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The portfolio flows of international investors☆

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Abstract

This paper explores daily international portfolio flows into and out of 44 countries from 1994 through 1998. We find several facts concerning the behavior of flows and their relationship with equity returns. First, we detect regional flow factors that have increased in importance through time. Second, the flows appear to be stationary, but far more persistent than returns. Third, flows are strongly influenced by past returns, a finding consistent with positive feedback trading by international investors. Fourth, inflows have positive forecasting power for future equity returns, and this power is statistically significant in emerging markets. Fifth, the sensitivity of local stock prices to foreign inflows is positive and large. Sixth, prices seem consistent with flow persistence, in that transitory inflows impact future returns negatively. © 2001 Elsevier Science S.A. All rights reserved.

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1. Introduction

How do international portfolio flows behave? Do flows affect asset 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, and are posed with greater urgency during times of financial upheaval. Frequently, the answers to these questions cast international investors in a poor light. It is often argued that foreign outflows lead to price overreaction and price contagion. An opposing view, espoused most often by financial economists, is that trading is merely the process by which information is incorporated into asset prices. Outflows do not create crises, they merely reflect the underlying state of fundamentals.

While there are numerous strongly held views, there is surprisingly little information on the behavior of international portfolio flows and their relation to local 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 (1994, 1995a,b), 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. Bohn and Tesar (1996) also find evidence that flows are positively correlated with lagged flows, and with contemporaneous and lagged measures of expected returns. However, the low frequency of previously available data is a severe limitation, given the poor statistical precision it permits. Partly as a result of this limitation, few researchers have explored topics related to international flows, such as the frequency and presence of herding or trend-following behavior among investors, or the dynamic interaction of international flows and local asset returns.[1]

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. Their clients 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 year-end 1998. We are able to track daily gross purchases into, and sales out of, as many as 76 countries, although we follow only 44 countries in this paper.

[1] An important exception to this assertion is Choe et al. (1999). Their work examines all trades on the Korean stock market from late 1996 through 1997.

Of course, every transaction can be viewed from the perspective of the buyer or the seller. This duality 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 that they identify a group that differs from other investors. For us, large institutional investors domiciled outside of the local market are that group. In our data, an inflow into the local market is defined as any purchase by a non-local investor that settles in the local currency. (Typically, local-market securities settle in the local currency. The most commonplace exceptions are depository receipts that trade and settle in a currency different than the underlying shares.) This definition of flow 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.

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. We also show how these regional flow factors have grown over time.

Second, we characterize the flow data by their persistence. A variety of market microstructure models predict that traders with private information reach their desired positions slowly, in order to mitigate transaction costs.[2] Thus, the order flow of informed traders is conditionally, and positively, autocorrelated. Institutional factors can also give rise to flow persistence. For example, structural shifts in asset allocation can be undertaken on a phased basis. 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 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 for 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.

[2] Slow incorporation of private information into prices may be the result of informed trader risk aversion, or monopolistic or oligopolistic power. See, for example, Kyle (1985), who derives transaction costs for a single trader which are quadratic in instantaneous order flow. See also Froot et al. (1992), who use large, nonstrategic, risk-neutral traders, for a similar result.

We find a statistically positive contemporaneous covariance between net inflows and both dollar equity and currency returns.[3] The data also reveal strong evidence of correlation between net inflows and lagged equity and currency returns, with the sign generally positive. This pattern suggests that international investors engage in positive feedback trading, also called "trend chasing." Indeed, positive feedback trading behavior, 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% of the quarterly covariance between net inflows and returns. The flows are also correlated with future equity and currency returns in emerging markets. The predictability of future equity returns explains between 15% and 35% of the covariance of quarterly returns and flows. This prediction is consistent with international investors having valuable private information on emerging markets. It is also consistent with a story in which price pressure by international investors, combined with the persistence of their flows, generates return predictability.

Fourth, we examine the conditional relationships between flows and returns. This exercise is worthwhile, 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, returns will predict flows. In this setting, a more stringent definition of trend-chasing would look for predictability of future inflows over and above that implied by past inflows. Alternatively, if current flows move current prices and if prices are positively autocorrelated, as we demonstrate to be true of emerging markets, then inflows are likely to predict returns. This reasoning gives rise to the question of whether inflows can predict returns after conditioning for the effects of past returns.

Using a bivariate VAR model to test these relationships, we find that returns help to predict 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 find that emerging market returns are predicted by the flows, after taking into account past returns. The direction of this effect is the same for developed countries, but with little statistical significance. One possibility is that the noise in flows allows lagged for developed country returns to pick up any predictive element in the flows that is incorporated into past return data.

[3] This finding is reminiscent of studies of order flow in other markets. See Warther (1995). Currency results are presented in Froot et al. (1998).

Of course, by using the data alone, we can only verify association, not causality. To understand the implications of a specific causal structure, we lay out a simple model. In this model, inflows are driven by past flows and past returns, while returns are driven by current and past flows. This specification seems reasonable and useful, and allows us to incorporate the commonly observed autocorrelation properties of index returns as an endogenous feature of the model. Using this tool, 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 contemporaneous 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, a shock to flows appears to generate expectations of additional future flows. The current price increase seems to reflect this expectation, leading to larger increases 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 implications for the recent crisis in Asia. The data reveal that international investors did not abandon emerging markets during the crisis. In fact, they remained net buyers of emerging market equities over the July 1997–July 1998 period, though at a reduced rate. Daily inflows into all emerging markets averaged 40% of their pre-crisis (1994–1997) levels, while for Asia the ratio was 30%. This fact may appear puzzling in view of the steep decline that took place in the equity prices of emerging markets. However, it dovetails with our interpretation of the structural model above. The persistence that characterizes flows suggests that prices in the region had been bid up in anticipation of future inflows. When these inflows failed to materialize, prices declined.

The rest of the paper is organized as follows. Section 2 provides a brief summary of related literature. Section 3 discusses the data in more detail, and provides summary statistics and variance ratios of flows. Section 4 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 5. Section 6 concludes.

2. Related literature

There are two main areas of work on which this paper builds. The closest is probably the small literature focused on international portfolio flows, which includes Tesar and Werner (1994, 1995a,b), 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, they present 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 with greater frequency than local investors in response to public information about local markets. If the prior expectations of international investors are more diffuse than those of local investors, suggesting that international investors have a "cumulative informational disadvantage," then positive information releases will cause asset holdings to be reallocated toward international investors. 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 recent Mexican crisis, and find that changes in net asset values tend to cause changes in fund prices on the NYSE. The implication is that trades in the underlying shares by local investors led to price changes that were incorporated later in international prices.

An open question is whether current flows move current prices too much, such 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 1980 s 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. Instead, the price change is permanent, and there is no further predictability.

There is, of course, a much larger empirical literature examining how the composition of investors impacts prices (see Stulz, 1997, for a review). Warther (1995) investigates aggregate monthly inflows into mutual funds and the impact they have on stock and bond prices. He finds unexpected increases in inflows, which appear to be a 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.

Wermers (1999) examines the extent of herding by institutional investors in U.S. stocks.[4] He finds that there is considerably greater herding in stocks that have experienced extreme returns in the prior quarter, with buy-side herding occurring most often in stocks that had past extreme positive returns, and sell-side herding occurring most often in stocks that had past extreme negative

[4] See also Lakonishok et al. (1992), and Grinblatt et al. (1995).

returns. This finding is reminiscent of our findings of positive-feedback trading. Wermers also finds that stocks that are purchased in herds have higher subsequent quarter returns, and that stocks sold in herds have lower subsequent quarter returns. This finding is consistent with our results in emerging markets, and suggests that the co-movement of contemporaneous flows and prices is attributable to private information on the part of institutional investors. Wermers assumes that the private information is about fundamentals because, like us, he finds no firm evidence of reversals. We would caution against this interpretation, however. If non-fundamental information, like demand shocks, is incorporated relatively quickly into prices, but is dispersed slowly, then standard tests will have little ability to discern private information on fundamentals from price pressure related to flows (see, for example, Hirshleifer et al., 1994).

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 risk-bearing capacity can drive prices away from estimates of fair value. Gompers and Lerner (2000) provide similar evidence for private equity. As noted above, if prices shoot up in response to flows, such effects are difficult to discern in short time series samples of short duration, such as the one used in this paper.

3. Data

Our flow data differ in a number of respects from those used in previous studies. The data are derived from proprietary information provided by State Street Bank & Trust (SSB). SSB is the largest U.S. master trust bank, the largest U.S. mutual fund custodian, with nearly 40% of the industry's funds under custody, and one of the world's largest global custodians. It has approximately $6 trillion of assets under custody. SSB records all transactions in these securities. From this database, we distinguish cross-border transactions by observing 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, transacted 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 44 countries, of which 16 are developed countries, and 28 are emerging markets. We divide the 44 countries into 5 exhaustive categories. These categories are Developed Countries, Latin America, Emerging East Asia, Emerging Europe, and Other Emerging Countries. Developed countries include Australia, Austria, Canada, Denmark, Finland, Germany, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and the U.K. Latin America includes Mexico, Venezuela, Columbia, Peru, Brazil, Argentina, and Chile. Emerging East Asia includes Korea, Hong Kong, Taiwan, Philippines, Indonesia, Singapore, Malaysia, Thailand, Pakistan, and India. Emerging Europe includes Czech Republic, Greece, Hungary, Poland, Portugal, and Turkey. Finally, Other Emerging Countries are Egypt, Israel, Morocco, South Africa, and Zimbabwe. There are two additional groups, World and All Emerging Markets, that aggregate the above categories. World includes all aforementioned regions, and All Emerging Markets includes Latin America, East Asia, Emerging Europe, and Other Emerging countries.

These data contain over $960 billion in equity purchases and sales. The data separately track daily purchases and sales of equities. 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 December 31, 1998.

Since these data use the currency of settlement as a reference point, they differ in a number of ways from data used in previous studies. Other work uses data from the U.S. Treasury, which reports equity and debt purchases by U.S. entities with non-U.S. 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 U.S. investors. Consider, for example, a U.S. mutual fund family that has received a deposit into one of its international stock funds (see Levich, 1994). If this fund purchases foreign equity directly, then the purchase is reflected in the Treasury accounts. But if the mutual fund first transfers the deposit to its affiliate in London, which in turn executes a third-country equity transaction, 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 U.K., even if the ultimate shares are purchased in other countries.

Our data present a significant improvement on this scenario. However, they also share several weaknesses with other sources, and these weaknesses should be kept in mind. First, a U.S. mutual fund will show up as the investor in the securities ultimately purchased. If the securities happened to be, for example, Thai stocks, then the data will record a U.S. inflow into Thailand. But clearly, if the mutual fund is a Thai equity fund, and if the purchase came from a deposit made by a Thai resident into that fund, then our data would misrepresent the foreign source of the flow. As a result, the degree of discretion exercised by the fund manager versus the beneficiary, of unknown origin, is unclear.

A second issue concerns American Depository Receipts (ADRs), and, in a related way, all international equity-linked derivatives. As is well known, ADRs settle in U.S. dollars on a U.S. exchange. So purchases of, say, Thai stock ADRs are not counted in our data as flows into Thailand. However, in most instances there is active arbitrage between the local Thai stocks and the U.S. ADRs. This arbitrage makes available sufficient ADR supply in the U.S. to keep the price essentially equal to that prevailing in Thailand. Thus, net ADR purchases will be funded by some entity going to the local market to buy an equivalent amount of local Thai stock. As a result, the problem with our data is not so much that we leave out ADRs, but that the entity doing the arbitrage is not necessarily a State Street client. Other equity-linked derivatives, including forward, futures, options, and structured notes, raise exactly the same set of issues. The bottom line here is that it is perfectly consistent to measure purchases and sales only of underlying securities, and to exclude derivatives. However, the Achilles heel of this strategy is that small deviations in the makeup of the investor base may result in flows that differ markedly from total flows across all foreign investors.

A third important issue is that we receive the flows dated as of their contractual settlement date, rather than their actual trade date. Since it is the trade date that is of interest, we must construct it by working backward from contractual settlement date. To do this calculation, we use the settlement conventions of each country. These conventions are easily documented, and are detailed in Table 1. As a result, all tests conducted in this paper use trade dates. However, it is very important to emphasize that we record flows on the contractual and not the actual settlement date. While late settlement is a serious problem in many contexts, affecting approximately 10% of developed-country trades and 20% of emerging-market trades, our dating conventions are immune to late settlements, since the contractual settlement date is established at the time of trade according to the settlement conventions of each country. A side effect of this issue is that our data include trades that ultimately fail to settle. Failed settlement affects a very small percentage of trades, and, in any case, it is unclear whether this drawback presents a significant problem for us. The information content and price impact of a trade may be the same regardless of whether it ultimately fails, and failure often occurs after a considerable time lapse. However, to the extent that failed trades engender additional transactions, such failures could result in a slight upward bias in estimates of flow persistence.

A fourth important issue concerns the representativeness of these data, prompting the question of how similar State Street's client trades are to those of other international investors. There are several points to discuss. First, even if a well-defined group of investors is not representative of all international investors, observing the flows that arise from the group's trader can lead to interesting conclusions. For example, the collected flows of the ten smartest, or the ten dumbest, cross-border traders would be interesting to review precisely because they are not representative. What makes a collection of investors interesting, in principal, is that they are relatively more homogenous among themselves than they are with other investors, and that there are interesting interactions between their trades over time, across countries, and with returns.

Second, and not withstanding the previous point, it is still interesting to know how representative the SSB data might be, by comparing the size and magnitude of our flows to cross-border aggregates. Naturally, as we have already discussed, we would not expect perfect correlation. After all, the SSB data account for only

Table 1
Settlement, turnover, and SSB holdings, 1997

This table presents settlement conventions, and a comparison of State Street Bank (SSB) flows and custody holdings with exchange turnover and market capitalization for 1997. Settlement and holdings data are provided by State Street Bank & Trust. Market capitalization and turnover data are taken from the *IFC Emerging Stock Markets Factbook 1999*, for the end-of-year 1997. The correlation coefficient for both stock and flow variables is shown for each region. The first data column presents the settlement period for each country. The "*" indicates different settlement convention for buys and sells, with the first number showing the period for buys and the second number showing the period for sells. The settlement period is used to change data marked with a settlement date to trade date by subtracting the correct number of days. Data shown is for the 1998 settlement period, in U.S. $ millions.

Region	Contractual settlement period	Exchange turnover	SSB gross trades	Exchange market capitalization	SSB holdings
Developed Markets					
Australia	T + 5	310,869	12,149	696,656	24,201
Austria	T + 3	24,630	1,308	35,724	1,047
Canada	T + 3	355,585	7,955	567,635	46,743
Denmark	T + 3	46,878	1,948	93,766	2,045
Finland	T + 3	36,368	3,308	73,322	4,976
Germany	T + 2	1,029,152	25,364	825,233	21,791
Ireland	T + 5	15,168	660	24,135	NA
Italy	T + 5/10*	NA	10,776	344,665	NA
Japan	T + 3	1,251,750	57,938	2,216,699	45,345
Netherlands	T + 3	284,869	15,146	468,736	17,358
New Zealand	T + 5	24,648	1,292	90,483	1,237
Norway	T + 3	46,421	2,351	66,503	1,396
Spain	T + 3	453,016	6,259	290,383	6,788
Sweden	T + 3	176,172	10,614	272,730	9,802
Switzerland	T + 3	494,912	16,577	575,338	21,916
U.K.	T + 5	829,131	43,219	1,996,225	84,373
Correlations:					
Turnover and trades			0.92		
Market capitalization and holdings					0.86
Latin America					
Argentina	T + 3	25,702	685	59,252	614
Brazil	T + 3	203,260	8,404	255,478	1,589
Chile	T + 2	7,445	37	72,046	74
Colombia	T + 3	1,894	227	19,530	71
Mexico	T + 2	52,646	3,360	156,595	1,936
Peru	T + 3	4,033	176	17,586	115
Venezuela	T + 5	3,858	126	14,581	17
Correlations:					
Turnover and trades			0.99		
Market capitalization and holdings					0.87

Table 1 (*continued*)

Region	Contractual settlement period	Exchange turnover	SSB gross trades	Exchange market capitalization	SSB holdings
Emerging East Asia					
Hong Kong	T + 2	489,365	18,330	413,770	7,122
Indonesia	T + 4	41,650	3,200	29,105	362
Korea	T + 2	170,237	2,726	41,881	1,335
Malaysia	T + 5/4*	147,036	6,783	93,608	825
Philippines	T + 4	19,783	1,919	31,361	624
Singapore	T + 5	63,954	4,909	106,317	2,561
Taiwan	T + 1	1,297,474	1,093	287,813	982
Thailand	T + 3	23,119	2,793	23,538	524
Correlations:					
Turnover and trades			0.04		
Market capitalization and holdings					0.80
Emerging Europe					
Czech Republic	T + 3	7,055	321	12,786	236
Greece	T + 3	21,146	885	34,164	1,156
Hungary	T + 5	7,684	375	14,700	151
Poland	T + 3	7,977	422	12,135	232
Portugal	T + 4	20,932	1,946	38,954	1,914
Turkey	T + 2	59,105	964	61,090	769
Correlations:					
Turnover and trades			0.38		
Market capitalization and holdings					0.59
Other Emerging Markets					
Egypt	T + 4/2*	5,859	320	20,830	245
India	T + 5	53,954	737	128,466	666
Israel	T + 0	10,727	285	45,268	279
Morocco	T + 3	1,048	53	12,177	99
Pakistan	T + 7	11,476	205	10,966	63
South Africa	T + 5	44,893	2,950	232,069	2,058
Zimbabwe	T + 7	532	61	1,969	12
Correlations:					
Turnover and trades			0.69		
Market capitalization and holdings					0.97

12% of the world's securities, and we employ a different definition of cross-border flows than used by other sources of aggregated data. In order to understand how representative the data are, we collected monthly net equity flows for Japan and Thailand. Japan was selected because the Ministry of Finance is relatively careful in its collection process, and because the data are available monthly rather than quarterly. Among developing countries, Thailand provides a good example of an emerging market with relatively free capital mobility and currency convertibility.

Fig. 1 compares the monthly net equity flow data from Japan and Thailand with the SSB data set. In the first graph, it is clear that the aggregate inflows recorded by the Japanese Ministry of Finance are highly correlated at the monthly level with the State Street flows. For this comparison, the correlation coefficient is 0.75. Such a high level of flow correlation is striking, particularly for a country like Japan. The rich diversity of foreign investors might lead one foreign investor to trade with another, rather than with local investors, so that trades made by foreign investors, as a group, are less correlated. This scenario is less likely in emerging markets, where diversity of foreign investors is more limited. As can be seen from the lower panel of Fig. 1, the correlation for Thailand is approximately 68%.

To shed further light on the representativeness of the data, we can examine how State Street's trade volume and aggregate holdings compare to local market turnover and capitalization. The first panel of Fig. 2 compares flows by plotting the cross-section of gross State Street trades, aggregating buys plus sells, against total turnover on each country's principal exchange. It is apparent from the figure that the correlation between the two is very high, at 0.89. Panel B of Fig. 2 compares holdings by plotting total State Street custody holdings against the aggregate market capitalization in each country at the end of 1997. Again, the correlation between the two is striking, at 0.91. Table 1 presents the data underlying these figures.

To scale the flows, denoted by $F_{i,t}$, we divide by local market capitalization, $M_{i,t}$, 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, or purchases less sales. To measure equity-market capitalization, we use MSCI indexes for 43 of the 44 countries. The exception is Zimbabwe, for which we employ a broad market index. A complete list of the equity index names is given in Table 2. We obtained daily currency prices against the U.S. dollar, using WM/Reuters rates, from Datastream.

4. The behavior of portfolio flows

In this section, we examine the univariate behavior of the flows.

4.1. Descriptive statistics

Table 3 provides general information about the SSB data set. Total transactions, the aggregate of buys plus sells, sum over $960 billion, from over 3.8

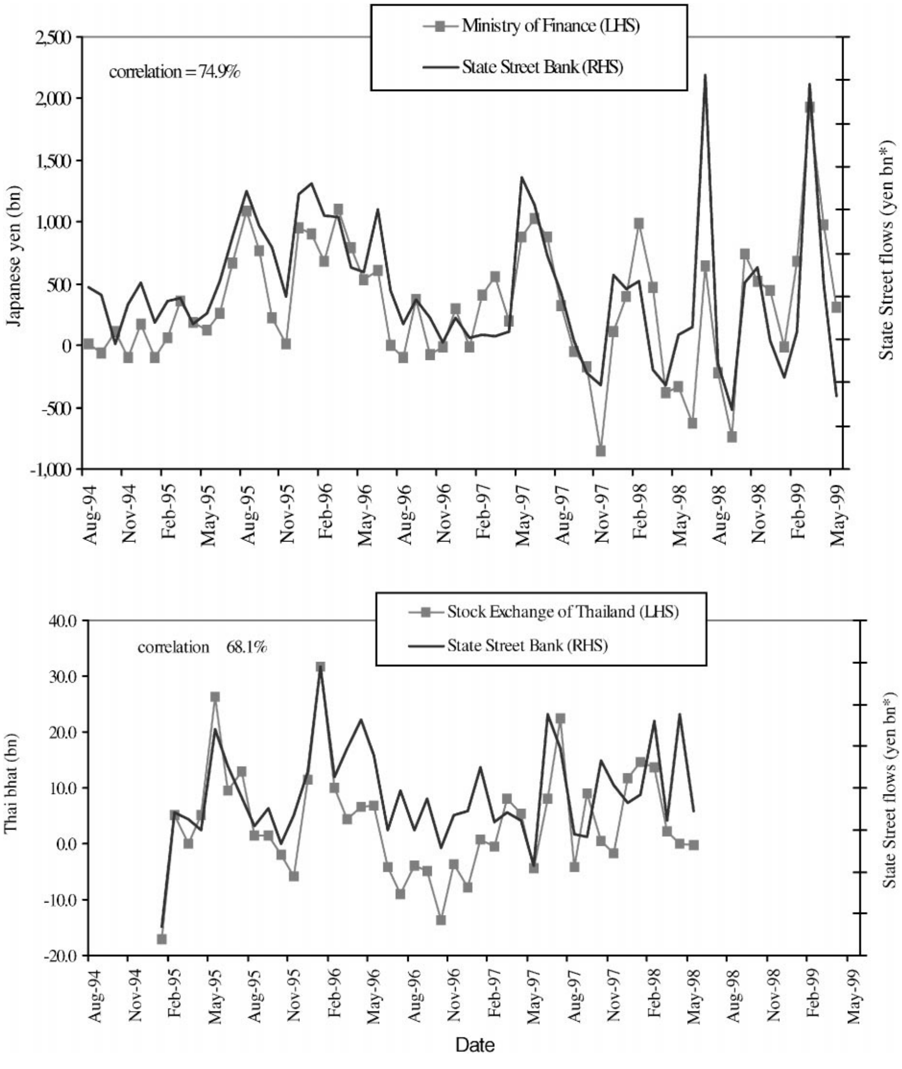

Fig. 1. Comparability of State Street data. The cross-border trades by institutions that use State Street Bank & Trust are representative of all cross-border flows into a given market. Below are two graphs that compare the net monthly flows, calculated as buys less sells, from State Street's clients with flows reported by an entire market. The first graph uses data provided by the Ministry of Finance in Japan. The second graph uses data from the Stock Exchange of Thailand. Both sources track all foreign flows into and out of the local stock markets. The data series have correlation coefficients of 74.9% and 68.1%, respectively, within the State Street data.

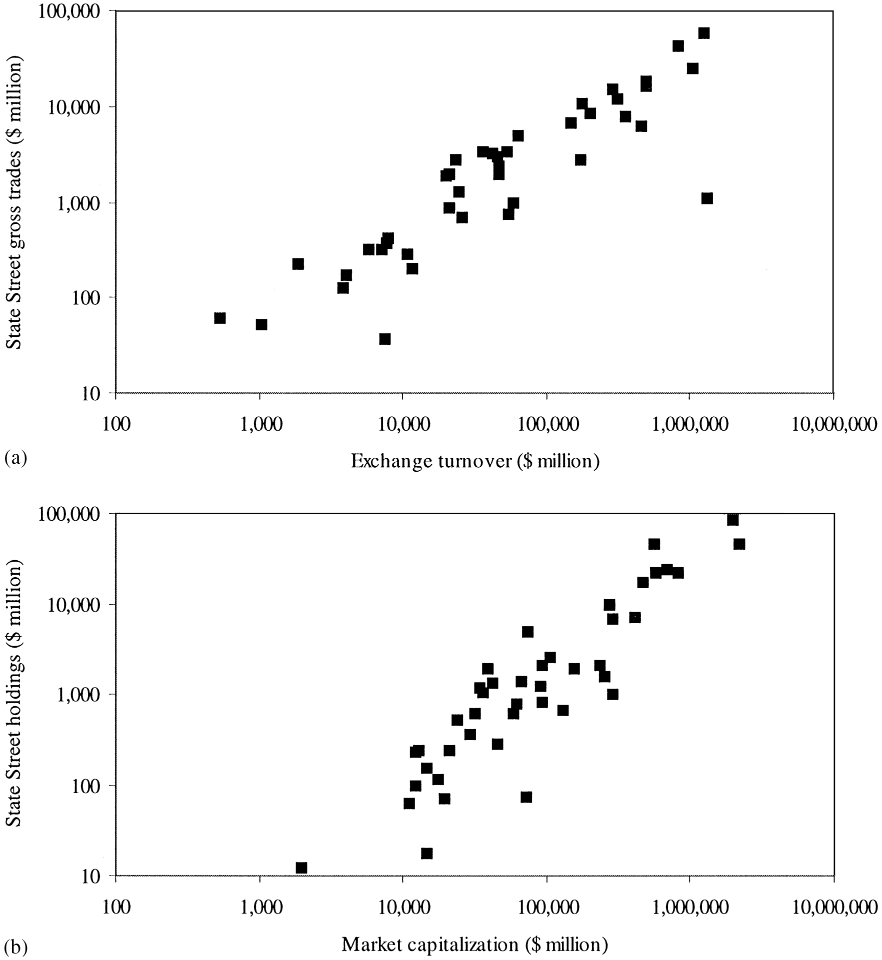

Fig. 2. Worldwide stock market turnover and capitalization compared to State Street trades and holdings. The first figure plots 1997 stock exchange turnover by country, against total cross-border trades, aggregating buys plus sells, in 1997 by clients of State Street Bank. All data are in $U.S millions. The data from this graph are from State Street Bank and the IFC. This plot corresponds to the first two data columns in Table 1. The second figure plots 1997 stock exchange market capitalization by country against total holdings of foreign equities in 1997 by clients of State Street Bank. All data are in $U.S. millions. The data for the second graph are from State Street Bank and the IFC. This plot corresponds to data columns three and four in Table 1. Note: Ireland and Italy are not shown. *Panel A: State Street gross trades vs. stock exchange turnover Panel B: State Street gross holdings vs. exchange market capitalization.*

million transactions during the sample period. The daily average of total transactions during the sample period is $832 million. The largest number of these cross-border transactions took place in Japan, followed by the U.K. and Hong Kong. While there are 76 transactions on average per day per country,

Table 2
Regions, countries, and indexes

This table shows the regional grouping of countries used in this paper. By grouping the countries into regions, we can compare trends in different types of markets. A major comparison category used is developed markets vs. emerging markets. Emerging markets, as a category, aggregates Latin America and all other emerging market categories. This table also shows the equity index used. In every case except Zimbabwe, the index is from Morgan Stanley (MSCI). The index is in local currency and is converted to $U.S. by multiplying by the appropriate exchange rate. Exchange rates are from the WMR/Reuters database, and are obtained through Datastream.

Region	Equity index
Developed markets	
Australia	MSCI – Australia Price Index
Austria	MSCI – Austria Price Index
Canada	MSCI – Canada Price Index
Denmark	MSCI – Denmark Price Index
Finland	MSCI – Finland Price Index
Germany	MSCI – Germany Price Index
Ireland	MSCI – Ireland Price Index
Italy	MSCI – Italy Price Index
Japan	MSCI – Japan Price Index
Netherlands	MSCI – Netherlands Price Index
New Zealand	MSCI – New Zealand Price Index
Norway	MSCI – Norway Price Index
Spain	MSCI – Spain Price Index
Sweden	MSCI – Sweden Price Index
Switzerland	MSCI – Switzerland Price Index
U.K.	MSCI – U.K. Price Index
Latin America	
Argentina	MSCI – Argentina Price Index
Brazil	MSCI – Brazil Price Index
Chile	MSCI – Chile Price Index
Colombia	MSCI – Colombia Price Index
Mexico	MSCI – Mexico Free Price Index
Peru	MSCI – Peru Price Index
Venezuela	MSCI – Venezuela Price Index
Emerging East Asia	
Hong Kong	MSCI – Hong Kong Price Index
Indonesia	MSCI – Indonesia Free Price Index
Korea	MSCI – Korea Price Index
Malaysia	MSCI – Malaysia Free Price Index
Philippines	MSCI – Philippines Free Price Index
Singapore	MSCI – Singapore Free Price Index
Taiwan	MSCI – Taiwan Price Index
Thailand	MSCI – Thailand Free Price Index

Table 2 (*continued*)

Region	Equity index
Emerging Europe	
Czech Republic	MSCI – Czech. Republic Price Index
Greece	MSCI – Greece Price Index
Hungary	MSCI – Hungary Price Index
Poland	MSCI – Poland Price Index
Portugal	MSCI – Portugal Price Index
Turkey	MSCI – Turkey Price Index
Other emerging markets	
Egypt	MSCI – Egypt Price Index
India	MSCI – India Price Index
Israel	MSCI – Israel Price Index
Morocco	MSCI – Morocco Price Index
Pakistan	MSCI – Pakistan Price Index
South Africa	MSCI – South Africa Price Index
Zimbabwe	Zimbabwe SE Industrials Price Index

our least active countries, Zimbabwe and Morocco, average only about one transaction per day.

Overall, the transactions account for a net average daily inflow of \$96 million, or approximately \$2.2 million into each of our 44 countries. This comes from \$20 million into emerging markets, predominantly into Latin America and East Asia, and \$77 million into developed countries. The average trade size ranges between about \$100,000, for Venezuela, Peru, and Turkey, to about \$450,000 for Switzerland, Germany, 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 in the spring of 1997. 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.

Table 4 shows these same descriptive measures for the Tequila and Asian crises. The rapid growth of the flows plus the longer Asian crisis leads to total flows that are nearly an order of magnitude larger for the latter subperiod, when compared to the overall flow data. In addition, average trade sizes, particularly those in emerging markets, have grown considerably since the prior subperiod.

4.2. The cross-correlation of flows

We begin by looking at the correlation matrix of the daily flows. Fig. 3 shows a "heat map" of these correlations, efficiently summarizing nearly 1000 correlation coefficients. Table 5 also provides average pairwise correlation coefficients by region. It is evident from the figure and table that the flow correlations are small, but consistently positive. The data strongly reject the hypothesis that the cross correlations are zero. In addition, the correlations are more positive within regions, particularly in Asia and the European Developed Countries, and somewhat in Latin America.

It is also useful to compare Fig. 3 with a similar heat map of stock return correlations, all reported in U.S. dollars. These stock return correlations are shown in Fig. 4. The regional character of stock returns is far more evident in Fig. 4, such that even a small amount of regionalism in flows appears associated with very strong regional return patterns. Note that countries with the lowest flow correlations with other countries, like the middle-eastern countries, also appear to have the lowest return correlations.

It is also interesting that the regional correlations of flows have increased substantially over time. This pattern is very noticeable in the Asian crisis period, in comparison with the Tequila crisis in Latin America in late 1994 and early 1995. The correlation coefficients can be seen in Table 5, which shows substantial increases in every region during the Asian crisis. Note, however, that it is possible that some of this increase may be attributed to the higher volatility of returns during that period (see Forbes and Rigobon, 1999). We doubt this effect is substantial, however, because return correlations and volatility also increased substantially in the Tequila crisis period. As a result, it appears that the importance of regional flow factors have indeed increased over time.

In view of these regional factors, it is worth comparing how these factors appear across regions. This comparison is presented in Fig. 5. Fig. 5 depicts cumulative inflows into each of the two major regions, Developed and Emerging, while Panel B of Fig. 5 graphs the two most important emerging regions, East Asia and Latin America. All series are market-capitalization weighted averages of the underlying country flows.

The figures serve to make several points. First, over the sample period, SSB investors purchased the same amount, approximately 1%, of both emerging-market and developed-country capitalization. Second, the timeline helps discern that there are actually three crisis periods during this sample, which are the Mexican peso "Tequila" crisis, the Asian crisis, and the Russian/LTCM crisis. These crises are clearly visible in both the emerging and developed country inflows. The Tequila crisis begins with Mexico's sudden devaluation in December 1994, and continues through the Spring of 1995. The Asian crisis begins with Thailand's devaluation in July 1997, and continues through the Spring of 1998. Finally, there is a crisis in late Summer 1998, with Russia devaluing the ruble in August and LTCM failing in September. All crisis episodes are clearly associated with a strong attenuation of inflows in general, and of emerging market inflows in particular. It appears that foreign investors held fast during the Mexican crisis, slightly withdrew some resources in the midst of the Asian crisis, and were hardly fazed by the Brazilian crisis. Interestingly, the LTCM failure

Table 3
Descriptive statistics for internal flow data

The sample consists of cross-border equity flows from August 1, 1994 to December 31, 1998 representing 1,154 trading days. The data are derived from proprietary data provided by State Street Bank & Trust. Daily flows are converted to $U.S. at the daily exchange rate. The first two data columns report the total volume of trades in $U.S. millions and number of trades. The third, fourth, and fifth data columns report net trading activity, in $ 000, where net trading is defined as buys minus sells. Data column five divides the net amount traded each day by the previous day's market capitalization to produce a unitless number, which we report in basis points or hundredths of a percent. The average fraction of net trades per day within a region is the simple average of countries within the region. The final two columns report the average daily trade size and the associated standard deviation. A list of countries and regions is given in Table 1.

Region	Total equity	Total equity transactions	Average daily net equity	Standard deviation	Daily net trades to market cap.	Daily average trade size	Standard deviation
Panel A: Regional aggregates							
World	961,270	3,870,000	97,260	169,750	0.112	215,870	298,940
Developed countries	768,870	2,748,100	77,643	143,390	0.116	289,080	296,820
All emerging markets	192,400	1,121,900	19,617	61,168	0.110	160,690	288,490
Latin America	33,213	162,850	3,486	42,511	0.036	154,730	317,610
Emerging East Asia	127,930	773,990	10,077	35,755	0.112	168,690	189,790
Emerging Europe	16,716	104,380	2,051	8,404	0.214	148,110	180,420
Other emerging	14,543	80,644	4,003	8,281	0.094	169,770	485,320
Panel B: Individual countries							
Argentina	2,387	17,834	139	1,869	0.039	137,740	219,660
Australia	34,063	187,720	2,954	13,619	0.066	201,640	131,900
Austria	5,314	28,713	342	4,643	0.108	204,760	274,760
Brazil	19,962	74,621	2,434	41,873	0.104	243,720	615,000
Canada	25,691	110,090	1,782	15,341	0.040	246,680	241,400
Chile	169	1,508	100	432	0.014	129,110	217,300
Columbia	494	4,075	43	616	0.027	119,230	135,030
Czech Republic	1,141	6,814	141	1,584	0.079	173,540	239,790
Denmark	7,135	29,127	610	4,798	0.098	284,750	315,450
Egypt	636	5,109	255	983	0.166	135,710	159,420
Finland	12,901	50,664	1,183	9,406	0.155	277,890	316,810

Germany	87,795	217,210	7,237	39,268	0.102	398,610	329,810
Greece	3,392	20,458	418	4,424	0.158	140,870	154,310
Hong Kong	53,931	254,660	1,093	25,234	0.034	204,550	102,620
Hungary	1,084	7,394	158	1,173	0.356	159,530	243,640
India	2,117	11,581	366	2,358	0.024	186,700	206,910
Indonesia	7,664	65,978	1,078	3,503	0.158	110,780	77,368
Ireland	1,007	8,679	238	1,477	0.058	127,030	135,430
Israel	2,545	13,800	681	2,469	0.385	223,950	354,730
Italy	38,362	132,760	4,349	21,247	0.161	244,030	277,890
Japan	209,180	911,850	26,413	74,969	0.081	237,890	136,970
Korea	8,662	45,611	1,838	7,649	0.170	212,300	223,730
Malaysia	21,438	158,160	1,648	10,117	0.067	143,090	105,300
Mexico	9,158	53,843	809	4,907	0.076	168,660	127,720
Morocco	227	1,692	− 11	462	0.013	161,500	217,370
Netherlands	51,542	124,560	3,240	21,997	0.082	412,660	252,490
New Zealand	4,654	32,445	177	3,906	0.050	167,080	179,360
Norway	8,456	41,316	549	5,051	0.128	239,510	379,950
Pakistan	509	4,722	231	846	0.210	129,380	277,270
Peru	760	7,447	− 60	666	− 0.033	104,720	125,860
Philippines	5,459	53,264	1,221	2,946	0.186	108,720	88,647
Poland	1,286	11,678	191	1,197	0.263	111,160	101,000
Portugal	6,667	30,636	830	5,991	0.313	202,490	188,860
Singapore	17,913	110,290	1,325	7,426	0.100	170,100	109,320
South Africa	9,906	47,724	2,907	7,320	0.116	245,270	973,750
Spain	24,207	83,109	882	12,044	0.040	303,280	399,290
Sweden	39,956	115,010	1,673	17,373	0.116	367,770	252,240
Switzerland	60,376	121,040	4,482	40,560	0.116	484,990	381,600
Taiwan	2,930	10,084	580	3,830	0.025	337,850	492,340
Thailand	9,932	75,945	1,295	4,413	0.154	133,600	82,260
Turkey	3,146	27,395	313	2,217	0.113	104,990	108,830
U.K.	156,700	548,700	21,090	45,590	0.128	284,090	120,260
Venezuela	285	3,521	22	419	0.025	95,411	130,360
Zimbabwe	143	1,137	18	298	0.077	122,430	221,060

Table 4

Descriptive statistics during the full sample, Tequila and Asian crisis periods

The sample consists of cross-border equity flows from August 1, 1994 to December 31, 1998 representing 1,154 trading days. Here, the data are broken up into different time periods. Specifically, the focus is on recent periods of market turbulence. The data are derived from proprietary data provided by State Street Bank & Trust. Daily flows are converted to $U.S. at the daily exchange rate. The first two data columns report the total volume of trades, in $ millions, and number of trades. The third, fourth, and fifth data columns report net trading activity, in $ thousands, where net trading is defined as buys minus sells. Data column five divides the net amount traded each day by the previous day's market capitalization to produce a unitless number which we report in basis points or hundredths of a percent. The average fraction of net trades per day within a region is the simple average of countries within the region. The final two columns report the average daily trade size and the associated standard deviation. A list of regions and countries is given in Table 1.

Region	Total equity	Total equity transactions	Average daily net equity	Standard deviation	Daily net trades to market cap.	Daily average trade size	Standard deviation
Panel A: Full sample							
World	961,270	3,870,000	97,260	169,750	0.112	215,870	298,940
Developed countries	768,870	2,748,100	77,643	143,390	0.116	289,080	296,820
All emerging markets	192,400	1,121,900	19,617	61,168	0.110	160,690	288,490
Latin America	33,213	162,850	3,486	42,511	0.036	154,730	317,610
Emerging East Asia	127,930	773,990	10,077	35,755	0.112	168,690	189,790
Emerging Europe	16,716	104,380	2,051	8,404	0.214	148,110	180,420
Other emerging	14,543	80,644	4,003	8,281	0.094	169,770	485,320
Panel B: Tequila period							
World	50,108	248,370	46,609	66,207	0.095	192,530	221,230
Developed countries	38,744	176,890	32,227	53,793	0.078	249,980	254,800
All emerging markets	11,364	71,480	14,381	24,626	0.105	141,530	170,980
Latin America	1,536	11,944	2,407	4,642	0.032	118,490	109,080
Emerging East Asia	9,006	52,965	8,416	23,496	0.061	170,230	178,260
Emerging Europe	381	3,528	983	3,011	0.238	103,520	148,660
Other emerging	440	3,043	2,576	3,915	0.115	161,270	254,660
Panel C: Asian crisis							
World	457,570	1,752,000	48,927	210,780	0.046	221,350	349,120
Developed countries	374,180	1,240,200	44,749	178,230	0.044	308,160	275,000
All emerging markets	83,391	511,800	4,178	82,318	0.046	159,910	381,470
Latin America	16,300	76,689	−2,041	57,599	−0.035	154,520	370,950
Emerging East Asia	47,541	326,230	873	47,326	0.082	141,070	202,360
Emerging Europe	11,038	63,766	1,818	11,425	0.068	164,600	176,590
Other emerging	8,512	45,110	3,527	10,939	0.069	196,030	716,540

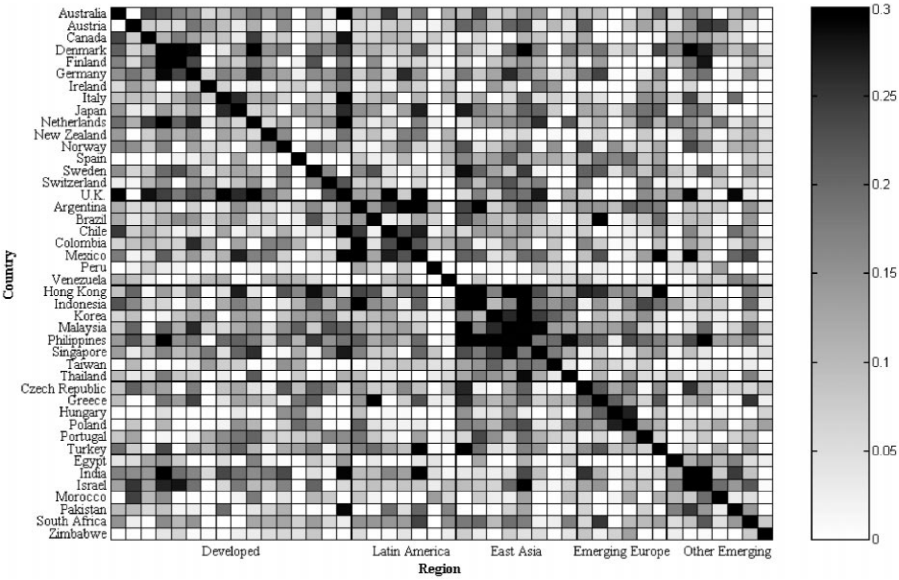

Fig. 3. Heatmap of weekly net portfolio flow correlations. The figure summarizes over 900 pairwise correlations. The net, cross-border flow of market purchases less sells into and out of one country is correlated with the net flow into and out of a second country. The data are derived from proprietary data provided by State Street Bank & Trust from August 1, 1994 to December 31, 1998. Table 5 presents the average pairwise correlation and the associated standard error for each region.

appears as the only shock that is associated with strong foreign equity selling. Russia's devaluation by itself seems to have left little imprint on flows. By contrast, during the intra-crisis periods, the inflows come rapidly, at an annual rate of approximately 50 basis points of market capitalization.

4.3. The persistence of flows

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

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

Table 5
Correlation within regions during the full sample, Tequila and Asian crisis periods

This table presents the average pairwise correlations for both weekly equity returns and weekly net equity flows. Figs. 3 and 4 provide a graphical depiction of the same statistic. Table 1 displays a complete list of countries by region. Equity returns are the daily, continuously compounded returns expressed in $U.S. We use the MSCI local country indexes and exchange rates from WMR/Reuters/Datastream. The flow data come from proprietary data provided by State Street Bank & Trust. Net equity flows are defined as buys minus sells. Standard errors, shown in parentheses, are computed by Monte Carlo simulation under the null hypothesis that the true correlations are zero.

	Full sample	Tequila crisis	Asian crisis
Panel A: Average pairwise correlation of equity returns			
World	0.2521	0.1127	0.3308
	(0.0053)	(0.0078)	(0.0066)
Developed Markets	0.4522	0.2247	0.5242
	(0.0115)	(0.0199)	(0.0133)
All Emerging Markets	0.2050	0.0804	0.2773
	(0.0084)	(0.0126)	(0.0109)
Latin America	0.3646	0.3743	0.5289
	(0.0443)	(0.0725)	(0.0464)
Emerging East Asia	0.4471	0.3943	0.5034
	(0.0262)	(0.0509)	(0.0267)
Emerging Europe	0.3875	0.2369	0.5278
	(0.0212)	(0.0531)	(0.0234)
Other emerging markets	0.1141	0.0686	0.1257
	(0.0212)	(0.0388)	(0.0324)
Panel B: Average pairwise correlation of net equity flows			
World	0.0772	0.0414	0.0686
	(0.0033)	(0.0075)	(0.0049)
Developed markets	0.1030	0.1108	0.0848
	(0.0088)	(0.0186)	(0.0135)
All emerging markets	0.0767	0.0181	0.0730
	(0.0054)	(0.0127)	(0.0078)
Latin America	0.1048	0.0252	0.0531
	(0.0245)	(0.0499)	(0.0280)
Emerging East Asia	0.1897	0.1323	0.2220
	(0.0143)	(0.0580)	(0.0202)
Emerging Europe	0.1190	− 0.0579	0.1163
	(0.0259)	(0.0426)	(0.0365)
Other emerging markets	0.0826	0.0012	0.1241
	(0.0235)	(0.0523)	(0.0285)

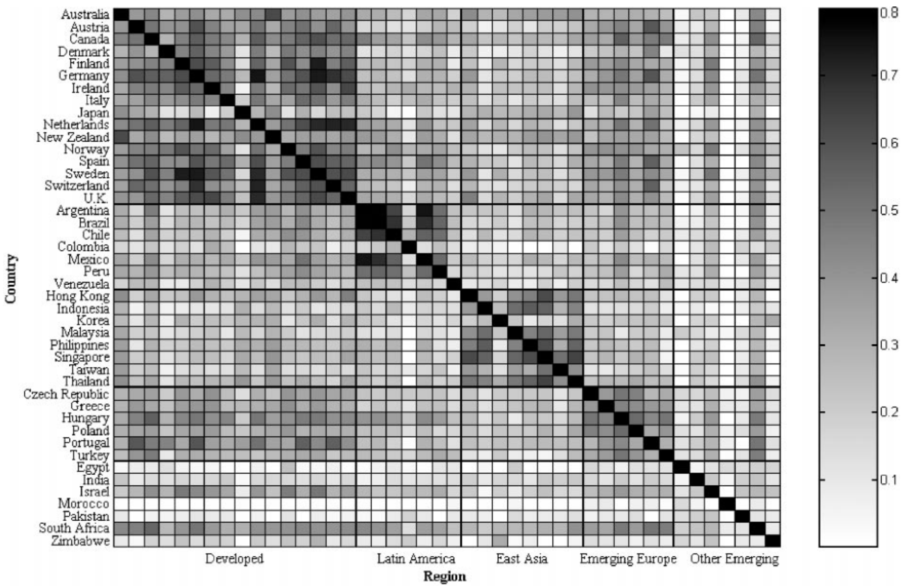

Fig. 4. Heatmap of weekly equity return correlations. The figure summarizes over 900 pairwise correlations. The equity return in $U.S. of one country is correlated with the equity return of a second country. The data are from the MSCI local country index, and are multiplied by the exchange rate available from WMR/Reuters from August 1, 1994 to December 31, 1998. Table 5 presents the average pairwise correlation and the associated standard error for each region.

where the last term is an adjustment for degrees of freedom. Because of the large number of countries, we report variance ratios only for our designated regions. The statistic reported for each region is the variance ratio of the equally weighted inflows. We calculated variance ratios using alternative weighting schemes, such as equal weighting, market capitalization weighting, 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.

Table 6 reports variance ratios of equity trades. The data are arranged in three panels, showing net flows as buys minus sells, inflows as buys, and outflows as sells. Heteroskedastic-consistent standard errors are reported beneath the point estimates.

Several facts come out of the data. First, it is clear that the flows are persistent. All of the variance ratios are statistically greater than one, and the point estimates display very large magnitudes. First-order correlation coefficients are in the range of 30% for developed-country and emerging-country groupings. It is worth noting that the ratios are higher for the larger baskets, so that

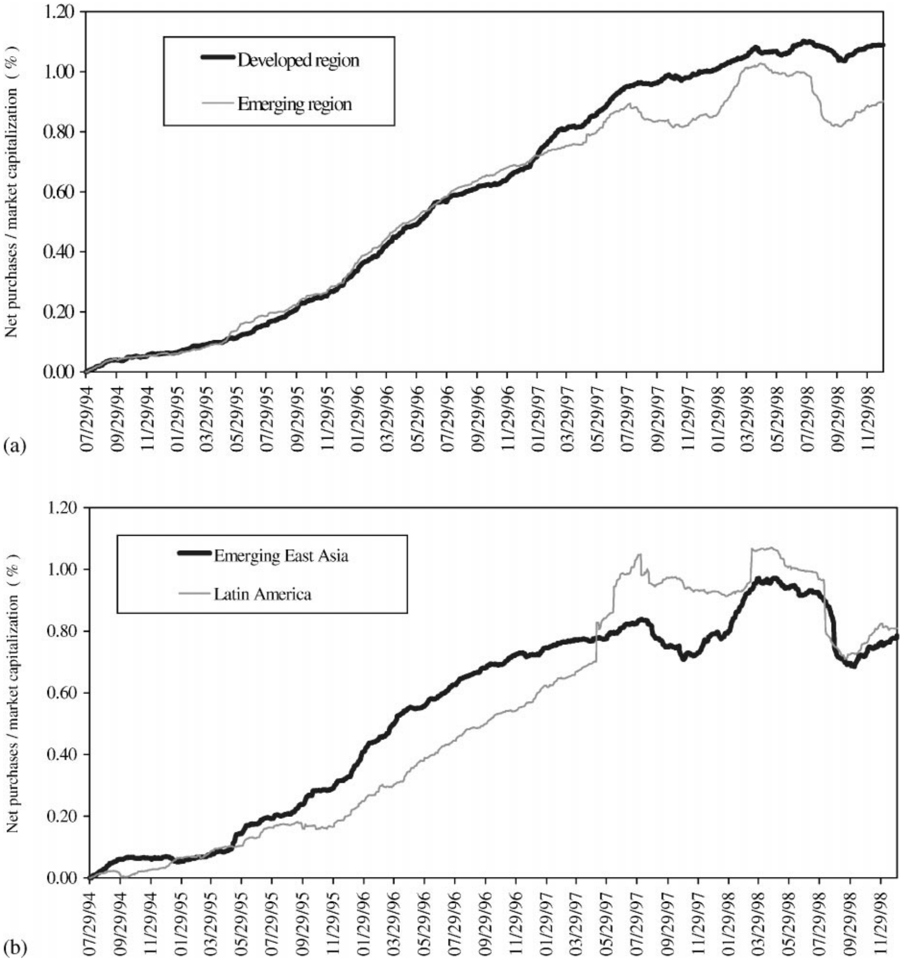

Fig. 5. Cumulative net equity flows. These figures show the cumulative net flows, calculated as buys minus sells, into both emerging markets and developed markets. The sample consists of cross-border equity flows from August 1, 1994 to December 31, 1998 representing 1,154 trading days. The data are derived from proprietary data provided by State Street Bank & Trust. Daily flows are divided by market capitalization. To make a regional flow index, individual country flows are weighted by market capitalization. *Panel A: Cumulated daily net equity flows into developed and emerging markets. Panel B: Cumulated daily net flow into Emerging East Asia and Latin America.*

the persistence of inflows for all emerging markets is generally greater than that for individual emerging subregions, and the persistence for the world overall is considerably greater than that for either developed-country or emergingcountry baskets. This result appears to be the combined result of persistent individual country flows and cross-country non-contemporaneous flow correlation.[5]

Second, regional flows are persistent at low frequencies as well as at high frequencies. The evidence for this observation is that the variance ratio statistics increase strongly with horizon. High-frequency persistence alone would lead variance ratios to level off as horizon increases. Our estimated variance ratios display no indication of leveling off at the frequencies we measure.

We also compared flow variance ratios with variance ratio of asset market excess returns for this time period and group of countries. The results show that developed market equity and currency returns show virtually no statistical evidence that the ratios differ from one, which represents the null hypothesis of no persistence.[6] Emerging market equities and currencies do show statistically detectable positive autocorrelations in excess returns, so that the variance ratios are above one. However, the magnitude of the deviations is very small in comparison with the deviations for the flows.

Finally, Table 7 shows the variance ratios computed for the Asian crisis and prior periods. The results suggest that the previously identified crisis periods do not produce detectable changes in persistence.

5. The Interaction between flows and returns

In this section we investigate 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 co-movement between the two data series at various horizons. We then examine their conditional covariation within a vector autoregression framework.

Our first evidence on the relationship between flows and prices is simply visual. Fig. 6 shows how the detrended emerging-market flows compare with detrended prices, in U.S. dollars, over the sample period. While there is too little data here to draw any statistical conclusions, the graph does suggest that flows and prices move together at low frequencies. The co-movement could be ascribed to a variety of factors, including overreaction, information shocks, or demand shocks. However, the presence of a clear regional component in this co-movement is not supportive of the Brennan and Cao hypothesis, which explains positive flow and price co-movement based on orthogonalized country-specific information.

[5] See Froot and Perold (1997) for a discussion of how persistence in stock return aggregates relates to individual stock return persistence.

[6] See Froot et al. (1998) for these results.

Table 6
Variance ratio statistics

This table shows the variance ratio (VR) statistic of daily portfolio flows from August 1994 through December 1998. The statistic is calculated at lags of 2 through 60 days, which amounts to approximately three months of trading. Results in this table are obtained by making an equal-weighted index of flows within a given region. Similar results are found using a market capitalization weighted index, or by reporting the average statistic of the individual countries within a given region. The variance ratio statistics use overlapping intervals and are corrected for bias in the variance estimators. The first panel displays the variance ratios for net flows, calculated as buys less sells. The second and third panels show the VR results for equity purchases and equity sales, respectively. Standard errors are asymptotic and heteroskedasticity consistent and are shown in parentheses. For a complete list of regions and countries, please see Table 1.

Region	VR(2)	VR(5)	VR(20)	VR(60)
Panel A: Net flows				
World	1.453	2.691	7.721	16.865
	(0.04)	(0.09)	(0.18)	(0.30)
Developed Markets	1.324	2.176	5.113	10.108
	(0.03)	(0.08)	(0.17)	(0.28)
All emerging markets	1.358	2.349	6.287	13.555
	(0.05)	(0.09)	(0.18)	(0.30)
Latin America	1.179	1.500	2.838	4.989
	(0.03)	(0.06)	(0.14)	(0.23)
Emerging East Asia	1.451	2.427	5.642	10.839
	(0.05)	(0.11)	(0.22)	(0.36)
Emerging Europe	1.138	1.693	3.887	8.324
	(0.06)	(0.12)	(0.19)	(0.29)
Other emerging	1.062	1.335	2.884	5.712
	(0.02)	(0.06)	(0.13)	(0.23)
Panel B: Equity buys				
World	1.579	3.089	9.011	20.039
	(0.04)	(0.09)	(0.20)	(0.32)
Developed Markets	1.435	2.500	6.482	13.524
	(0.04)	(0.09)	(0.18)	(0.30)
All emerging markets	1.516	2.850	7.796	17.246
	(0.05)	(0.10)	(0.20)	(0.33)
Latin America	1.207	1.601	2.973	5.742
	(0.03)	(0.06)	(0.16)	(0.31)
Emerging East Asia	1.595	3.002	8.469	19.806
	(0.07)	(0.13)	(0.26)	(0.41)
Emerging Europe	1.309	2.101	4.348	7.499
	(0.05)	(0.11)	(0.20)	(0.29)
Other emerging	1.030	1.292	2.928	6.287
	(0.02)	(0.06)	(0.13)	(0.23)

Table 6 (*continued*)

Region	VR(2)	VR(5)	VR(20)	VR(60)
Panel C: Equity sales				
World	1.686	3.577	12.043	33.047
	(0.04)	(0.08)	(0.17)	(0.29)
Developed Markets	1.464	2.718	7.886	19.011
	(0.04)	(0.08)	(0.17)	(0.29)
All emerging markets	1.658	3.460	11.486	31.969
	(0.04)	(0.09)	(0.18)	(0.30)
Latin America	1.201	1.578	2.975	5.229
	(0.04)	(0.06)	(0.13)	(0.23)
Emerging East Asia	1.692	3.332	9.944	27.017
	(0.06)	(0.12)	(0.21)	(0.33)
Emerging Europe	1.433	2.633	7.607	20.227
	(0.04)	(0.09)	(0.17)	(0.28)
Other emerging	1.206	1.872	5.111	12.523
	(0.03)	(0.08)	(0.17)	(0.30)

5.1. 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,

$$\mathrm{cov}[r_{i,t}(k),\ f_{i,t}(k)] > 0, \quad \text{for } k \cong 60 \text{ trading days.}$$

where $r_{i,t}(k)$ is the k-period return on equity, and $f_{i,t}(k)$ is cumulative sum of daily flows from $t-k+1$ to t. 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. Component A is the covariance between current flows and past returns. Component B is the contemporaneous covariance between daily flows and returns. Finally, Component C captures the covariance between current flows and future returns, or past flows and current returns. Specifically,

$$\mathrm{cov}[r_{i,t}(k),\ f_{i,t}(k)] = \underbrace{\sum_{s=1}^{k-1}(k-s)\,\mathrm{cov}[r_{i,t-s},\ f_{i,t}]}_{\text{Component A}} + \underbrace{k\,\mathrm{cov}[r_{i,t},\ f_{i,t}]}_{\text{Component B}} + \underbrace{\sum_{s=1}^{k-1}(k-s)\,\mathrm{cov}[r_{i,t+s},\ f_{i,t}]}_{\text{Component C}}. \quad (3)$$

Table 7
Variance ratio statistics by time period

Table 7 shows the variance ratio statistic of daily portfolio flows over two time periods, before and during the Asian financial crisis. The pre-crisis period is August 1994-June 1997. The Asian crisis period is July 1997 to December 1998. The statistic is calculated at lags of 2 through 60 days, representing approximately three months of trading. Results in this table are obtained by making an equal-weighted index of flows within a given region. Similar results are found using a market capitalization weighted index or by reporting the average statistic of the individual countries within a given region. The variance ratio statistics use overlapping intervals and are corrected for bias in the variance estimators. The first panel displays the variance ratios for net flows, calculated as buys less sells. The second and third panels show the VR results for equity purchases and equity sales, respectively. Standard errors are asymptotic and heteroskedasticity-consistent and are shown in parentheses. For a complete list of countries and regions, see Table 1.

	Pre-crisis period				Asian crisis period			
Region	VR(2)	VR(5)	VR(20)	VR(60)	VR(2)	VR(5)	VR(20)	VR(60)
Panel A: Net flows								
World	1.292	1.994	4.243	9.105	1.522	2.972	9.341	21.829
	(0.05)	(0.10)	(0.20)	(0.33)	(0.06)	(0.14)	(0.30)	(0.50)
Developed markets	1.252	1.884	3.892	7.076	1.344	2.199	5.163	11.204
	(0.04)	(0.09)	(0.19)	(0.33)	(0.06)	(0.13)	(0.29)	(0.48)
All emerging markets	1.199	1.704	3.564	8.016	1.464	2.771	7.962	17.907
	(0.06)	(0.13)	(0.23)	(0.35)	(0.07)	(0.14)	(0.30)	(0.49)
Latin America	1.195	1.518	2.573	4.288	1.124	1.306	2.235	2.829
	(0.04)	(0.09)	(0.21)	(0.35)	(0.04)	(0.07)	(0.17)	(0.28)
Emerging East Asia	1.460	2.499	5.052	9.303	1.447	2.387	5.946	13.603
	(0.06)	(0.11)	(0.22)	(0.36)	(0.07)	(0.14)	(0.29)	(0.48)
Emerging Europe	1.044	1.382	2.888	5.922	1.258	2.063	4.743	9.449
	(0.09)	(0.16)	(0.25)	(0.36)	(0.06)	(0.14)	(0.28)	(0.45)
Other emerging	1.017	1.054	1.576	1.867	1.116	1.717	4.538	10.566
	(0.02)	(0.08)	(0.16)	(0.26)	(0.03)	(0.09)	(0.22)	(0.41)
Panel B: Equity buys								
World	1.540	2.935	7.406	14.165	1.536	2.706	6.854	14.023
	(0.05)	(0.11)	(0.24)	(0.37)	(0.07)	(0.15)	(0.30)	(0.50)
Developed markets	1.433	2.565	6.696	13.682	1.400	2.111	4.484	8.776
	(0.04)	(0.10)	(0.21)	(0.34)	(0.08)	(0.15)	(0.30)	(0.51)
All Emerging markets	1.449	2.577	5.725	9.790	1.491	2.628	5.942	11.882
	(0.06)	(0.13)	(0.26)	(0.40)	(0.08)	(0.16)	(0.31)	(0.50)
Latin America	1.223	1.612	2.825	4.285	1.165	1.512	2.561	2.911
	(0.04)	(0.08)	(0.21)	(0.41)	(0.04)	(0.09)	(0.24)	(0.37)
Emerging East Asia	1.647	3.220	7.468	12.439	1.473	2.386	5.615	12.529
	(0.06)	(0.13)	(0.24)	(0.38)	(0.09)	(0.18)	(0.35)	(0.54)

Table 7 (*continued*)

Region	Pre-crisis period				Asian crisis period			
	VR(2)	VR(5)	VR(20)	VR(60)	VR(2)	VR(5)	VR(20)	VR(60)
Emerging Europe	1.277	1.987	3.535	6.000	1.324	2.088	3.723	6.060
	(0.06)	(0.14)	(0.26)	(0.36)	(0.07)	(0.14)	(0.28)	(0.46)
Other emerging	1.018	1.149	2.034	2.518	0.952	1.187	2.722	5.520
	(0.02)	(0.06)	(0.15)	(0.25)	(0.04)	(0.10)	(0.24)	(0.41)
Panel C: Equity sales								
World	1.578	3.147	8.927	17.030	1.403	2.137	3.128	3.463
	(0.05)	(0.11)	(0.24)	(0.38)	(0.06)	(0.13)	(0.26)	(0.43)
Developed markets	1.358	2.272	5.349	9.256	1.326	2.038	3.956	6.507
	(0.05)	(0.11)	(0.22)	(0.34)	(0.06)	(0.13)	(0.27)	(0.45)
All emerging markets	1.559	3.081	8.653	16.612	1.370	2.061	3.030	3.481
	(0.06)	(0.14)	(0.28)	(0.43)	(0.06)	(0.12)	(0.24)	(0.42)
Latin America	1.409	2.277	4.533	6.080	1.091	1.171	1.548	1.172
	(0.06)	(0.12)	(0.24)	(0.38)	(0.04)	(0.07)	(0.16)	(0.26)
Emerging East Asia	1.618	3.145	8.231	14.225	1.507	2.223	2.797	3.044
	(0.05)	(0.11)	(0.23)	(0.37)	(0.09)	(0.16)	(0.29)	(0.45)
Emerging Europe	1.328	2.218	5.204	11.004	1.276	1.917	2.932	3.797
	(0.06)	(0.12)	(0.23)	(0.36)	(0.05)	(0.16)	(0.29)	(0.45)
Other emerging	1.049	1.178	1.983	3.558	1.096	1.489	3.055	4.727
	(0.02)	(0.05)	(0.16)	(0.27)	(0.05)	(0.11)	(0.25)	(0.44)

Note that the three components of quarterly covariance are labeled in Eq. (3). It is of interest to know which of these components drives quarterly covariance. If Component A turns out to be the largest fraction of quarterly covariance, we can hypothesize that returns can be predicted on the basis of current flows.

The high frequency of our data allows us to calculate these components separately. As a convenient numeraire, we divide the quarterly covariance by k times the daily variance of the flows. In doing so, we estimate the following covariance ratio statistic, or CVR:

$$CVR_i^k = \frac{\operatorname{cov}[r_{i,t}(k),\, f_{i,t}(k)]}{k\operatorname{var}[\, f_{i,t}]} = \frac{\sum_{t=k}^{T}\left[\sum_{s=0}^{k-1}(r_{i,t-s}-\bar{r}_i)\right]\left[\sum_{s=0}^{k-1}(f_{i,t-s}-\bar{f}_i)\right]}{k\sum_{t=1}^{T}(f_{i,t}-\bar{f}_i)^2}. \tag{4}$$

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

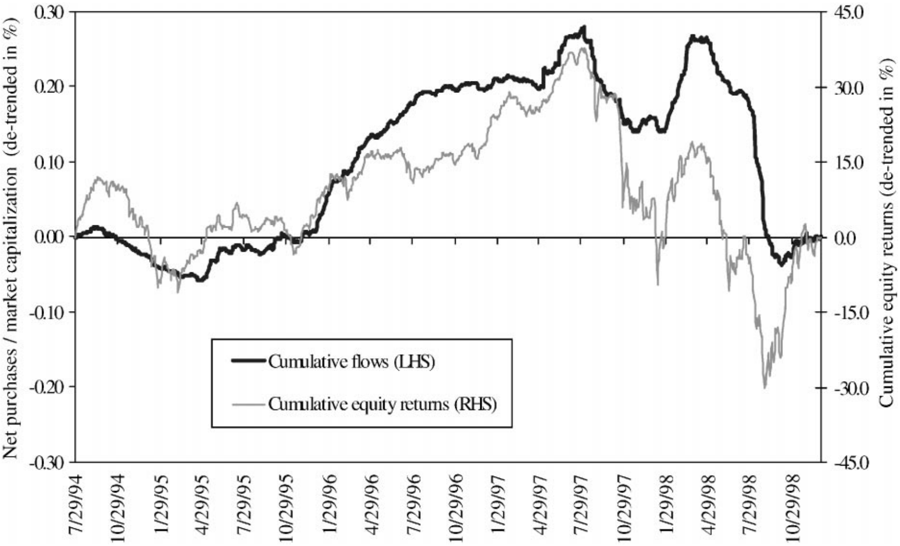

Fig. 6. De-trended cumulative net equity flows and equity returns: emerging markets. This figure shows the de-trended cumulative net flows, calculated as buys minus sells, and equity returns. The flows are divided by market capitalization. To make a regional index, individual country flows and equity returns are weighted by market capitalization. For a complete list of countries within this region, see Table 1. Equity returns are the daily, continuously compounded returns expressed in $U.S. We use the MSCI local country indexes, and exchange rates from WMR/Reuters/Datastream. The flow data come from proprietary data provided by State Street Bank & Trust.

returns, but rather k times the variance of flows. The statistic can therefore be thought of as the coefficient from a regression of k-period returns on k-period flows. From the covariance decomposition shown in Eq. (3), it follows directly that:

$$CVR_i^k = \underbrace{\sum_{s=1}^{k-1}\left(1-\tfrac{s}{k}\right)\beta(r_{i,t-s},\, f_{i,t})}_{\text{Component A}} + \underbrace{\beta(r_{i,t},\, f_{i,t})}_{\text{Component B}} + \underbrace{\sum_{s=1}^{k-1}\left(1-\tfrac{s}{k}\right)\beta(r_{i,t+s},\, f_{i,t})}_{\text{Component C}}, \tag{5}$$

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 Eq. (5) allows us to decompose quarterly covariance, and make statistical inferences.

Table 8 presents the decomposition of the quarterly covariance of flows and dollar equity returns at the regional level. The table reports the results from equally weighted regional flow indexes. Similar results are found using indexes weighted by market capitalization, or by averaging across the covariance ratios from individual countries in each region. The first data column reports the actual CVR statistic with k set equal to 60, to represent a quarterly decomposition. For the purposes of inference, the variance of the CVR statistic and its components is estimated from the heteroskedastic consistent variances of the daily β coefficient estimates.[7]

The first point to note about the tables is the benefit of using daily instead of monthly or quarterly data. As we can see from Panel B of Table 8, contemporaneous covariance accounts for at most 8.5% of measured quarterly covariance. On average, less than a quarter of the quarterly covariance between flows and equity returns can be attributed to the period from 5 days before to 5 days after trades are recorded.

Table 8 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, described above as the covariance between current flows and past returns. As mentioned earlier, the size and significance of component A suggest positive feedback trading behavior for these international investors. In other words, positive local stock market returns are associated with future international inflows.

For the world overall, there is a fair amount of predictability of future returns from current flows. However, most of this effect can be attributed to the emerging markets. If we concentrate on developed markets only, Table 8 shows evidence that flows predict negative future equity returns, a result which suggests evidence of overreaction or price pressure. Note, however, that this finding is not statistically significant. In addition, this finding for developed markets disappears once we account for the behavior of past returns in the following section.

In any case, flows into emerging markets predict positive equity returns, and seem to do so at short as well as long horizons. Over the upcoming week and the rest of the following month, the coefficients for all emerging market regions are positive. At the quarterly horizon, Emerging East Asia and Other Emerging Markets are the only emerging regions that show negative coefficients. The emerging markets covariance ratio is largest for the period between 6 and 20 days, suggesting that an inflow is associated with a tendency toward positive emerging market returns over many days into the future. This finding is consistent with the view that international investors may have better marginal information than local investors have in emerging markets.

These findings seem inconsistent with the Brennan and Cao view that the positive covariance between emerging market returns and inflows is attributable

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[7] In Froot et al. (1998), we provided results both for equity and currency returns. To save space, the results on currencies have been eliminated here, but they were generally similar to those on dollar equity returns.

Table 8
Quarterly covariance decomposition

This table decomposes the covariance ratio statistic for 60-day equity returns against 60-day net equity flows. The data are derived from proprietary data provided by State Street Bank & Trust from August 1, 1994 to December 31, 1998. Results in this table are obtained by making an equal-weighted index of flows within a given region. Similar results are found using a market capitalization weighted index or by reporting the average statistic of the individual countries within a region. The decomposition is based on Eq. (5) in the text, which captures a covariance ratio (CVR) comprised of the covariance of current flows and past returns, current daily flows and returns, and current flows and future returns. Panel A shows the actual CVR statistic and its components. Panel B shows the composition in terms of percentages. For a complete list of regions and countries, see Table 1.

	Flows and lagged returns				Contemp. component	Flows and future returns		
Region	CVR(60)	Days 21–60	Days 6–20	Days 2–5		Days 2–5	Days 6–20	Days 21–60
Panel A: Decomposition of CVR								
World	1,555.30	629.67	416.06	197.67	61.25	53.21	163.19	34.26
	(15.17)	(10.95)	(11.41)	(10.64)	(3.35)	(2.91)	(4.43)	(0.58)
Developed markets	419.95	248.84	155.92	66.76	17.56	− 6.73	− 8.16	− 54.24
	(5.98)	(6.24)	(6.46)	(5.65)	(1.52)	(− 0.54)	(− 0.31)	(− 1.34)
All emerging markets	1,380.30	458.41	356.52	192.67	61.96	56.87	176.71	77.08
	(14.70)	(8.65)	(10.61)	(10.79)	(3.45)	(3.45)	(5.32)	(1.44)
Latin America	895.22	213.98	215.22	115.61	53.18	45.55	166.16	85.52
	(10.29)	(5.46)	(8.01)	(6.30)	(3.65)	(3.51)	(5.70)	(1.40)
Emerging East Asia	1,034.50	348.81	351.84	269.26	88.39	0.43	51.17	− 75.37
	(6.71)	(3.96)	(6.52)	(9.72)	(2.41)	(0.02)	(0.96)	(− 0.87)
Emerging Europe	174.06	− 3.25	53.57	40.32	14.19	4.88	26.07	38.28
	(4.70)	(− 0.15)	(3.90)	(5.75)	(2.02)	(0.76)	(2.07)	(1.83)
Other emerging	253.11	166.19	60.74	22.13	1.63	12.84	11.60	− 22.01
	(4.79)	(5.30)	(3.06)	(2.82)	(0.17)	(1.41)	(0.66)	(− 0.75)

Panel B: Decomposition in percent terms								
World	1,555.30	40.5%	26.8%	12.7%	3.9%	3.4%	10.5%	2.2%
Developed markets	419.95	59.3%	37.1%	15.9%	4.2%	– 1.6%	– 1.9%	– 12.9%
All emerging markets	1,380.30	33.2%	25.8%	14.0%	4.5%	4.1%	12.8%	5.6%
Latin America	895.22	23.9%	24.0%	12.9%	5.9%	5.1%	18.6%	9.6%
Emerging East Asia	1,034.50	33.7%	34.0%	26.0%	8.5%	0.0%	4.9%	– 7.3%
Emerging Europe	174.06	– 1.9%	30.8%	23.2%	8.2%	2.8%	15.0%	22.0%
Other emerging	253.11	65.7%	24.0%	8.7%	0.6%	5.1%	4.6%	– 8.7%

to the information disadvantage of international investors. 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 of Table 8 suggests.

Finally, Fig. 7 shows how the covariance of low-frequency flows with returns is affected by the sample period. The figure graphically depicts the results from Table 8, breaking them up into a pre-Asian crisis period and an Asian crisis period. The graph suggests that the character of emerging market flows was essentially unaffected by the Asian crisis. Interestingly, much of the negative covariance in developed-country flows with future returns comes from the pre-crisis subsample. During the Asian crisis, developed country inflows better predict the direction of future equity returns.

5.2. 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 (VAR). Specifically, we ask two questions. First, do returns predict flows over and above the predictions of lagged flows? Second, do flows predict returns over and above the predictions of lagged returns?

To answer these we estimate both an unrestricted VAR and a VAR subject to restrictions. For the unrestricted VAR, we estimate a two-equation system where we cast the joint dynamics of f_{it} and r_{it} for each country as a pth-order Gaussian vector autoregression:

$$\begin{bmatrix} f_{it} \\ r_{it} \end{bmatrix} = \begin{bmatrix} \alpha_f \\ \alpha_r \end{bmatrix} + \begin{bmatrix} \phi_{11}(L) & \phi_{12}(L) \\ \phi_{21}(L) & \phi_{22}(L) \end{bmatrix} \cdot \begin{bmatrix} f_{it-1} \\ r_{it-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{it}^{f} \\ \varepsilon_{it}^{r} \end{bmatrix}, \tag{6}$$

$$\begin{bmatrix} \varepsilon_{it}^{f} \\ \varepsilon_{it}^{f} \end{bmatrix} \approx N[0, \Sigma_i], \quad \Sigma_i = \begin{bmatrix} \sigma_{if}^2 & \rho\sigma_{if}\sigma_{ir} \\ \rho\sigma_{if}\sigma_{ir} & \sigma_{ir}^2 \end{bmatrix}.$$

This system can be written succinctly as

$$\boldsymbol{y}_{it} = \boldsymbol{\alpha}_i + \boldsymbol{\Phi}_1 \boldsymbol{y}_{i,t-1} + \boldsymbol{\Phi}_2 \boldsymbol{y}_{i,t-2} + \dots + \boldsymbol{\Phi}_p \boldsymbol{y}_{i,t-p} + \boldsymbol{\varepsilon}_{it} \tag{7}$$

for $i = 1, \dots, N$, $t = 1, \dots, T$, where $\boldsymbol{y}_{it} = [f_{it}\ r_{it}]'$, $\boldsymbol{\alpha}_i$ is a vector of country-specific constants, and the $\{\boldsymbol{\Phi}_i\}$ are 2×2 parameter matrices to be estimated. The diagonal coefficients ϕ_{11} and ϕ_{22} represent conditional momentum in flows and returns. The off-diagonal coefficients ϕ_{12} and ϕ_{21} represent conditional positive feedback trading, wherein flows follow returns, and conditional anticipation effects wherein returns follow flows. The off-diagonal elements of $\sum_i$ capture capture the price-impact effect of flows on returns.

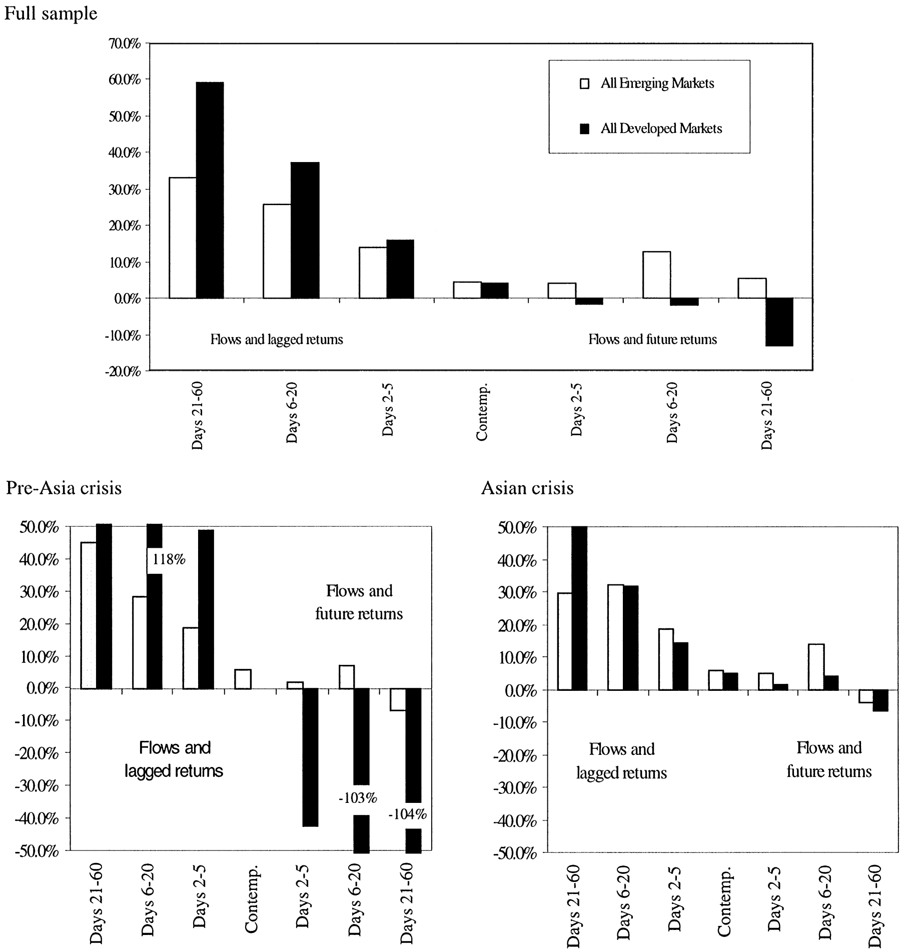

Fig. 7. Quarterly covariance decomposition: flows and equity returns. This figure shows the decomposition of the covariance ratio statistic for 60-day equity returns against 60-day net equity flows. The decomposition is done in percentage terms, as shown on the bottom of Table 8, and based on Eq. (5) in the text. The first figure shows the results for developed markets and emerging markets for the entire sample (see Table 8, Panel B). The next two figures show the decomposition from before and during the recent Asian crisis. The data are derived from proprietary data provided by State Street Bank & Trust from August 1, 1994 to December 31, 1998. Results in this table are obtained by making an equal-weighted index of flows within a given region. Similar results are found using a market capitalization weighted index or by reporting the average statistic of the individual countries within a region. For a complete list of regions and countries, see Table 1.

In order to conserve on the number of parameters, we restrict the parameters in Eq. (7) to be equal across countries. In this instance, maximum likelihood estimates of the $\{\boldsymbol{\Phi}_i\}$ and $\boldsymbol{\Omega}_i$ can be obtained by iterated least squares. The lag length is chosen by looking both at the Akake Information Criterion (AIC) and the likelihood ratio for various choices of p. In general, the data support the use of up to 40 daily lags, which seems consistent with the evidence of persistent unconditional cross-effects already discussed.

Table 9 presents F-tests of the hypothesis that the coefficients on each term are jointly equal to zero. Generalized least squares (GLS) standard errors are used in the calculation. The results show that lagged returns are strongly significant in predicting both flows and returns. Lagged flows are also strongly significant in predicting future flows. The evidence for the predictability of returns by flows, is however, more ambiguous. In developed markets, there is no statistical evidence of predictability. For emerging markets, however, the evidence for predictability is strong, although less so for the Emerging Europe region.

We also use the estimates of $\boldsymbol{\Phi}$ to form impulse response functions (IRFs), shocking flows or returns and then examining the effects. Panel B of Table 9 presents tests of the significance of the IRFs for returns following a 1bp shock to flows, and Figs. 8 and 9 display graphs of the IRF responses along with 90% confidence intervals.

The impulse responses in Figs. 8A and B make several interesting points. First, for emerging markets overall, a shock of one basis point to flows generates an additional 1.5 basis point greater inflow over the subsequent 45 days. The figure shows the persistence of flows to be very pronounced, with the standard error of the forecasts being very small in relation to the magnitude. Second, the same shock of one basis point results in a 40 basis point increase in equity prices, with most of the increase coming in the first 30 or so days. Once again, these results are easily significant at the 5% level. Note that this elasticity of 40 is very high, in that it is several times the magnitude found in studies of the responses of U.S. stocks to mutual fund inflow. Third, a shock of 100 basis points to returns results in about 0.05 basis points in additional inflow over the next two or three months. Although this response is economically small, it is statistically significant. Finally, a 100 basis-point shock to equities results in a positive equity response of about 25 basis points. The effect comes from a combination of the autocorrelation in emerging-market index returns, the effect of a shock to returns on subsequent flows, and the effect of further flows on subsequent returns. In any case, fully half of the response, or 12.5 basis points, occurs on the day after the shock, a direct result of the strongly positive first-order autocorrelation coefficient found in emerging-market index returns.

A slightly different perspective can be given to the data by putting more structure on the estimation problem. To do this, we estimate a model that makes

Table 9
VAR estimates

This table summarizes results from the following vector autoregression (VAR) with the number of lags (P) set to 40 days. Coefficients are constrained to be the same for all countries within a given region. Estimation is general least squares (GLS) that allows for heterskedasticity by country. f_t is net, or buy and sell, flow at time t and r_t is equity return at time t. Equity returns are expressed in U.S.$ and are from MSCI (local) country indexes. Panel A presents F-tests of joint coefficient significance from the VAR. Also included is the estimated, contemporaneous correlation coefficient between shocks to net flows and shocks to equity returns. Panel B presents the cumulative impulse response function of returns, in basis points (bp) from a 1 bp shock to flows. Values are shown at 40 days and 60 days after the shock. Parameter estimates are from the VAR, below. Diagrams of the impulse response functions for emerging markets are presented in Fig. 8. FX rates are from WMR/Reuters and obtained from Datastream. The flow data come from proprietary data provided by State Street Bank & Trust. Data is from the period August 1, 1994 to December 31, 1998. A complete list of regions and countries is given in Table 1.

$$f_t = \alpha_F + \sum_{p=1}^{P} \prod_{11\,p} f_{t-p} + \sum_{p=1}^{P} \prod_{12\,p} r_{t-p} + \varepsilon_{t,F}$$

$$r_t = \alpha_R + \sum_{p=1}^{P} \prod_{21\,p} f_{t-p} + \sum_{p=1}^{P} \prod_{22\,p} r_{t-p} + \varepsilon_{t,R}$$

	F-test of joint significance (P-value shown)				$\text{Corr}(e_F, e_T)$
	Π_{11}	Π_{12}	Π_{21}	Π_{22}	
Panel A: F-tests					
World	—	—	—	—	—
Developed markets	0.0000	0.0000	0.4615	0.0000	0.0307
All emerging markets	0.0000	0.0000	0.0157	0.0000	0.0444
Latin America	0.0000	0.0000	0.0000	0.0000	0.0409
Emerging East Asia	0.0000	0.0000	0.0000	0.0000	0.0842
Emerging Europe	0.0000	0.0000	0.3337	0.0000	0.0496
Other emerging markets	0.0000	0.0000	0.1391	0.0000	− 0.0026

	Impulse response			
	40 days later		60 days later	
	(bp)	P-value	(bp)	P-value
Panel B: Impulse response functions of equity returns from a 1bp shock to flows				
World	—	—	—	—
Developed markets	14.672	0.033	18.753	0.016
All emerging markets	34.147	0.008	39.044	0.002
Latin America	54.180	0.065	46.943	0.138
Emerging East Asia	− 22.062	0.230	− 31.093	0.810
Emerging Europe	37.133	0.000	45.245	0.000
Other emerging markets	55.109	0.014	61.423	0.024

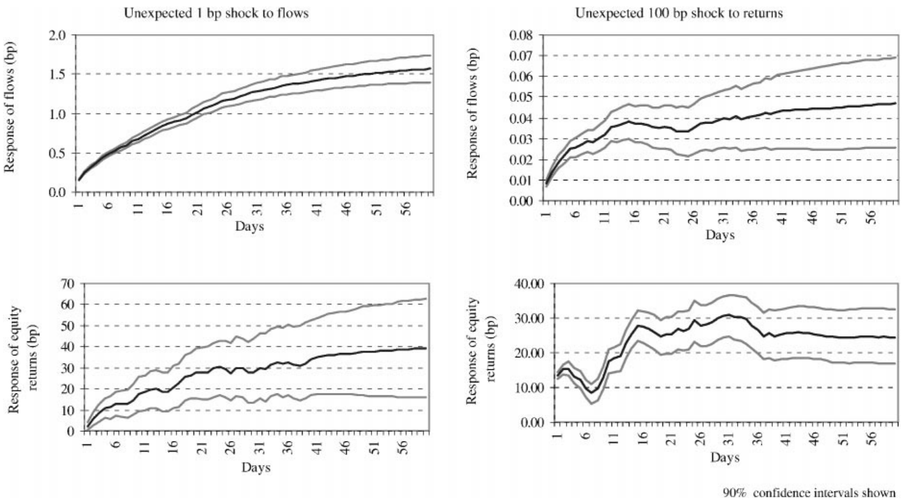

Fig. 8. Impulse response functions: all emerging markets. Graphs of the cumulative impulse response functions for emerging market flows and equity returns. Parameters are from the VAR reported in Table 9. Each impulse response comes from shocking either flows or returns, while holding the other variable constant. The IRFs are shown with the 90% confidence intervals, which are obtained by Monte Carlo simulation. Parameters values are drawn from the asymptotic joint distribution of parameters, and the impulse response function is calculated. This procedure is then repeated 500 times.

several assumptions about the causality of flows and returns. First, we assume that the decision to buy a country's equity depends on past inflows and past returns. Past inflows matter because they are correlated with the disparity between current price and future price, as perceived by investors. This perception can be accurate either because investors have information about the true value of the equity investment, or because the investors are large in size and wish to minimize the price impact of their trades. Past returns enter the equation because some investors are not informed and cannot observe inflows. These investors therefore rely more on past returns as a proxy for information.

Second, prices set by market makers are a function of past inflows and past returns, as well as current inflows. This provision means that we are assuming that current inflows affect current prices, and that the causality does not run from contemporaneous returns to flows. This case would occur if market makers perceive current inflows to contain information about value, as in Kyle (1985). However, lagged inflows may also affect current price. They may do so in two ways. First, lagged inflows affect unexpected current flows. With current inflows given, the larger are past inflows, the greater will be the anticipated value for the

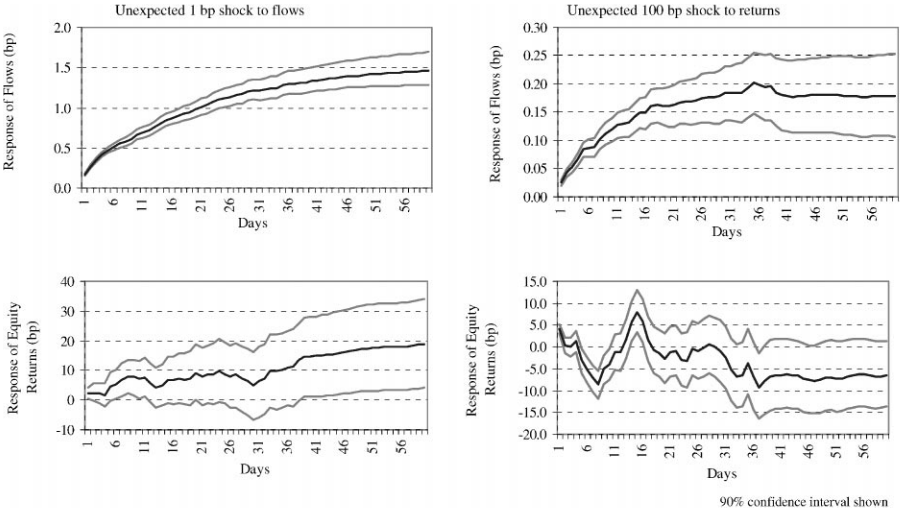

Fig. 9. Impulse response functions: all developed markets. Graphs of the cumulative impulse response functions for developed market flows and equity returns. Parameters are from the VAR reported in Table 9. Each impulse response comes from shocking either flows or returns, while holding the other variables constant. The IRFs are shown with the 90% confidence intervals, which are obtained by Monte Carlo simulation. Parameters values are drawn from the asymptotic joint distribution of parameters, and the impulse response function is calculated. This procedure is then repeated 500 times.

current flow. Thus, the amount of the unexpected current flow, is smaller, and prices should therefore fall. By this logic, lagged inflows have a negative impact on current returns. Second, inflows may contain more or less information about the future than the market maker expects. If the market maker underestimates the information content of current flow, then lagged inflow positively forecasts future returns. If the market maker overestimates the information content of current flow, lagged inflow will forecast returns negatively.

This more structural model can be summarized in the following way:

$$\begin{bmatrix} f_{it} \\ r_{it} \end{bmatrix} = \begin{bmatrix} \alpha_{if} \\ \alpha_{ir} \end{bmatrix} + \begin{bmatrix} B_{11}(L) & B_{12}(L) \\ B_{21}(L) & B_{22}(L) \end{bmatrix} \cdot \begin{bmatrix} f_{it-1} \\ r_{it-1} \end{bmatrix} + \begin{bmatrix} 0 \\ B_X f_{it} \end{bmatrix} + \begin{bmatrix} u_{it}^{f} \\ u_{it}^{r} \end{bmatrix}, \tag{8}$$

where B_{11} and B_{12} are respective persistence and trend following parameters for order flow, B_x describes the price impact of unexpected order flow on returns, and B_{21} represents the impact of lagged inflow on returns. Our structural model can be thought of as a restricted version of the reduced form model in Eq. (7), with the contemporaneous correlations between the u's equal to zero.

This model is estimated in an autoregressive form, similar to that in Eq. (7), but imposing the necessary restrictions on the covariance matrix. Specifically, we estimate the exactly identified system:

$$B_0 \cdot y_{it} = -\boldsymbol{B} \cdot x_{it} + u_{it}, \tag{9}$$

where

$$-\boldsymbol{B} = [\alpha\, B_1\, B_2\, \dots\, B_P], x_t = \begin{bmatrix} 1 \\ y_{it-1} \\ y_{it-2} \\ \vdots \\ y_{it-p} \end{bmatrix}, B_0 = \begin{bmatrix} 1 & 0 \\ -B_x & 1 \end{bmatrix}, \begin{bmatrix} u_{it}^f \\ u_{it}^r \end{bmatrix} \approx N[0, D] \tag{10}$$

and

$$D = \begin{bmatrix} \sigma_{u,f}^2 & 0 \\ 0 & \sigma_{u,r}^2 \end{bmatrix} \tag{11}$$

Table 10 reports information on the parameter vectors, B_{11}, B_{12}, B_{21} and the scalar B_x. Our estimates of B_x are all positive, and in some cases are statistically significant. The emerging markets estimate suggests that a positive shock to inflows equal to 1 basis point of capitalization results in a contemporaneous increase in prices of 0.6 basis points. The corresponding coefficient for developed countries is less than 0.1 basis points.

The estimates of B_{21}, the impact of lagged inflow on returns, are universally negative for the emerging markets. This result suggests that temporary inflows result in temporary price increases. It does not mean, however, that inflows forecast returns negatively. Inflows are strongly persistent, as we have seen, making it unlikely that inflows today will subside fully tomorrow.

This story has interesting implications for the crises in emerging markets. Much of the recent debate about the recent crises has focused on whether international investors sold at the beginning or in the midst of the crisis. While we have already shown that net sales are small, these last results suggest that prices fall when international inflows were previously high, and then fall. Prices, which were rationally high in expectation of further inflows, were not justifiably once the inflows ceased. Thus, our estimates of B_{21} and B_x suggest how a fall, but not a reversal, in emerging market inflows can be associated with price declines. We produced estimates for Tables 9 and 10 for both the pre-Asian and Asian crisis periods. The results are not importantly different, though the power of the statistical tests, particularly during the relatively short Asian crisis period, is lower.

Table 10
Structural model estimates

This table summarizes results from the following structural model with the number of lags (P) set to 40 days. Coefficients are constrained to be the same for all countries within a given region. Estimation is by GLS, and allows for heterskedasticity by country. This structural model is a just-identified version of the VAR presented in Table 9. ft is net, buy or sell flow at time t and r_t is equity return at time t. Equity returns are expressed in $U.S. and are from MSCI (local) country indices. FX rates are from WMR/Reuters and obtained from Datastream. The flow data cover the period August 1, 1994 to December 31, 1998. A complete list of regions and countries is given in Table 1.

$$f_{it} = \alpha_{if} + \sum_{p=1}^{P} B_{11p} f_{it-p} + \sum_{p=1}^{P} B_{12p} r_{it-p} + u_{it}^{f}$$

$$r_{it} = \alpha_{ir} + \sum_{p=1}^{P} B_{21p} f_{it-p} + \sum_{p=1}^{P} B_{22p} r_{it-p} + B_X f_{it+} u_{it}^{r}$$

Due to the large number of coefficients estimated, we present only the average coefficient across countries in a given region. Below the average value is the standard deviation of this average, computed by Monte Carlo simulation. In the case of the contemporaneous parameter (B_x), we compute a p-value that the average coefficient in the region is greater than zero.

	Average coefficient value across countries in region				
Region	B_{11}	B_{12}	B_{21}	B_{22}	B_X
Developed markets	1.5E − 02	1.9E − 03	8.8E − 04	− 2.3E − 03	8.7E − 02
	4.6E − 03	9.6E − 04	1.2E − 03	8.7E − 04	$p = 0.31$
All emerging markets	1.6E − 02	3.7E − 04	− 6.0E − 03	4.6E − 03	5.9E − 01
	4.5E − 03	2.7E − 04	5.2E − 03	8.2E − 04	$p = 0.15$
Latin America	1.6E − 02	1.6E − 04	− 1.0E − 02	4.4E − 03	8.2E − 01
	5.4E − 03	2.8E − 04	9.3E − 03	2.3E − 03	$p = 0.22$
Emerging East Asia	1.6E − 02	6.9E − 06	− 8.1E − 01	5.1E − 03	3.4E + 01
	6.0E − 03	5.5E − 06	4.4E − 01	1.7E − 03	$p = 0.03$
Emerging Europe	1.5E − 02	− 7.9E − 06	2.2E − 01	1.5E − 03	1.9E + 01
	3.0E − 03	1.2E − 05	1.0E − 01	2.0E − 03	$p = 0.00$
Other emerging markets	1.5E − 02	1.1E − 05	4.3E − 01	7.7E − 03	2.5E + 00
	3.9E − 03	5.2E − 06	2.0E − 01	1.5E − 03	$p = 0.47$

6. 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:

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.

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.

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.

There is also some ability for international inflows to forecast returns. In emerging markets, inflows predict positive future returns on average. 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. We cannot say in this paper whether the predictability of future returns is the result of superior information held by international investors or whether flows, which are persistent, predict future price pressure.

In developed markets, inflows do not forecast positive returns. At longer horizons, returns are negative.

Transitory inflows lead to partially transitory price increases.

The forecasting power of inflows for future returns occurs because current inflows predict future inflows, and future inflows drive up prices.

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 trades. 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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