IMF Staff Papers
Vol. 50, No. 1

A Panic-Prone Pack? The Behavior of Emerging Market Mutual Funds

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This article explores the behavior of emerging market mutual funds using a novel database covering the holdings of individual funds over the period January 1996 to December 2000. The degree of herding among funds is statistically significant, but moderate. Herding is more widespread among open-ended funds than among closed-end funds, but not more prevalent during crises than during tranquil times. We find some evidence that funds tend to follow momentum strategies, selling past losers and buying past winners. [JEL F21, G15]

Episodes of high volatility in international capital flows and currency crises in the 1990s have put international investors in the limelight. Frequently, international investors are seen as the culprits of the bouts of instability and crises,[1] and casual observation does suggest the presence of episodes of panic and contagion. Yet the fundamental question remains as to whether there is a tendency for certain market participants to disregard fundamental economic conditions in emerging

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[1] See, for example, Aitken (1998).

markets, responding only to what other investors are doing or are expected to do. The presence of such herding behavior could, to the extent it dominates international capital flows, help to explain the seemingly excessive observed volatility and have important policy implications.

Assessing the behavior of international investors in a systematic way, however, poses big challenges. Most of the available financial information consists of data on prices. It is nearly hopeless to attempt to control for all “fundamental” news that leads to changes in asset prices, making it impossible to convincingly establish that a specific change in asset prices was due to herding behavior by certain groups of investors. Moreover, herding behavior by international investors may have adverse consequences for countries even in the absence of a large impact on prices.

For these reasons, researchers have begun to examine investor behavior in emerging markets directly using data on investors’ portfolios and transactions. Such data are scarce, however, and the evidence presented so far for emerging markets is limited. The most comprehensive dataset used so far is probably the daily data from State Street Bank and Trust examined by Froot, O’Connell, and Seasholes (2001). The authors find evidence for persistence and trend following in portfolio flows. In addition, their data indicate that inflows have forecasting power for future returns in emerging markets, but not mature markets. While their dataset is very detailed on transactions, it does not allow the researcher to differentiate between different classes of investors. Other studies have had a regional or country-specific focus.

This article contributes to this literature by exploring a novel dataset that covers more than 400 dedicated emerging market equity funds on a monthly basis over the period January 1996–December 2000; it is the first study to document the behavior of mutual funds on a global scale. While the period is relatively short, it encompasses the Asian, Czech, Russian, and Brazilian crises. The aim of the study is to provide some tentative answers to the following questions. Is there evidence of herding among these funds during tranquil and during turbulent times? Are there meaningful differences in the behavior of different types of fund? Do funds systematically buy past winners and sell past losers?[2]

Note that it makes sense to search for evidence of herding only within a subset of investors, since the whole market cannot move in the same direction (since for every seller, there must be a buyer). In this regard, our database has the advantage of covering a well-specified subclass of investors for which it is meaningful and interesting to pose these questions. By examining a specific and important group of market players, we can contribute more broadly to a better understanding of the supply of capital to emerging markets. Although we hope our findings will add a piece to the overall puzzle, our results should probably not be seen as characterizing the behavior of *all* international investors.

We find that the degree of herding among dedicated emerging market funds is significantly different from zero, but lower than one might have expected. Herding is less pronounced among closed-end funds, suggesting that herding behavior might, to a significant extent, be traceable to the behavior of individual investors

[2]We do not examine the impact of funds’ behavior on their performance here.

rather than fund managers. There is some evidence that emerging market funds follow momentum strategies and do this more when selling than when buying.

I. Herding, Momentum Trading, and Institutional Investors

The tendency of some market participants to buy or sell assets simply because they observe other investors doing so has been labeled herding. Rationalizations of herding include informational learning (cascades), principal-agent problems, or other externalities.[3] Informational cascades occur when actions are observable but information is partly private. In such situations, agents' actions provide valuable information to others, and in some cases it may be optimal for investors to rely exclusively on observation of the actions of others when making investment decisions. This is particularly relevant if there are fixed costs of acquiring information about a company or, in the case of interest in this study, a country.[4] Herding that results from informational cascades constitutes a case for more "transparency"—that is, for governments and international institutions to provide markets with more and more timely information.[5]

On the one hand, since institutional investors are better informed about each other's trades than individual investors are, it is sometimes argued that the former are more prone to herding than the latter.[6] An example of a principal-agent explanation of herd behavior, on the other hand, is given by the possibility that fund managers are evaluated based on relative, instead of absolute, performance, which provides them with an incentive to mimic the actions of other managers.[7]

A related behavior of investors is the use of "momentum strategies." In the finance literature, it has been documented that domestic U.S. mutual funds engage in "positive feedback trading,"[8] buying assets whose prices have been rising and selling assets whose prices have been falling. This behavior can be the result of extrapolative price expectations, collateral or margin calls, or dynamic hedging strategies.[9]

Lastly, international investors may appear to behave like a herd if they react simultaneously to the same fundamentals. In this case, their behavior speeds up the adjustment of prices and is not destabilizing.[10] In an efficient market, however, speedy price adjustment should occur without many actual trades having to take place. Moreover, the question remains why international investors react differently to information than domestic investors.

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[3] See Devenow and Welch (1996) for an overview of rational herding models and Bikhchandani and Sharma (2001) for a more recent survey of the theoretical and empirical literature.

[4] For an example, see Calvo and Mendoza (2000).

[5] See Eichengreen and others (1998), p. 23.

[6] See Lakonishok, Shleifer, and Vishny (1992).

[7] See Scharfstein and Stein (1990) or Calvo and Mendoza (2000).

[8] See DeLong and others (1990).

[9] See Eichengreen and others (1998) and Kim and Wei (2002b). Professional investment managers occasionally recommend this strategy to their clients. For example, the *Los Angeles Times* quotes Templeton Developing Markets manager Mark Mobius as suggesting, with respect to holdings of emerging market funds, that "You say, 'If the fund goes down this much, I'm out.'" See Lim (1999).

[10] See Lakonishok, Shleifer, and Vishny (1992).

The empirical literature directly examining the behavior of international investors is still sparse. Apart from Froot, O'Connell, and Seasholes (2001), a few researchers have looked at specific regions and time frames. Kim and Wei (2002a) examine the transactions of different types of portfolio investors in Korea before and during the Asian crisis, finding that nonresident institutional investors were always positive-feedback traders while resident investors were contrarian traders before the crisis but became positive-feedback traders during the crisis. Herding appears to be more widespread among individual and nonresident investors than among institutional and resident investors. In another study, Kim and Wei (2002b) compare trading behavior in Korea of offshore investment funds with that of funds registered in the United States and the United Kingdom, finding herding behavior less prevalent among offshore funds. Choe, Kho, and Stulz (1998) also study transaction data from the Korean stock market during the crisis and find evidence for return-chasing and herding among foreign investors before the crisis, but no evidence for a destabilizing effect of foreign investors over the entire sample period. While their data are of high frequency, they are not able to trace trades originating from the same investor.[11] Kaminsky, Lyons, and Schmukler (2000) investigate trading strategies for 13 U.S. funds investing in Latin America, reporting evidence on momentum strategies. The present article examines these issues on a global scale.

II. Data

The data used in this study are from a comprehensive database purchased from *eMergingPortfolio.com* (formerly Emerging Market Funds Research, Inc). They cover, on a monthly basis, the geographic asset allocation of hundreds of equity funds with a focus on emerging markets for the period 1996:1–2000:12. According to the provider, the database covers about 80 percent of dedicated emerging market equity funds worldwide, with a coverage of roughly 90 percent in terms of assets.[12] Moreover, the sample is particularly interesting, given the number of emerging market crises that occurred over the period.

At the beginning of the sample, the database includes 382 funds managing assets totaling $116.5 billion; at the end of the period, the number of funds included is 642, managing $120.0 billion of assets. Note that although the total number of funds increased over the period, some funds were dropped from the database, mostly because they were merged or liquidated. According to the data vendor, the exiting funds did not share specific characteristics that would result in a serious bias of the sample. For critical calculations, however, we will provide results for both a balanced subsample and for the whole database. There are 231 funds that stay in the sample throughout the period.

[11] A few studies have investigated the herding and momentum trading behavior of U.S. mutual and pension funds. See Lakonishok, Shleifer, and Vishny (1992); Grinblatt, Titman, and Wermers (1995); and Wermers (1999). Another study of herding in international, but not emerging, financial markets is Kodres and Pritsker (1996), which analyzes daily position data of large institutional futures market participants.

[12] To our knowledge, the frequency of these data is higher than the data frequency of all other studies of herding covering more than one emerging market and higher than all but one study of herding behavior in the United States, for which quarterly or biannual data were used.

Slightly more than half of the funds covered are international, global emerging market, or regional funds, with the rest being single-country funds (mainly for Asian countries). In February, 1999, the sample consisted of 9 international funds (not necessarily focusing on emerging markets), 53 global emerging market funds, 125 Asian regional funds (18 of which included equity holdings in Japan), 170 Asian single-country funds, 13 Latin American single-country funds, 52 regional Latin American funds, and 51 funds focusing on other geographic areas (12 of which were single-country funds). Approximately one-quarter of the funds are closed-end funds. The funds are domiciled mostly in advanced economies and offshore banking centers.

Table 1 provides an overview of the types and number of funds and their holdings in different geographic regions. The first interesting observation is that although the total holdings of these mutual funds increased in Latin America, Europe, the Middle East, and Africa, their holdings in Asia decreased. An examination of the time series shows that, not surprisingly, the major drop in the value of the Asian assets occurred during the Asian crisis of 1997. Nevertheless, after the crisis, total holdings in Asia were still more than twice as large as those in Latin America and significantly exceeded those in emerging Europe. Asia remains the region with by far the largest number of single-country funds.

How important are these funds as investors in emerging equity markets? Reliable and comprehensive statistics on foreign equity holdings in, and flows to, emerging markets are hard to come by. Some evidence, however, indicates that the assets of these funds represent a modest, but not insignificant fraction of the total market capitalization. For example, for Argentina, the funds held approximately 6.5 percent of the total stock market capitalization in August 1998, while the corresponding share was around 4.5 percent in both Hungary and Korea. Table 2 provides a comparison of total monthly value traded, fund holdings, and market capitalization by region. The funds in our database seem to be more important players in emerging Europe and Latin America than in the Middle East and Africa region and Asia. Another way of ascertaining the importance of these funds is to compare their flows with total equity flows to emerging markets. Here, the World Bank (2001) estimates that total equity flows to developing countries were $15.6 billion in 1998, compared with a $1.8 billion net inflow from the funds in our sample. For 1999, total flows were estimated at $34.5 billion, compared with a net outflow of $1.3 billion from the funds in our sample.

One limitation of the dataset is that it provides asset *positions* in each country, although we are mainly interested in the *flows* to individual countries. We calculate implied flows from the asset-position data under some assumptions concerning the stock valuation changes. In particular, we assume that funds hold a portfolio of stocks that is well approximated by the International Finance Corporation's U.S. dollar total return investable index.[13] We assume that flows

[13]In cases for which the IFC does not compute an investable index, we used the global index. For countries not covered by the IFC, we employed Morgan Stanley Capital International's U.S. dollar index data or national indices converted into U.S. dollars. (We also redid the main calculations using MSCI data exclusively without qualitatively altering the results.)

Table 1. Total Holdings and Number of Funds, by Region

(holdings in billion U.S. dollars)

	Asia		Latin America		Emerging Europe		Middle East and Africa	
Type of Fund	Number	Holdings	Number	Holdings	Number	Holdings	Number	Holdings
Single-country								
January 1996	166	14.8	10	1.9	9	0.4	3	0.3
December 2000	162	7.3	14	1.9	12	0.3	4	0.3
Regional								
January 1996	118	30.9	30	4.3	7	0.5	3	0.2
December 2000	188	19.4	78	5.9	63	2.9	18	0.2
Global emerging markets								
January 1996	38*	9.0	37*	6.3	36*	2.3	37*	1.1
December 2000	115*	15.0	113*	11.4	114*	5.1	115*	4.7
International								
January 1996	9*	8.0	9*	2.2	9*	13.8**	6*	0.2
December 2000	9*	9.2	19*	1.9	20*	15.0**	4*	0.1
Total								
January 1996	**331**	**62.7**	**86**	**14.7**	**61**	**17.0**	**49**	**1.8**
December 2000	**474**	**50.9**	**224**	**21.1**	**209**	**23.3**	**141**	**5.3**

Source: Authors' calculations based on data from *eMergingPortfolio.com.*

Note: Holdings are as of the end of the month. An asterisk (*) indicates that the number provided includes all global emerging markets or international funds with assets in the respective region. Two asterisks (**) indicate that the holdings are comprised mostly of assets in mature European markets. (International funds are the only class of funds in the sample with substantial holdings in mature markets.)

Table 2. Market Capitalization, Value Traded, and Total Assets of Funds for 1996–2000, by Region
(average per month, in billion U.S. dollars)

	Latin America	Asia	Emerging Europe	Middle East and Africa
Market capitalization	505	1,851	274	336
Holdings	21	59	32	4
Monthly value traded	16	214	18	7

Sources: For market capitalization and turnover: International Finance Corporation; for holdings: *eMerging.Portfolio.com.*

occur halfway through the period. For each country *c* and fund *i* in month *t*, we therefore calculate the flow in the following way:

$$Flow_{cit} = [Assets_{i,c,t} - Assets_{i,c,t-1} - Index\ return_{ct} \cdot Assets_{i,c,t-1}] / (1 + Index\ return_{ct})^{1/2} \quad (1)$$

This obviously represents an approximation, and, in certain cases, we might be introducing nonnegligible errors by using this procedure. If individual fund managers were able to beat the index, we would overstate the flow of funds into a country. Consistency checks for closed-end funds, however, show that our approximation is quite close.[14] Moreover, for most of the statistics discussed later in this article, the sign of the change in the position is essentially what matters. It is unlikely that this method alters the sign of a fund's transaction, in which case we would erroneously classify net buyers as net sellers or vice versa. Nevertheless, we conduct a variety of robustness checks in the following sections.

One first way of examining whether all funds move together is to look at gross flows into and out of regions. Figure 1 displays flows into the four major geographical regions for the whole period, with net flows broken down into gross positive and negative flows. In order to eliminate effects arising from the addition or deletion of funds from the sample, we focus on the much smaller balanced subsample.

The graphs and panels of Figure 1 indicate that, except for the case of the Middle East and Africa, inflows contemporaneously coexist with outflows of similar magnitude.[15] On the one hand, this indicates that not all funds systematically

[14] A look at the closed-end funds in our sample allows us to ascertain the extent to which this approximation is a good one. (This comparison is not possible with open-ended funds, since they are subject to redemptions, for which we do not have data.) For these funds, the change in total assets $A_t - A_{t-1}$ should be equal to the return on all country holdings $A_{i,t} - A_{i,t-1} = \sum Index\ return_{c,t} \cdot Total\ assets_{i,c,t-1}$. Without taking into account returns on fixed income, the correlation between imputed and actual changes in total assets is 0.93. Even for single-country funds, which can be expected to specialize in stock picking and therefore to deviate significantly from the index in their returns, the correlation is 0.87. Note that for closed-end, single-country funds, we can, ignoring timing issues, directly infer the flows into and out of the respective country from changes in the cash position.

[15] The large outflows from the Middle East and Africa in November 2000 reflect sharp outflows from Israel and South Africa.

move as a herd. On the other hand, they also suggest that, measured on a net basis, funds did pull out of markets just before major crises. For Asia, we observe sizable net outflows starting one month before the collapse of the Thai baht in early July 1997 and ending in November of that year. For Europe, there is a substantial drop in net inflows at the outset of the Russian crisis in July 1998 and lasting until the following November. For Latin America, the figures show a sharp outflow one month before the Brazilian devaluation in December of 1998.

III. Testing for Herding

In this section, we compute and discuss a quantitative measure for the degree of herding among funds. This measure, originally introduced by Lakonishok, Shleifer, and Vishny (1992), allows an assessment of whether funds move in the same direction more often than one would expect if they traded independently and randomly. The indicator, denoted by *HM* (for herding measure), is given by

$$HM_{it} = |p_{it} - E[p_{it}]| - E|p_{it} - E[p_{it}]|, \tag{2}$$

where p_{it} is the proportion of all funds active in country i in month t that are buyers, and $E[p_{it}]$ is its expected value. $E[p_{it}]$ may vary over time, and we approximate it by the total number of net buyers across all countries, divided by the total number of funds active in that month. Since the distribution of the absolute value of the first expression is not centered around zero, we need to subtract its expected value. Under the null hypothesis of no herding, this expected value is calculated assuming that the number of buyers follows a binomial distribution.

Again, as discussed previously, if news is not incorporated quickly into prices, high *HM* values may indicate that funds are reacting to the same fundamentals. This does not render the measure less interesting, since it is not clear why this class of investors should systematically react to news in the same way (as opposed to the type of investors on the other side of the trades).

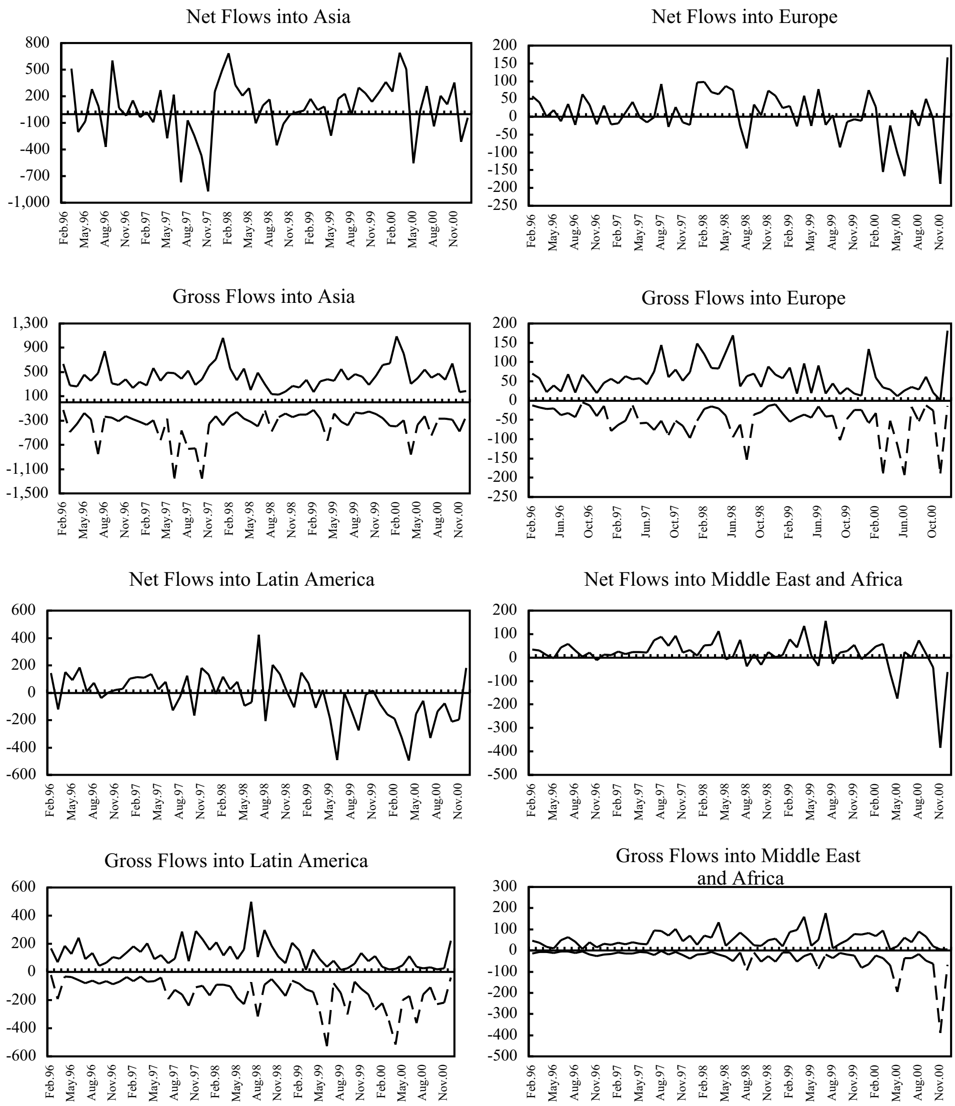
In order to restrict our attention to a meaningful notion of a “herd,” we calculate the herding measure for only those cases in which the number of active funds in country i at time t, N_{it} exceeds five. Moreover, in order to limit the impact of errors introduced by our calculation of flows, we classify a fund as buyer or seller only if the absolute value of the calculated flow into (or out of) a country is larger than 3 percent of the fund’s assets in that country.[16] HM_{it} can be calculated for different subgroups of funds, groups of countries, and time periods. Note that our data do not allow us to differentiate directly between herding by managers and by individual investors; we are, however, able to obtain some indirect evidence on the issue, which will be discussed later in this article.

The results indicate the presence of significant, but not dramatic herding behavior. Table 3 reports average values for *HM* for the four major regions and three subperiods. The overall mean is 7.7 percent. In other words, for a given country, the number of funds moving in the same direction was approximately 8 percent larger than one would have expected if they acted independently and randomly.

[16] We also used other error margins. See the discussion of robustness later in this article.

Figure 1. Gross and Net Flows, by Region

(balanced subpanel; figures in millions of U.S. dollars)



Sources: Authors' calculations based on data from *eMergingPortfolio.com;* and International Finance Corporation.

Table 3. Mean Herding Measures, by Region
(in percent)

	All	Asia	Latin America	Emerging Europe	Middle East and Africa
1996	7.1	6.9	7.2	5.7	9.3
	(0.6)	(0.8)	(1.1)	(1.4)	(1.7)
1997	6.9	7.0	4.6	5.8	10.1
	(0.6)	(0.8)	(1.0)	(1.2)	(2.0)
1998	7.8	7.6	8.4	7.4	6.6
	(0.6)	(0.8)	(1.2)	(1.2)	(1.9)
1999	7.7	8.2	8.4	5.7	7.4
	(0.5)	(0.8)	(1.1)	(1.1)	(1.7)
2000	8.8	8.7	8.6	8.9	10.1
	(0.5)	(0.8)	(1.1)	(1.1)	(1.6)
Whole period	7.7	7.9	7.4	6.8	8.9
	(0.2)	(0.4)	(0.5)	(0.5)	(0.8)

Sources: Authors' calculations based on data from *eMergingPortfolio.com;* and International Finance Corporation.

Notes: The standard error of the mean is given in parentheses. All results are significant at the 1 percent level.

This number is more than twice as large as the values found by Wermers (1999) and Lakonishok, Shleifer, and Vishny (1992) for U.S. institutional investors. Interestingly, the value is very similar to the one reported by Kim and Wei (2002a) for nonresident institutional investors investing in Korea around the time of the Korean crisis. It is not, however, as large a figure as conventional wisdom might have led one to expect. There is little variation in this average across regions and over time. The numbers for Europe are initially lower but increase over time.

We also looked more specifically at the results around crisis episodes, without finding evidence for higher herding: as shown in Table 4, the herding measure across countries during crisis months was 7.5 percent.[17] Nevertheless, specific months following large outflows that were documented earlier are characterized by large herding measures (for example, the herding measure for Brazil one month prior to the country's crisis is 15 percent). What we do not observe is that herding increases systematically across countries during crises. It is worth stressing again that since we are focusing on dedicated emerging market funds, we cannot say much about herding into and out of the emerging market asset class as a whole. This is true despite the fact that even dedicated funds can temporarily avoid holding assets in most emerging markets by switching to cash holdings.

There might be important differences across different types of fund. For example, the inclusion of single-country funds may tend to lower the overall

[17]Periods include 1997:08–1997:12, 1998:06–1998:10, and 1998:11–1999:02, which correspond to crises in Asia, Russia, and Brazil, respectively.

Table 4. Mean Herding Measure During Crises, by Region
(in percent)

All	Asia	Latin America	Europe	Middle East and Africa
7.5	8.6	6.9	6.7	7.3
(0.5)	(0.7)	(1.0)	(1.0)	(1.6)

Sources: Authors' calculations based on data from *eMergingPortfolio.com*; and International Finance Corporation.

Note: Crisis periods include 1997:08–1997:12, 1998:06–1998:10, and 1998:11–1999:02, which correspond to crises in Asia, Russia, and Brazil, respectively.

Table 5. Mean Herding Measures, by Type of Fund
(based on average size of all funds over time)

	Smallest 20 Percent	Largest 20 Percent	Closed-End	International and Global Emerging Markets	Non-Single-Country	Offshore
Whole period	4.6	7.0	5.9	7.4	7.7	6.2
	(0.4)	(0.3)	(0.4)	(0.3)	(0.3)	(0.3)

Sources: Authors' calculations based on data from *eMergingPortfolio.com*; and International Finance Corporation.

Notes: Standard error of the mean is given in parentheses. All results are significant at the 1 percent level.

herding measure if these funds are required to hold a specific fraction of their assets in a particular country or if they are limited in their ability to hold cash instead. Similarly, offshore investment funds may display different investment patterns owing to lower regulatory constraints and different tax treatments they face. Closed-end funds are not subject to redemptions and are therefore less likely to move as a herd.[18] Table 5 shows the herding measures for different types of fund.[19]

The results show that excluding single-country funds does not alter the result. In line with the results of Kim and Wei (2002b), offshore funds tend to herd less than other funds. Confirming our expectations, there is also less herding among smaller funds.[20] Large, global, and international funds do not differ significantly from the average in their herding behavior. In line with our a priori reasoning, herding is also less pronounced among closed-end funds (which are not subject to

[18] See Kaminsky, Lyons, and Schmukler (2000) for an attempt to distinguish between herding by managers and by individual investors.

[19] Offshore funds are defined as those having their domiciles in tax havens. An alternative definition would have classified funds as "offshore" if they did not invest primarily in the country in which they were located. However, a few funds do focus on the stock market of the country in which they are domiciled. (Korean funds are among these.) Excluding those "onshore" funds did not affect the main results. The results for different types of fund were calculated using $E[p_{it}]$ from the whole sample.

[20] Note, however, that the smaller figure for small funds may reflect the fact that these funds experienced a lower-than-average growth of inflows.

Table 6. Mean Herding Measures, by Stock Market Capitalization and by Liquidity

	Ten Smallest	Ten Largest	Ten Least Liquid	Ten Most Liquid
Whole period	5.3	8.1	7.2	7.7
	(0.4)	(0.5)	(0.5)	(0.5)

Sources: Authors' calculations based on data from *eMergingPortfolio.com*; and International Finance Corporation.

Notes: Standard errors of the means are given in parentheses. All results are significant at the 1 percent level. Liquidity is measured as value traded divided by market capitalization.

redemptions), suggesting that the observed tendency for herding might, to a significant extent, be traceable to the behavior of individual investors.[21] To some extent, this contradicts the presumption, mentioned earlier, that institutional investors are more likely to herd since they can observe each other's actions more easily.

There might be sizable differences in the degree of herding, depending on market size. For smaller markets, it may be more difficult, or at least relatively more costly, to obtain accurate information about fundamentals. On the one hand, if that is true, fund managers may be more inclined to imitate the behavior of managers of other funds.[22] On the other hand, when their funds are subject to large inflows or outflows, managers may go first to the most liquid markets and then, gradually, to the less liquid ones. Table 6 displays the herding measures for the smallest and largest as well as for the 10 least and most liquid stock markets that are covered by the International Finance Corporation (IFC).[23] There is more herding for the largest stock markets than for the smallest, and the difference is statistically significant at the 1 percent level. The difference between highly liquid and less liquid markets, however, is not statistically significant.

Simulating the Herding Measure Distribution

In order to gain a better grasp of the quantitative importance of our results, we follow Wermers (1999) in comparing the distributions of the actual monthly herding measures to a simulated distribution obtained under the assumption that funds make their buying decisions independently.[24] The distributions differ sharply: in contrast to the actual distribution, the simulated distribution is nearly symmetric

[21] This, of course, raises questions regarding the incentives for individual investors to herd; such incentives would appear to be more difficult to explain than those at the fund manager level.

[22] See Banerjee (1992) and Calvo and Mendoza (2000) for models illustrating similar arguments.

[23] These calculations provide the means of herding measures across the respective countries and over time and are based on all funds in the sample that are active in those countries. Concerning the selection of the smallest markets, although there are even smaller ones in our sample, comparability of market capitalization figures and, more importantly, the often very small number of transactions in such markets led us to focus on the stock markets covered by the IFC in making this comparison. Liquidity is measured as monthly trading volume divided by market capitalization.

[24] Details of the Monte Carlo simulation are given in the appendix.

around zero and the moments differ significantly (Figure 2). The simulated distribution also confirms that the previously obtained results are significantly different from what would be expected under the null hypothesis of independent and random trading.[25]

Alternative Specifications and Robustness

We undertook several exercises to ascertain the robustness of our results. First, one could argue that despite controlling for time-varying propensities to buy, the herding measure might overstate the extent of actual herding if there are many funds entering our sample, since these funds will naturally tend to grow and therefore buy frequently. We therefore carried out the calculations with a balanced subsample—that is, only with funds that stayed within the sample throughout the 60 months—obtaining very similar, albeit somewhat lower, results. (The overall mean herding measure was 7.1 percent; the region with the lowest herding overall measure was, again, Europe, with 6.0 percent, and the one with the highest was Asia, with 7.9 percent). During crises, herding was slightly lower (with a mean of 6.9 percent).

Second, the relevant unit for our analysis may not be the individual fund, but the firm, since many funds within one firm may be managed by the same fund manager. We therefore also calculated the herding measure aggregating all funds that belong to the same firm. This would be appropriate in the extreme case in which there were only one fund manager managing all the mutual funds of a firm. After aggregation, we are left with an average of only 84 funds per month. The mean herding measure obtained in this way is somewhat lower, at 5.3 percent. The lowest value was obtained for the Middle East and Africa (3.9 percent) and the highest for Asia (6.5 percent).

Third, to address the question of measurement errors in our flows, we calculated the herding measures counting only those flows that exceeded 1 or 5 (instead of 3) percent of the fund's assets in the last period measured. The results were barely altered: for example, when there was 5 percent error margin, the overall herding measure became 7.4 percent.

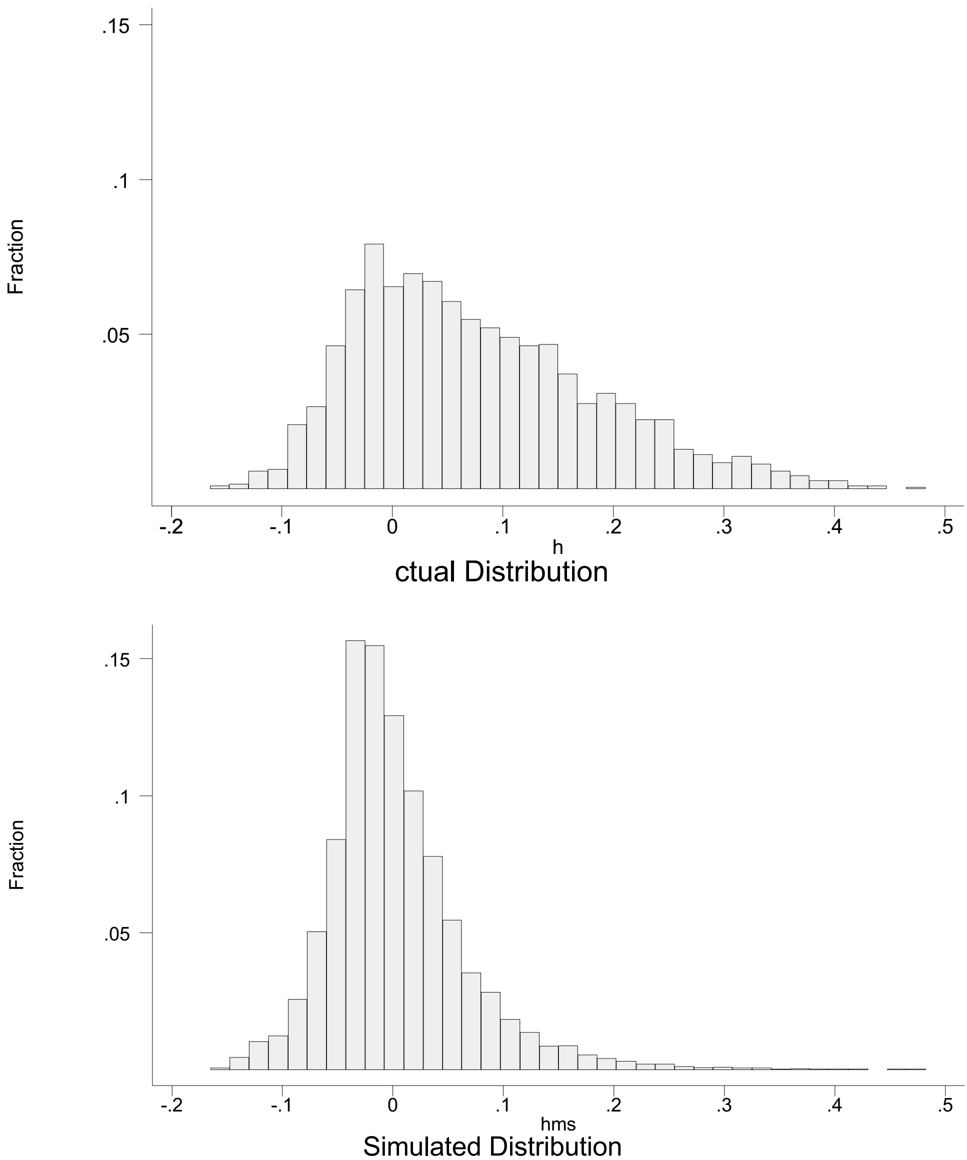
Fourth, in contrast to herding at the country level, herding might be greater at the regional level; for example, at a particular time, everybody might want to move into Latin America, but not necessarily into the same country markets. We investigated this possibility by treating whole regions as individual assets and focusing on global or international funds, finding weaker evidence for herding: the overall mean was 4.3 percent, with the average herding measure being highest for Latin America (4.8) and lowest for the Middle East and Africa (3.1).[26] Again, during crises, the mean is lower, at 2.4 percent.

Last, we redid the calculations using only those country-months in which the number of funds active in the country in question, N_{it}, exceeded 15 (instead of 5), obtaining very similar results: the mean of *HM* was 7.8 percent.

[25] For example, the ninety-fifth percentile of the mean of the empirical distribution is 6.9 percent.

[26] See Lakonishok, Shleifer, and Vishny (1992) for an analogous exercise using industries instead of individual stocks.

Figure 2. Actual and Simulated Herding Measure Distributions



Sources: Authors' calculations based on data from eMergingPortfolio.com; and International Finance Corporation.

Notes: For actual distribution (h), number of observations = 1,882; mean = 0.0770; median = 0.0581; standard deviation = 0.1082; and kurtosis = 3.040. For simulated distribution (hms), number of observations = 188,200; mean = 0.0037; median = –0.0074; standard deviation = 0.0642; and kurtosis = 8.209.

Herding and Volatility

What is the impact of herding on stock return behavior? If the amount of herding that we detected among our group of investors had important effects on stock markets, we would expect to observe a positive correlation between the degree of herding and stock return volatility. In order to investigate this issue, we regressed the variance of stock-index returns (computed for each country over the whole period) on the country mean of the computed herding measures. The result from an ordinary-least-squares regression using 40 countries reveals a statistically significant relationship between the two variables. The coefficient on the mean herding variable is 0.47, with a t-statistic of 14.6 and an R^2 of 0.10. While this suggests that herding affects volatility, the results should not be accepted without qualification, given that we did not control for other factors. Moreover, reverse causality might be present.[27]

A more appropriate technique than the simple regression might be a GARCH framework. We estimated a GARCH (1,1) model in which the monthly herding measure entered the variance equation for each country individually and found mixed evidence for the link between herding and volatility. For the 39 countries with sufficient observations, the herding variable entered significantly positively (at the 5 percent level) in 15 cases, with an average coefficient of 0.04 and an average t-statistic of 3.44. In 5 cases, by contrast, the coefficient was significantly negative, with an average coefficient of –0.04 and an average t-statistic of –3.06. In the remaining cases, the coefficient on the herding variable was not statistically significant.

Overall, the evidence on the relationship between herding and volatility is mixed. Possibly, the degree of herding observed in our sample is too low to affect volatility in a systematic, significant way.

IV. Testing for Positive-Feedback Trading

Another way of looking at these funds' investment strategies is to examine the extent to which they follow "positive-feedback" or "momentum" strategies. For this purpose, we first examine whether the degree of herding can be related to past returns. If funds follow momentum strategies, we should observe herding to be more pronounced for extreme prior-month returns.[28] We also compute two measures of excess demand proposed by Lakonishok, Shleifer, and Vishny (1992) and examine their correlation with prior returns. The first measure, defined in their article as the numbers ratio (NR), is given for every given month t and country i by the total number of buyers, divided by the total number of funds active in that country:

[27]We also attempted to relate the level of stock market returns to herding. Regressions of returns on contemporaneous and lagged herding measures did not show a significant relationship, and mean returns are not significantly higher or lower in those country-months with exceptionally high (in the top 20 percent) lagged or contemporaneous herding measures.

[28]See Wermers (1999).

$$NR(i,t) = \#buyers(i,t)/\#active(i,t). \tag{3}$$

The second measure, called the dollar ratio (*DR*), is the difference between inflows and outflows, divided by the sum of inflows and outflows to a country:

$$DR = (inflows(i,t) - outflows(i,t))/(inflows(i,t) + outflows(i,t)). \tag{4}$$

We compute the correlations of both *NR* and *DR* with past-month returns. Following the literature, we also present the averages of *NR* and *DR* for different centiles of past-months' returns. More specifically, we sort all country-months into five prior-month-return quintiles, with lagged returns ranging from the lowest 20 percent to the highest 20 percent. For each of these quintiles, we present corresponding means of *NR* and *DR*. This exposition is also useful if there are non-linearities in the relationship between the excess-demand measures and prior returns—for example, *NR* and *DR* may differ from their overall mean only for periods of very pronounced overperformance or underperformance. Note that, in principle, *DR* and *NR* can yield opposite results; in any given period, the majority of funds may be sellers, but a few large buyers may dominate the overall picture.

The results are mixed. There is only a small overall correlation between the herding measures and past-month returns, namely 0.05 (Table 7). The correlation is statistically significant, however, and herding is significantly more pronounced for the lowest and highest past-month-return quintiles than for average prior-month returns. Similarly, the correlation between the country's prior stock performance and the subsequent proportion of funds (*NR*) buying in that market is statistically significant, but small (6 percent). *NR* increases from 0.48 for the lowest past-month-return quintile to 0.53 for the highest past-month-return quintile. Interestingly, momentum trading seems most pronounced in the most liquid markets, while the relationship between excess demand and past returns is not statistically significant for the less liquid ones. There does not seem to be more momentum trading during crises: while the *NR* measures increase monotonically by past-month-return quintile during crises, the correlation between the two variables during crises is the same as the one for the whole period (0.05) and, given the smaller number of observations, is not statistically significant. Momentum trading is less pronounced among the smallest and largest funds.

The picture obtained from examining the relationship between the imbalance measured in dollars (by *DR*) and lagged returns is similar (Table 8). There is a small but statistically significant relationship between lagged returns and *DR*, which is *less* pronounced during crises. In the case of *DR*, however, we do not find more accentuated momentum trading behavior for the most liquid markets.

A different methodology to assess the importance of momentum strategies has been proposed by Grinblatt, Titman, and Wermers (1995). Their momentum measure is given by

$$M = \frac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{N}\left(w_{j,t} - w_{j,t-1}\right)R_{j,t-1}, \tag{5}$$

Table 7. Past-Month Performance, Herding Measures, and Numbers Ratio (*NR*), by Fund Type and Market Size

		Numbers Ratios						
Past-Month-Performance Quintile	Herding Measure *(HM)*[1]	All funds	Single-country funds	Large funds *(largest 20 percent)*	Small funds *(smallest 20 percent)*	Ten most liquid markets	Ten least liquid markets	All funds during crises
1 (Worst)	8.0 (0.5)	0.48	0.43	0.49	0.50	0.49	0.51	0.45
2	7.0 (0.5)	0.49	0.42	0.51	0.47	0.50	0.46	0.47
3	7.0 (0.5)	0.50	0.50	0.52	0.54	0.54	0.48	0.48
4	7.7 (0.6)	0.49	0.50	0.50	0.51	0.50	0.47	0.49
5 (Best)	8.8 (0.6)	0.53	0.50	0.54	0.53	0.53	0.54	0.50
Overall correlation	0.05*	0.06*	0.06*	0.04	0.03	0.14*	0.03	0.05

Sources: Authors' calculations based on data from *eMergingPortfolio.com*; and International Finance Corporation.

Notes: Crisis periods include 1997:08–1997:12, 1998:06–1998:10, and 1998:11–1999:02, which correspond to crises in Asia, Russia, and Brazil, respectively. Correlations marked with an asterisk (*) are significant at the 5 percent level.

[1]The numbers in parentheses in this column are standard errors.

Table 8. Past-Month Performance and Dollar Ratio (*DR*), by Fund Type and Market Size

Past-Month-Performance Quintile	All Funds	Single-Country Funds	Large Funds (*largest 20 percent*)	Small Funds (*smallest 20 percent*)	Ten Most Liquid Markets	Ten Least Liquid Markets	All Funds During Crises
1 (Worst)	–0.10	–0.35	–0.07	–0.21	0.03	–0.12	–0.10
2	–0.18	–0.43	–0.14	–0.35	0.03	–0.22	–0.14
3	–0.11	–0.30	–0.10	–0.32	0.03	–0.17	–0.14
4	–0.10	–0.38	–0.10	–0.28	0.03	–0.15	–0.07
5 (Best)	0.00	–0.36	–0.01	–0.22	0.02	–0.04	–0.05
Overall correlation	0.05*	0.02	0.02	0.05*	0.05	0.05	0.01

Sources: Authors' calculations based on data from *eMergingPortfolio.com*; and International Finance Corporation.

Notes: Crisis periods include 1997:08–1997:12, 1998:06–1998:10, and 1998:11–1999:02, which correspond to crises in Asia, Russia, and Brazil, respectively. Correlations marked with an asterisk (*) are significant at the 5 percent level.

where $w_{j,t}$ and $R_{j,t}$ denote portfolio weights and returns of country j at time t. This is a momentum measure based on changes in portfolio weights in reaction to returns in the previous period. It is positive if there is momentum trading.

Compared with *NR* and *DR*, this measure has advantages and drawbacks. On the one hand, it focuses on strategies pursued by managers rather than individual investors, since a withdrawal by individual investors would not, per se, result in a change of weights. On the other hand, it also captures "passive" momentum strategies, since portfolio weights might change as a result of price movements without any trades taking place—but allowing such shifts in weights is done consciously by decision of the portfolio manager and is therefore of interest in this context. To complement the results from *DR* and NR, we therefore follow Grinblatt, Titman, and Wermers (1995) in documenting correlations between past returns and changes in weights. We adopt a slightly different (and, in our view, more intuitive) approach, however, by reporting the coefficients of regressions from $(w_{jt} - w_{jt-1})$ on $R_{i,t-1}$.

According to these regressions, momentum strategies are more prevalent on the sell side than on the buy side (Table 9). In most cases, the coefficients on past returns are much higher for cases in which portfolio weights decreased compared with those in which weights increased. Similarly, as was found using the *NR* measure, momentum trading is more pronounced in more liquid markets; in fact, the coefficient for the less liquid markets is negative, indicating that funds tended to buy past losers and sell past winners.[29] Similarly, as found before, large funds seem less prone to engage in momentum trading, while, in contrast to the results discussed previously, momentum trading seems more prevalent among the smallest funds. Interestingly, during crises, the tendency to buy past winners seems to be more prevalent while selling past losers is *less* prevalent.[30]

[29] Note that this type of behavior can be as destabilizing as positive-feedback trading.

[30] Kaminsky, Lyons, and Schmukler (2000) find that the propensity to buy past winners and sell past losers is stronger during non-crisis periods.

Table 9. Changes in Portfolio Weights in Response to Lagged Returns

	All Funds	Single-Country Funds	Large Funds (*largest 20 percent*)	Small Funds (*smallest 20 percent*)	Ten Most Liquid Markets	Ten Least Liquid Markets	All Funds During Crises[1]
Overall	0.81	3.42	0.30	1.54	0.86	–0.63	1.24
	(10.86)	(5.41)	(4.62)	(5.88)	(7.08)	(–5.57)	(8.95)
Buy	0.23	0.11	0.11	0.74	0.37	–0.66	0.50
	(3.22)	(0.17)	(1.53)	(2.95)	(3.17)	(–6.18)	(3.69)
Sell	0.34	2.39	–0.08	0.98	0.55	–0.40	0.04
	(3.53)	(2.86)	(–1.06)	(2.83)	(3.40)	(–2.68)	(0.22)

Sources: Authors' calculations based on data from *eMergingPortfolio.com*; and International Finance Corporation.

Notes: The figures show the coefficients from regressions of $(w_{jt} - w_{jt-1})$ on $R_{i,t-1}$ and fund fixed effects, where w_{jt} denotes the portfolio weight of country i at time t and $R_{i,t-1}$ stands for the prior-month return in country i. The results reported in the Buy (Sell) row are those from regressions restricted to observations where $(w_{jt} - w_{jt-1}) > 0$ (< 0). The t-statistics are given in parentheses. The R^2s of the regressions (not shown) were very low, mostly below 0.01. The coefficients on time dummies are omitted.

[1]Periods include 1997:08–1997:12, 1998:06–1998:10, and 1998:11–1999:02, which correspond to crises in Asia, Russia, and Brazil, respectively.

V. Conclusion

We find statistically significant evidence for herding behavior, but its magnitude is smaller than what anecdotal evidence might have led one to expect. There are no dominant patterns across funds and over time, although herding is more prevalent in larger emerging markets. Herding is less pronounced among closed-end funds, suggesting that herding behavior might, to a significant extent, be traceable to individual investors' behavior. Differences in the degree of herding across countries are correlated with stock-return volatility. To some extent, emerging market funds also follow momentum strategies, selling past losers and buying past winners. This behavior is more pronounced when selling than when buying, but not more prevalent during crises.

Overall, although we have gathered some circumstantial evidence, the case against emerging market mutual funds remains to be proven. Herding and positive feedback trading appear to be relevant phenomena among dedicated emerging market equity funds. The observed degree of herding and momentum trading, however, is probably too limited to account for the large observed volatility on international capital markets. Other considerations clearly play a role in the asset allocations of these funds; this remains a subject for further research.[31]

[31]Disyatat and Gelos (2001) have recently shown that a model of mean-variance optimization around a benchmark index helps to explain funds' asset allocations. Fund managers do not seem to be guided by past returns when assessing expected returns, but historical correlation matrices appear to be good approximations of expected correlations.

APPENDIX

Simulating the Herding Measure Distribution

Following Wermers (1999), we use a Monte Carlo simulation procedure to generate a simulated distribution of herding measures under the null hypothesis of independent trading. For each month t, the number of funds investing in a given country i in month t is generated as a draw from a binomial distribution. More precisely, if n_{it} is the number of actual trades in a country (if n_{it} is greater than or equal to 5), we produce n_{it} draws from a $U(0,1)$ distribution with a random number generator. Each draw is rounded up to 1 if it is greater than $1- E[p_{it}]$ (where $E[p_{it}]$ is the actual proportion of funds buying in that year, as explained in Section III); otherwise, it is rounded down to zero. These outcomes are summed up, yielding a draw from a binomial distribution $b(n_{it}, E[p_{it}])$. Based on this simulated data, we calculate the simulated herding measures. We repeat this procedure 100 times, obtaining a sample of 188,200 simulated herding measures.

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