0.30)*
Other Emerging		1.126	1.561	3.656	9.083
		(0.03)	*(0.07)*	*(0.18)*	*(0.31)*

Panel B: Equity Buys

Region					
World	VR stat	1.722	3.567	11.187	26.054
	s.e.	*(0.05)*	*(0.11)*	*(0.23)*	*(0.37)*
All Developed Markets		1.572	3.045	8.905	19.188
		(0.06)	*(0.11)*	*(0.21)*	*(0.34)*
All Emerging Markets		1.667	3.263	9.475	22.324
		(0.06)	*(0.12)*	*(0.24)*	*(0.39)*
Latin America		1.417	2.289	4.055	6.415
		(0.09)	*(0.20)*	*(0.33)*	*(0.43)*
East Asia		1.645	3.189	9.264	22.458
		(0.07)	*(0.14)*	*(0.27)*	*(0.43)*
Emerging Europe		1.378	2.274	4.951	9.037
		(0.05)	*(0.11)*	*(0.20)*	*(0.32)*
Other Emerging		1.150	1.685	4.405	11.615
		(0.03)	*(0.08)*	*(0.18)*	*(0.32)*

Panel C: Equity Sales

Region					
World	VR stat	1.789	3.979	13.332	34.879
	s.e.	*(0.05)*	*(0.10)*	*(0.22)*	*(0.36)*
All Developed Markets		1.560	3.084	9.001	20.461
		(0.05)	*(0.11)*	*(0.22)*	*(0.35)*
All Emerging Markets		1.775	3.842	12.368	33.799
		(0.06)	*(0.12)*	*(0.24)*	*(0.39)*
Latin America		1.443	2.522	6.304	12.904
		(0.05)	*(0.11)*	*(0.23)*	*(0.35)*
East Asia		1.723	3.510	10.573	28.243
		(0.07)	*(0.13)*	*(0.25)*	*(0.40)*
Emerging Europe		1.391	2.526	6.851	17.400
		(0.04)	*(0.10)*	*(0.19)*	*(0.31)*
Other Emerging		1.129	1.272	2.793	5.897
		(0.05)	*(0.10)*	*(0.22)*	*(0.37)*

Table 4

Variance Ratio Statistics from Financial Returns

Variance ratio statistic at lags of 2 through 60 days (sixty days is approximately three months of trading.) Returns are the log daily change of the equity index expressed in USD. Portfolio flows are formed using equal weighting. Results are similar when market capitalization weighting is applied and when simple currency returns are used. The variance ratio statistics use overlapping intervals and are corrected for bias in the variance estimators. Standard errors are asymptotic and heteroskedastically consistent.

Panel A: Equity Indices Returns

Region		**VR(2)**	**VR(5)**	**VR(20)**	**VR(60)**
World	VR stat	1.260	1.539	1.819	2.657
	z-stat	*(3.02)*	*(3.15)*	*(2.70)*	*(3.65)*
All Developed Markets		1.055	1.097	1.076	1.044
		(0.86)	*(0.77)*	*(0.33)*	*(0.12)*
All Emerging Markets		1.342	1.727	2.146	3.442
		(4.23)	*(4.43)*	*(3.71)*	*(5.09)*
Latin America		1.220	1.359	1.484	1.878
		(3.89)	*(2.78)*	*(1.86)*	*(2.14)*
East Asia		1.353	1.654	1.735	2.388
		(4.49)	*(4.08)*	*(2.10)*	*(2.36)*
Emerging Europe		1.195	1.453	1.760	2.089
		(3.37)	*(3.99)*	*(3.53)*	*(3.18)*
Other Emerging		1.136	1.548	2.562	3.913
		(1.92)	*(4.15)*	*(6.86)*	*(8.07)*

Panel B: Excess Currency Returns

Region		**VR(2)**	**VR(5)**	**VR(20)**	**VR(60)**
World	VR stat	1.081	1.222	1.492	1.957
	z-stat	*(1.94)*	*(2.60)*	*(2.60)*	*(2.90)*
All Developed Markets		0.987	1.033	1.081	1.119
		(-0.32)	*(0.39)*	*(0.44)*	*(0.38)*
All Emerging Markets		1.240	1.501	1.993	3.132
		(3.78)	*(3.65)*	*(3.13)*	*(3.92)*
Latin America		1.031	1.133	1.439	1.475
		(0.45)	*(0.80)*	*(1.30)*	*(0.92)*
East Asia		1.306	1.569	1.815	2.674
		(3.49)	*(2.97)*	*(1.82)*	*(2.20)*
Emerging Europe		1.042	1.070	1.073	1.184
		(1.02)	*(0.84)*	*(0.40)*	*(0.60)*
Other Emerging		1.094	1.257	1.934	2.951
		(1.96)	*(2.43)*	*(4.29)*	*(5.28)*

Table 5

Quarterly Covariance Decomposition: Flows and Equity Returns

This table decomposes the covariance ratio statistic for 60-day equity returns against 60-day net equity flows. Portfolio flows are constructed using the factor weights in each region. Equity returns are the market cap. weighted returns for the region. The decomposition is based on Equation (8) in the text. Panel A shows the actual CVR statistic and its components. Panel B shows the composition in terms of percentages.

Panel A: Decomposition of CVR

Region		CVR(60)	(a) Flows and Lagged Returns Days 21-60	Days 6-20	Days 2-5	(b) Contem-poraneous Component	(c) Flows and Future Returns Days 2-5	Days 6-20	Days 21-60
World	CVR	1,344.70	588.44	385.11	195.25	**73.86**	36.68	25.65	39.73
	z-stat	*(9.49)*	*(7.21)*	*(7.91)*	*(8.02)*	***(2.92)***	*(1.34)*	*(0.50)*	*(0.49)*
All Developed Markets		361.78	323.94	194.27	90.38	**18.98**	-17.28	-77.86	-170.64
		(2.73)	*(4.31)*	*(4.20)*	*(4.02)*	***(0.78)***	*(-0.76)*	*(-1.64)*	*(-2.22)*
All Emerging Markets		1,551.00	235.14	372.55	255.67	**102.50**	82.11	130.78	372.25
		(11.86)	*(3.06)*	*(8.31)*	*(11.04)*	***(3.88)***	*(3.28)*	*(3.00)*	*(5.05)*
Latin America		302.56	84.37	80.14	63.14	**10.18**	7.49	37.31	19.93
		(6.86)	*(3.54)*	*(5.24)*	*(6.97)*	***(1.25)***	*(0.97)*	*(2.36)*	*(0.76)*
East Asia		972.84	25.67	276.34	258.82	**125.98**	40.06	52.24	193.73
		(6.35)	*(0.29)*	*(5.32)*	*(10.59)*	***(3.60)***	*(1.34)*	*(0.99)*	*(2.25)*
Emerging Europe		-85.71	-109.13	3.31	16.23	**-3.62**	-0.34	0.68	7.16
		(-1.53)	*(-3.35)*	*(0.16)*	*(1.67)*	***(-0.47)***	*(-0.03)*	*(0.04)*	*(0.22)*
Other Emerging		7,100.30	1,406.17	627.67	-437.54	**16.36**	365.05	1,498.65	3,624.00
		(3.65)	*(1.38)*	*(1.02)*	*(-1.58)*	***(0.07)***	*(1.40)*	*(1.89)*	*(2.93)*

Panel B: Decomposition in Percent Terms

		CVR(60)	Days 21-60	Days 6-20	Days 2-5	Contermp. Component	Days 2-5	Days 6-20	Days 21-60
World	% of Cov	1,344.70	43.8%	28.6%	14.5%	**5.5%**	2.7%	1.9%	3.0%
All Developed Markets		361.78	89.5%	53.7%	25.0%	**5.2%**	-4.8%	-21.5%	-47.2%
All Emerging Markets		1,551.00	15.2%	24.0%	16.5%	**6.6%**	5.3%	8.4%	24.0%
Latin America		302.56	27.9%	26.5%	20.9%	**3.4%**	2.5%	12.3%	6.6%
East Asia		972.84	2.6%	28.4%	26.6%	**12.9%**	4.1%	5.4%	19.9%
Emerging Europe		-85.71				*N.M.*			
Other Emerging		7,100.30				*N.M.*			

N.M. Negeative CVR statistics are not decomposed.

Table 6
Quarterly Covariance Decomposition: Country-Specific Component of Flows and Equity Returns

This table decomposes the covariance ratio statistic for 60-day equity returns against 60-day net equity flows. Portfolio flows are constructed using the country specific component of the flows in each region - see Equation (1) in text. Equity returns are the market cap. weighted returns for the region. The decomposition is based on Equation (8) in the text.

			(a) Flows and Lagged Returns			(b)	(c) Flows and Future Returns		
Region		**CVR(60)**	**Days 21-60**	**Days 6-20**	**Days 2-5**	**Contem-poraneous Component**	**Days 2-5**	**Days 6-20**	**Days 21-60**
World	CVR	141.68	86.37	47.63	35.42	**-1.13**	13.12	-27.81	-11.92
	z-stat	*(1.18)*	*(1.24)*	*(1.11)*	*(1.79)*	***(-0.06)***	*(0.64)*	*(-0.65)*	*(-0.17)*
All Developed Markets		6.07	-64.81	64.78	46.71	**-8.00**	4.77	-67.98	30.60
		(0.05)	*(-0.90)*	*(1.43)*	*(2.13)*	***(-0.38)***	*(0.22)*	*(-1.46)*	*(0.41)*
All Emerging Markets		272.27	68.18	58.64	30.20	**12.28**	11.96	54.07	36.94
		(7.66)	*(3.22)*	*(4.96)*	*(4.89)*	***(1.83)***	*(2.11)*	*(4.65)*	*(1.79)*
Latin America		28.62	4.38	-0.74	-9.58	**-1.77**	4.65	21.83	9.85
		(1.43)	*(0.44)*	*(-0.12)*	*(-2.26)*	***(-0.67)***	*(1.71)*	*(3.60)*	*(0.70)*
East Asia		2,323.50	482.98	315.67	226.75	**178.47**	154.56	149.29	815.75
		(8.16)	*(3.10)*	*(3.37)*	*(4.90)*	***(4.16)***	*(2.43)*	*(1.38)*	*(4.84)*
Emerging Europe		25.42	-58.35	-28.66	14.46	**-8.67**	21.58	35.40	49.67
		(0.44)	*(-1.76)*	*(-1.37)*	*(1.48)*	***(-0.86)***	*(2.18)*	*(1.79)*	*(1.54)*
Other Emerging		357.89	199.32	124.51	43.42	**-30.71**	23.30	17.04	-18.99
		(2.96)	*(2.95)*	*(3.24)*	*(1.83)*	***(-1.12)***	*(1.14)*	*(0.41)*	*(-0.27)*

Table 7

Quarterly Covariance Decomposition: Flows and Excess Currency Returns

This table decomposes the covariance ratio statistic for 60-day excess currency returns against 60-day net equity flows. Portfolio flows are constructed using the factor weights in each region. We use excess currency returns that are market cap. weighted by region. Results do not vary when simple currency returns are used. The decomposition is based on Equation (8) in the text. Panel A shows the actual CVR statistic and its components. Panel B shows the composition in terms of percentages.

Panel A: Decomposition of CVR

Region		CVR(60)	(a) Flows and Lagged Returns Days 21-60	Days 6-20	Days 2-5	(b) Contem-poraneous Component	(c) Flows and Future Returns Days 2-5	Days 6-20	Days 21-60
World	CVR	-107.33	24.14	-3.94	-11.95	**-1.65**	-4.47	-18.93	-90.53
	z-stat	*(-2.58)*	*(0.99)*	*(-0.26)*	*(-1.74)*	***(-0.27)***	*(-0.63)*	*(-1.31)*	*(-3.85)*
All Developed Markets		-123.87	-15.57	-10.25	-3.79	**-1.01**	-7.03	-16.68	-69.55
		(-3.35)	*(-0.71)*	*(-0.76)*	*(-0.60)*	***(-0.18)***	*(-1.14)*	*(-1.33)*	*(-3.32)*
All Emerging Markets		140.05	21.57	31.98	20.51	**4.70**	4.08	12.07	45.15
		(7.59)	*(2.00)*	*(5.01)*	*(6.56)*	***(1.62)***	*(1.32)*	*(1.92)*	*(4.20)*
Latin America		190.78	85.95	28.81	30.05	**3.67**	5.49	24.08	12.73
		(5.53)	*(4.59)*	*(2.42)*	*(4.22)*	***(0.48)***	*(0.86)*	*(1.93)*	*(0.64)*
East Asia		62.85	-33.29	16.03	27.95	**6.90**	-4.88	4.79	45.35
		(2.10)	*(-1.91)*	*(1.55)*	*(5.42)*	***(1.33)***	*(-0.94)*	*(0.48)*	*(2.59)*
Emerging Europe		23.16	14.52	2.44	0.25	**2.25**	-1.05	1.59	3.15
		(1.70)	*(1.80)*	*(0.45)*	*(0.10)*	***(0.89)***	*(-0.55)*	*(0.36)*	*(0.43)*
Other Emerging		-11.10	-3.70	-1.26	0.19	**-0.22**	-0.26	-1.86	-3.98
		(-4.46)	*(-2.60)*	*(-1.45)*	*(0.46)*	***(-0.71)***	*(-0.60)*	*(-2.03)*	*(-2.74)*

Panel B: Decomposition in Percent Terms

		CVR(60)	Days 21-60	Days 6-20	Days 2-5	Contermp. Component	Days 2-5	Days 6-20	Days 21-60
World	% of Cov	-107.33				*N.M.*			
All Developed Markets		-123.87				*N.M.*			
All Emerging Markets		140.05	15.4%	22.8%	14.6%	**3.4%**	2.9%	8.6%	32.2%
Latin America		190.78	45.1%	15.1%	15.8%	**1.9%**	2.9%	12.6%	6.7%
East Asia		62.85	-53.0%	25.5%	44.5%	**11.0%**	-7.8%	7.6%	72.2%
Emerging Europe		23.16	62.7%	10.5%	1.1%	**9.7%**	-4.5%	6.9%	13.6%
Other Emerging		-11.10				*N.M.*			

N.M. Negeative CVR statistics are not decomposed.

Table 8

Quarterly Covariance Decomposition: Country-Specific Component of Flows and Excess Currency Returns

This table decomposes the covariance ratio statistic for 60-day excess currency returns against 60-day net equity flows. Portfolio flows are constructed using the country specific flows from each region. We use excess currency returns that are market cap. weighted by region. Results do not vary when simple currency returns are used. The decomposition is based on Equation (8) in the text.

			(a) Flows and Lagged Returns			(b) Contem-poraneous	(c) Flows and Future Returns		
Region		**CVR(60)**	**Days 21-60**	**Days 6-20**	**Days 2-5**	**Component**	**Days 2-5**	**Days 6-20**	**Days 21-60**
World	CVR	-152.62	-77.85	-32.37	-4.44	**-3.92**	0.75	-8.54	-26.25
	z-stat	*(-2.73)*	*(-2.37)*	*(-1.63)*	*(-0.47)*	***(-0.37)***	*(0.08)*	*(-0.42)*	*(-0.84)*
All Developed Markets		-339.44	-178.10	-59.48	-19.83	**-20.02**	-8.56	-30.78	-22.67
		(-5.04)	*(-4.55)*	*(-2.45)*	*(-1.57)*	***(-1.78)***	*(-0.83)*	*(-1.33)*	*(-0.59)*
All Emerging Markets		8.99	13.59	3.37	2.38	**1.41**	1.57	1.10	-14.43
		(1.23)	*(3.19)*	*(1.42)*	*(1.93)*	***(1.54)***	*(1.99)*	*(0.46)*	*(-3.18)*
Latin America		-14.82	-8.41	-3.34	-2.03	**-0.22**	-0.74	-1.08	1.00
		(-4.59)	*(-4.81)*	*(-2.72)*	*(-2.77)*	***(-0.33)***	*(-1.34)*	*(-0.97)*	*(0.55)*
East Asia		636.71	191.80	79.29	31.74	**12.14**	23.12	47.29	251.34
		(9.31)	*(4.89)*	*(3.37)*	*(2.77)*	***(1.29)***	*(1.97)*	*(2.09)*	*(6.07)*
Emerging Europe		-63.44	-20.51	-9.41	1.76	**-4.12**	-1.35	-10.57	-19.23
		(-3.01)	*(-1.65)*	*(-1.08)*	*(0.45)*	***(-0.99)***	*(-0.46)*	*(-1.61)*	*(-1.70)*
Other Emerging		-150.13	-29.46	-18.75	-9.89	**-9.84**	-7.38	-32.48	-42.33
		(-4.74)	*(-1.56)*	*(-1.69)*	*(-1.71)*	***(-2.05)***	*(-1.43)*	*(-3.08)*	*(-2.33)*

Table 9
VAR Structural Model

Panel A shows the parameter estimates of the following VAR structural model:

$$\begin{bmatrix} f_t \\ r_t \end{bmatrix} = \begin{bmatrix} \alpha_f \\ \alpha_r \end{bmatrix} + \begin{bmatrix} a\lambda^f(L) & b\lambda^r(L) \\ c\lambda^f(L) & 0 \end{bmatrix} \cdot \begin{bmatrix} f_{t-1} \\ r_{t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ ef_t \end{bmatrix} + \begin{bmatrix} \varepsilon_t^f \\ \varepsilon_t^r \end{bmatrix}$$

Panel B shows the impulse response from a 1bp shock to flows. Flows are from the regional factor of net equity flows. Returns are the log daily price change of the regional index in USD. Standard errors are heteroskedastically consistent.

Panel A: VAR Parameter Estimates

Region		a	b	c	e	lf	lr
World	Parameter	0.387	1.0E-04	-12.018	67.789	0.219	0.941
	z-stat	*(9.44)*	*(4.52)*	*(-0.80)*	*(2.50)*	*(2.58)*	*(44.21)*
All Developed Markets		0.226	1.2E-04	-28.961	90.940	0.632	0.660
		(7.85)	*(2.99)*	*(-2.78)*	*(3.50)*	*(11.95)*	*(4.23)*
All Emerging Markets		0.256	4.4E-04	-34.888	300.480	0.516	0.332
		(6.52)	*(5.88)*	*(-3.10)*	*(11.77)*	*(7.28)*	*(2.33)*
Latin America		0.224	5.8E-04	-11.686	81.618	0.596	0.477
		(4.99)	*(4.81)*	*(-3.00)*	*(9.38)*	*(7.73)*	*(3.56)*
East Asia		0.183	5.5E-04	-33.511	253.860	0.664	0.313
		(4.43)	*(5.13)*	*(-2.93)*	*(7.23)*	*(9.18)*	*(2.25)*
Emerging Europe		0.068	3.0E-04	-22.848	358.090	0.917	0.335
		(4.89)	*(3.18)*	*(-5.03)*	*(44.14)*	*(41.26)*	*(1.42)*

Panel B: Impulse Response Function
from a 1bp shock to flows

The table shows the cumulative response of flows and returns to a 1bp shock to flows. A 90% confidence interval around the estimate was obtained through monte carlo simulation. The numbers reported are the cumulative change after initial shock. In the case of returns, the initial 1bp shock to flows has a contemporaneous effect on returns. The magnitude of this effect is parameter "e" from Panel A (above.)

Region		Cumulative Change to Flows (bp)	Cumulative Change to Returns (bp)
World	coef	1.302	52.942
	90% interval	[0.96 , 1.86]	[-32.96 , 163.61]
All Developed Markets		1.607	-58.65
		[1.16 , 2.49]	[-184.96 , 55.86]
All Emerging Markets		2.1168	411.82
		[1.52 , 3.35]	[226.91 , 738.23]
Latin America		1.577	54.3
		[0.93 , 3.51]	[9.66 , 138.02]
East Asia		2.0015	209.96
		[1.24 , 4.25]	[-7.19 , 692.98]
Emerging Europe		2.2309	119.23
		[1.54 , 3.29]	[5.09 , 277.60]

Table 10

VAR Reduced Form Model

This table shows the parameter estimates of the following VAR reduced form model:

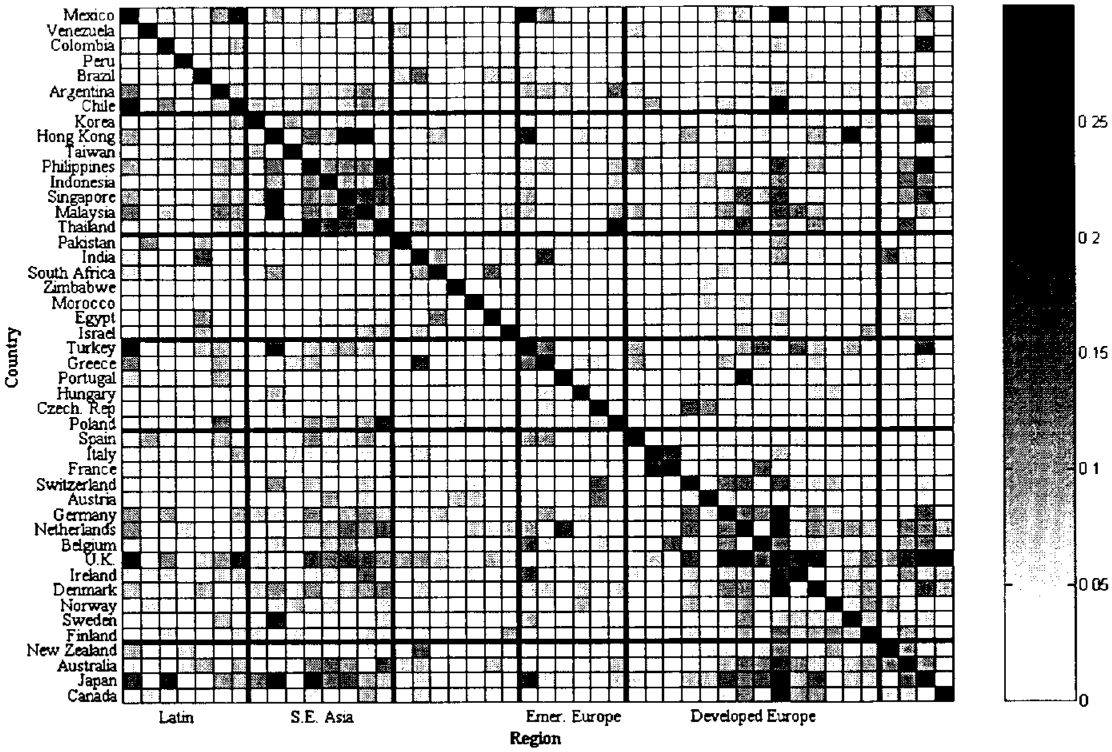
$$\begin{bmatrix} f_t \\ r_t \end{bmatrix} = \begin{bmatrix} \alpha_f \\ \alpha_r \end{bmatrix} + \begin{bmatrix} \pi_{11}\lambda^f(L) & \pi_{12}\lambda^r(L) \\ \pi_{21}\lambda^f(L) & \pi_{22}\lambda^r(L) \end{bmatrix} \cdot \begin{bmatrix} f_{t-1} \\ r_{t-1} \end{bmatrix} + \begin{bmatrix} u_t^f \\ u_t^r \end{bmatrix}$$

Flows are the regional factor of net equity flows. Returns are the log daily price change of the regional index in USD. Standard errors are heteroskedastically consistent.

Panel A: VAR Parameter Estimates

Region		p11	p12	p21	p22	lf	lr
World	Parameter	0.358	2.0E-04	3.503	0.038	0.412	0.544
	z-stat	*(9.15)*	*(4.10)*	*(0.28)*	*(0.89)*	*(6.18)*	*(4.25)*
All Developed Markets		0.224	1.2E-04	-13.170	-0.009	0.633	0.692
		(7.76)	*(3.05)*	*(-1.41)*	*(-0.31)*	*(11.92)*	*(4.89)*
All Emerging Markets		0.317	3.8E-04	16.205	0.239	0.423	0.222
		(7.22)	*(5.11)*	*(1.44)*	*(3.19)*	*(5.70)*	*(1.10)*
Latin America		0.244	5.4E-04	0.925	0.126	0.569	0.276
		(5.29)	*(3.92)*	*(0.28)*	*(1.95)*	*(7.03)*	*(1.43)*
East Asia		0.254	5.0E-04	1.662	0.195	0.506	0.272
		(5.38)	*(4.90)*	*(0.13)*	*(2.27)*	*(6.05)*	*(1.67)*
Emerging Europe		0.082	1.7E-04	-0.562	0.138	0.896	0.303
		(4.32)	*(1.59)*	*(-0.31)*	*(2.83)*	*(30.96)*	*(1.25)*
Other Emerging		0.040	-6.3E-06	40.861	0.095	0.969	0.443
		(3.28)	*(-1.76)*	*(1.14)*	*(1.01)*	*(40.01)*	*(1.45)*

Figure 1: Correlation matrix of daily net equity flows, 7/94-1/98



Correlation coefficients truncated on the interval [0 0.3]

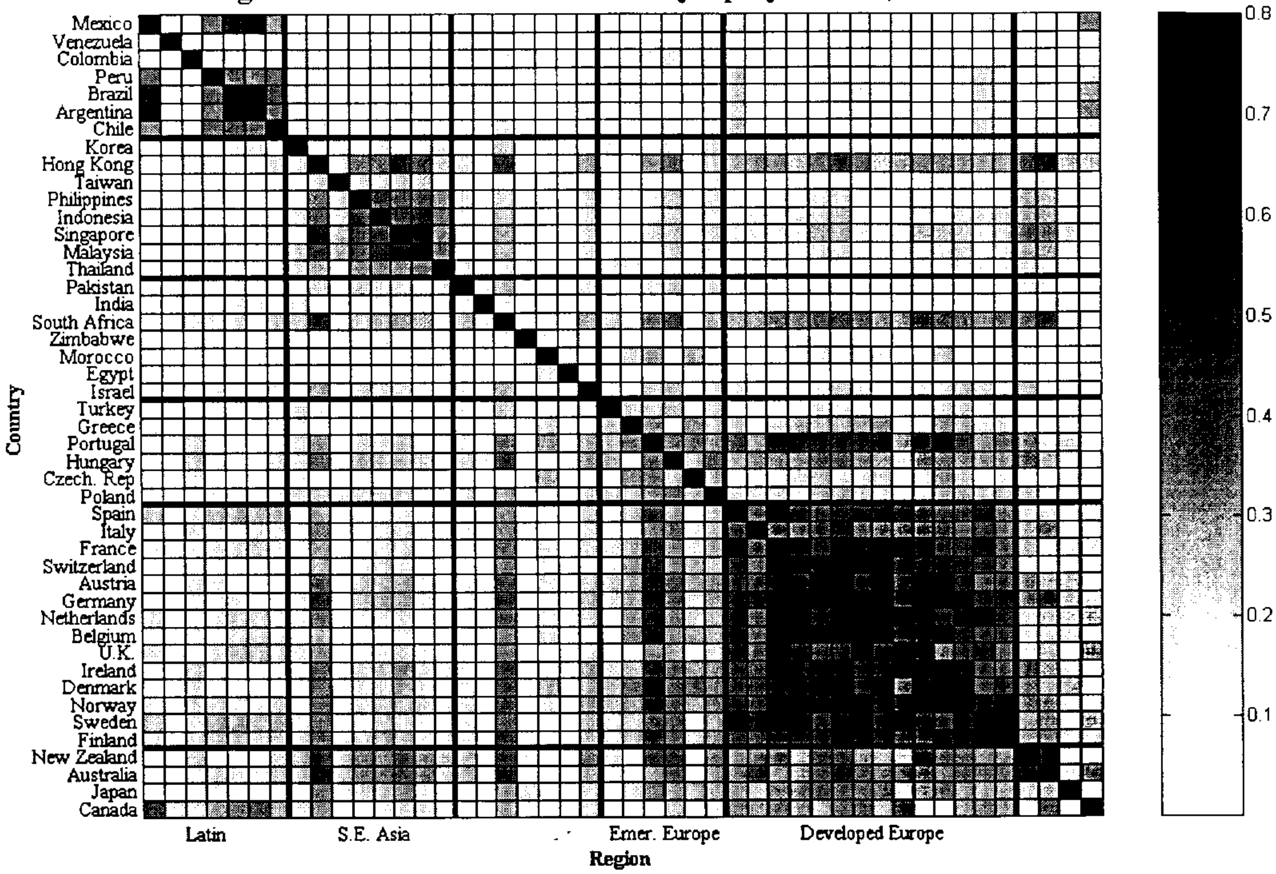
Figure 1 - Continued

Flow Correlation

	Full Sample	Inter-Crisis Sample	Latin Crisis	Asian Crisis
	1-Aug-94 15-May-98	1-Apr-95 30-Jun-97	1-Dec-94 31-Mar-95	1-Jul-97 15-May-98
World	0.0242	0.0261	0.0085	0.0229
All Developed Markets	0.0417	0.0417	0.0016	0.0466
All Emerging Markets	0.0227	0.0256	0.0189	0.0255
Latin America	0.0363	0.0333	0.0175	0.0688
East Asia	0.1006	0.0758	0.0670	0.1214
Emerging Europe	0.0259	0.0228	(0.0063)	0.0631
Other Emerging	0.0044	0.0065	0.0298	(0.0051)

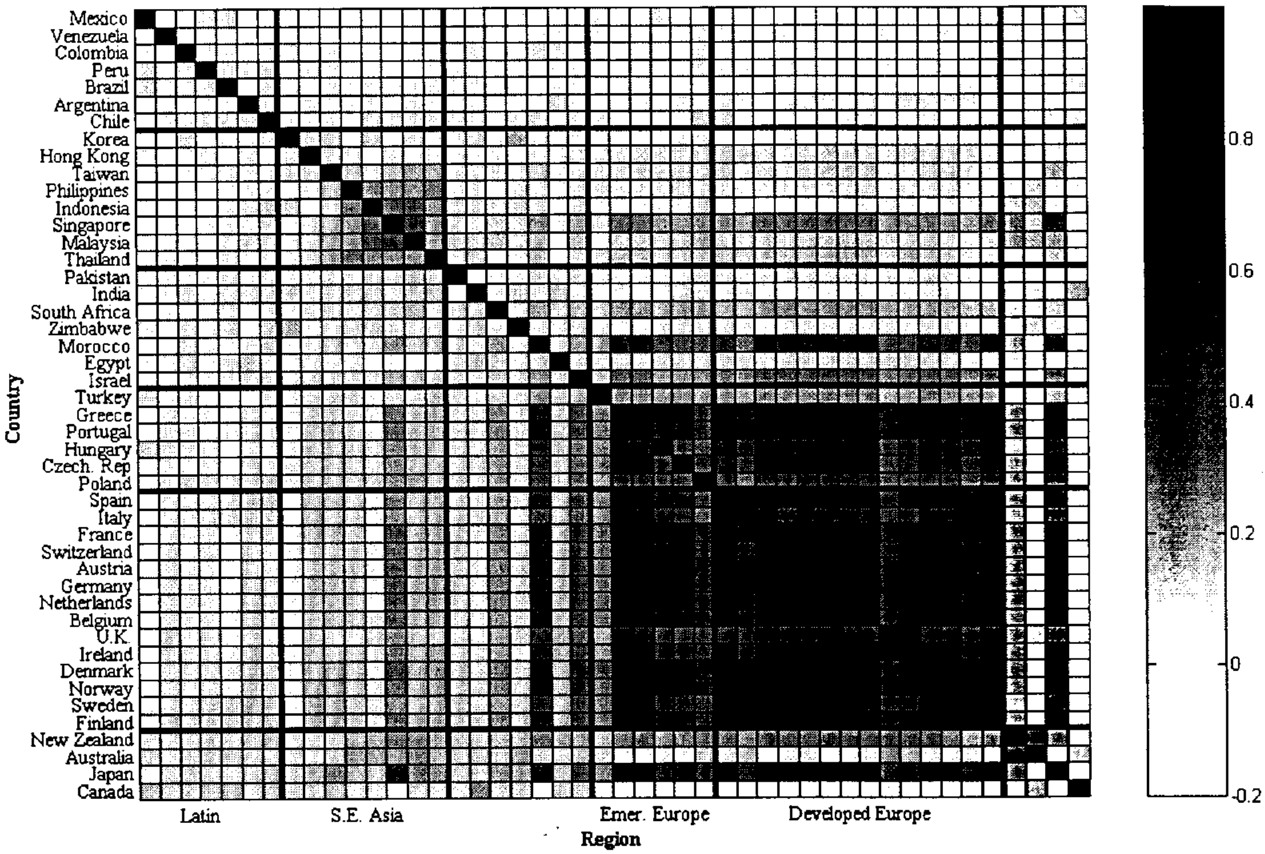
Note: Average correlation coefficient of daily net equity purchases by region. Standard errors, calculated by simulation under the null that flows are i.i.d., reveal that all full-sample estimates (except Other Emerging) are highly statistically significant.

Figure 2: Correlation matrix of daily equity returns, 7/94-1/98



Correlation coefficients truncated on the interval [0 0.8]

Figure 3: Correlation matrix of daily hedged currency returns, 7/94-1/98



Correlation coefficients truncated on the interval [-0.2 1]

Figure 4

Different Weighting Schemes for Flows
(All Emerging Markets)

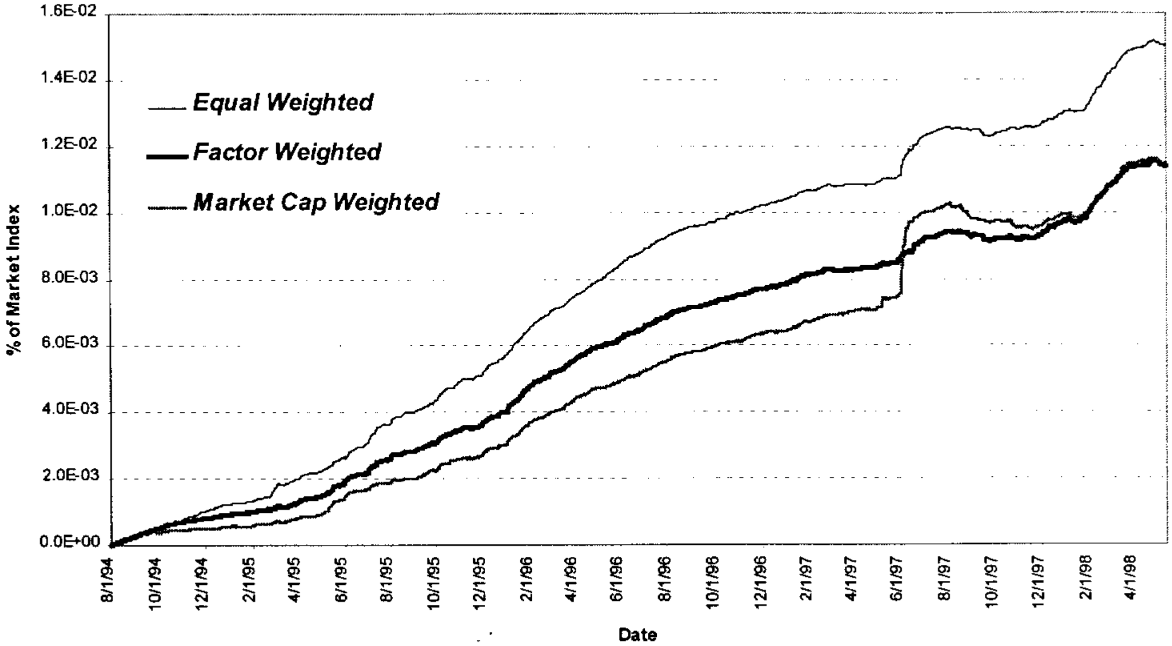


Figure 5

Cummulative Flows and Equity Returns
(All Emerging Markets)

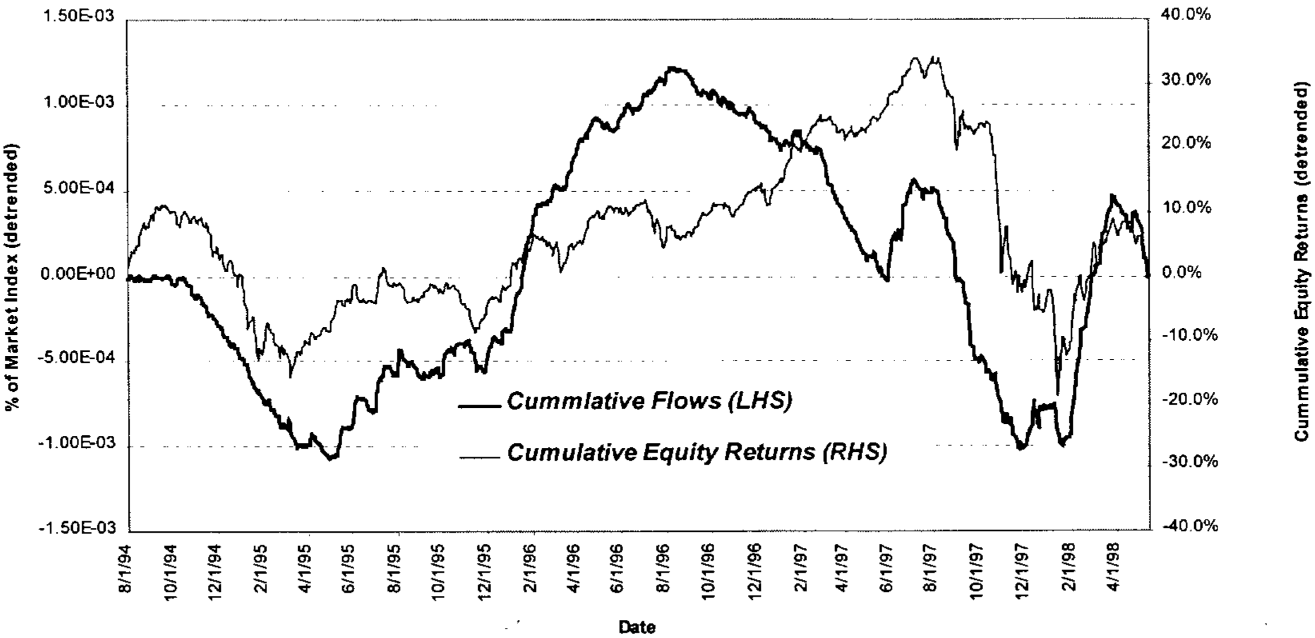


Figure 6

Cummulative Flows and Excess Currency Returns (All Emerging Markets)

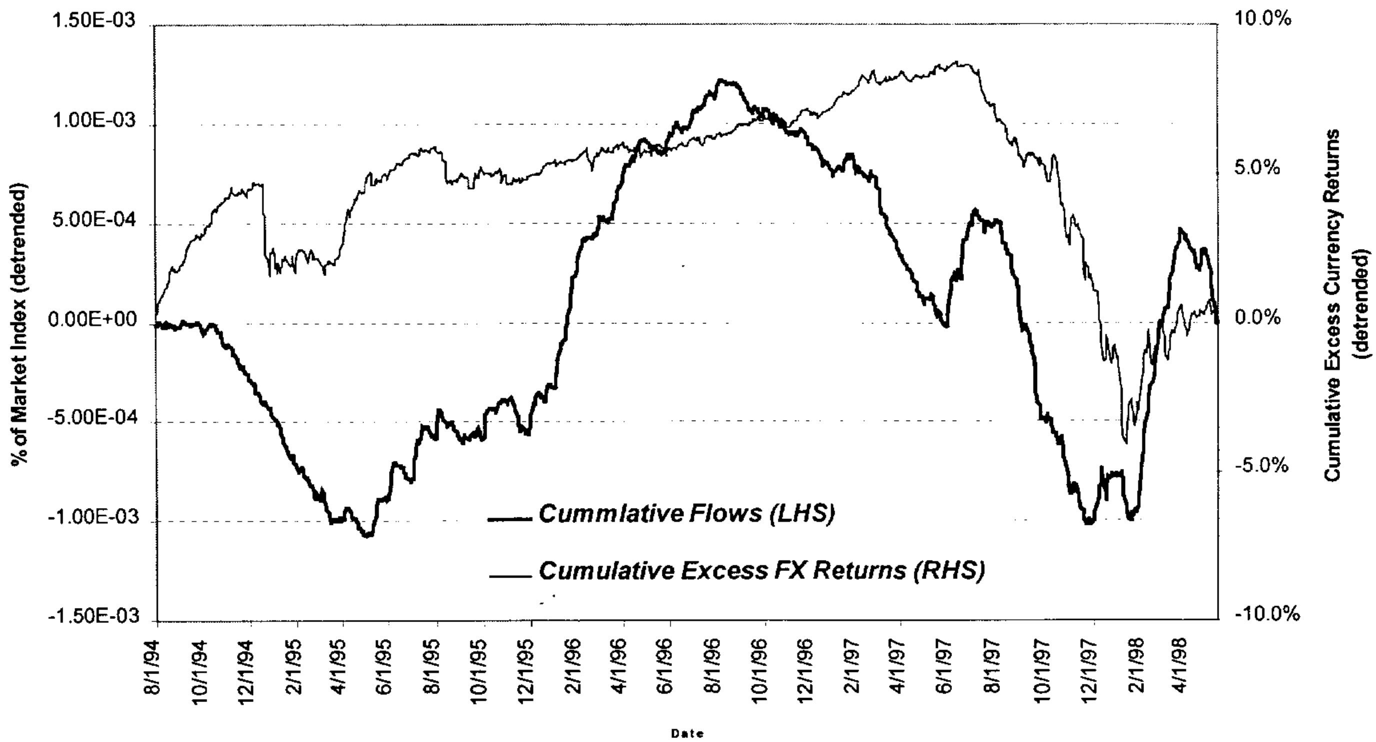


Table A-1
Regional Breakdown; Equity Indices; and Weighting Schemes

TableA-1 lists the countries and their associated regions. For each country the equity index used to calculate returns is also listed. Indices represent either broad market indices, well known indices (i.e. used in the "Financial Indicators" and "Emerging-Market Indicators" section of the Economist), or both.

Regio	Country	Equity Index Used	Mkt Cap Weights as of May 15, 1998	Factor Weights
Developed Markets				
	Australia	AUSTRALIA SE ALL ORDINARY - PRICE INDEX	2.7%	6.7%
	Austria	AUSTRIAN TRADED INDEX - PRICE INDEX	0.4%	1.4%
	Belgium	BEL 20 - PRICE INDEX	1.6%	6.7%
	Canada	TORONTO SE 300 COMPOSITE - PRICE INDEX	5.8%	6.2%
	Denmark	COPENHAGEN SE GENERAL - PRICE INDEX	0.9%	9.0%
	Finland	HEX GENERAL - PRICE INDEX	1.0%	4.8%
	France	SBF 250 - PRICE INDEX	8.2%	0.6%
	Germany	DAX 30 PERFORMANCE - PRICE INDEX	10.5%	7.9%
	Ireland	IRELAND SE OVERALL (ISEQ) – PRICE INDEX	0.2%	3.9%
	Italy	MILAN COMIT GENERAL - PRICE INDEX	4.9%	2.7%
	Japan	NIKKEI 225 STOCK AVERAGE - PRICE INDEX	20.3%	9.1%
	Netherlands	AMSTERDAM EOE (AEX) - PRICE INDEX	5.7%	8.9%
	New Zealand	NEW ZEALAND SE ALL - PRICE INDEX	0.3%	4.2%
	Norway	OSLO SE GENERAL - PRICE INDEX	0.7%	4.3%
	Spain	MADRID SE GENERAL - PRICE INDEX	3.9%	-0.4%
	Sweden	AFFARSVARLDEN WEIGHTED ALL SHR - PRICE INDEX	3.2%	4.5%
	Switzerland	SWISS MARKET - PRICE INDEX	6.7%	7.0%
	UK	FTSE 100 - PRICE INDEX	23.0%	12.7%
Latin America				
	Argentina	ARGENTINA MERVAL - PRICE INDEX	7.8%	17.8%
	Brazil	BRAZIL BOVESPA - PRICE INDEX	51.9%	3.2%
	Chile	CHILE GENERAL (IGPA) - PRICE INDEX	9.4%	23.4%
	Colombia	BOGOTA SE (IBB) - PRICE INDEX	3.0%	14.6%
	Mexico	MEXICO IPC (BOLSA) - PRICE INDEX	23.9%	25.4%
	Peru	LIMA SE GENERAL(IGBL) - PRICE INDEX	2.5%	12.3%
	Venezuela	VENEZUELA SE GENERAL - PRICE INDEX	1.6%	3.2%
East Asia				
	Hong Kong	HANG SENG - PRICE INDEX	36.3%	17.0%
	Indonesia	JAKARTA SE COMPOSITE - PRICE INDEX	1.4%	12.5%
	Korea	KOREA SE COMPOSITE (KOSPI) - PRICE INDEX	5.0%	10.0%
	Malaysia	KUALA LUMPUR COMPOSITE - PRICE INDEX	10.8%	13.0%
	Philippines	PHILIPPINES SE COMPOSITE - PRICE INDEX	4.1%	15.6%
	Singapore	SINGAPORE STRAITS TIMES INDUSTRIAL - PRICE IND	8.7%	15.2%
	Taiwan	TAIWAN SE WEIGHTED - PRICE INDEX	30.2%	10.2%
	Thailand	BANGKOK S.E.T. - PRICE INDEX	3.3%	6.5%
Emerging Europe				
	Czech Republic	PRAGUE PX 50 - PRICE INDEX	7.2%	9.8%
	Greece	ATHENS SE GENERAL - PRICE INDEX	27.0%	29.6%
	Hungary	BUDAPEST (BUX) - PRICE INDEX	4.2%	18.8%
	Poland	WARSAW GENERAL INDEX - PRICE INDEX	4.4%	10.5%
	Portugal	PORTUGAL BVL 30 (REINVESTED) - PRICE INDEX	28.5%	8.5%
	Turkey	ISTANBUL SE NATIONAL - 100 - PRICE INDEX	28.8%	22.7%
Other Emerging				
	Egypt	EGYPT EFG - PRICE INDEX	2.5%	213.7%
	India	BOMBAY SE 30 SHARE SENSITIVE - PRICE INDEX	22.3%	-21.2%
	Israel	TEL AVIV SE MISHTANIM 100 - PRICE INDEX	8.1%	214.5%
	Morocco	MOROCCO SE CFG 25 - PRICE INDEX	2.4%	-187.7%
	Pakistan	KARACHI SE 100 - PRICE INDEX	1.7%	78.6%
	South Africa	JOHANNESBURG SE ALL SHARE - PRICE INDEX	62.8%	-234.5%
	Zimbabwe	ZIMBABWE SE INDUSTRIALS - PRICE INDEX	0.3%	36.6%