## Asset Fire Sales and Purchases and the International Transmission of Financial Shocks.\*

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#### Abstract

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# Asset Fire Sales and Purchases and the International Transmission of Financial Shocks

#### Abstract

We provide new evidence on the channels through which financial shocks are transmitted across international borders. Employing monthly data from 1996 to 2008 on over 1,000 developed country-domiciled mutual and hedge funds, we show that inflows and outflows experienced by these funds translate into significant changes in their portfolio allocations in 25 emerging markets. Despite funds' efforts to ameliorate the price impact of these portfolio allocation shifts, they substantially impact emerging market equity returns and are associated with increases in co-movement between emerging and developed markets.

## 1. Introduction

How do asset returns across countries move together, and what drives changes in their co-movement over time? These questions come up naturally when tracing the transmission of crises across markets, or when evaluating the benefits of international portfolio diversification (a few recent papers on the subject include Heston and Rouwenhorst (1994), King, Sentana and Wadhwani (1994), Longin and Solnik (1995), Bekaert, Harvey and Ng (2005) and Bekaert, Hodrick and Zhang (2008)). Theoretically, changes in return co-movement should be driven by changes in fundamentals, such as trade between countries or common variation in macroeconomic variables, and this source has been identified to have important effects (see, for example, Eichengreen, Rose, and Wyplosz (1996), Sachs, Tornell and Velasco (1996), Eichengreen and Rose (1998), Rigobon (1998) and Glick and Rose (1999)). However, there are situations in which the movement of fundamentals does not fully explain co-movement between markets, and others in which co-movement is attributed solely to non-fundamental sources (the latter is commonly referred to as 'contagion,' especially as it relates to emerging markets; see Forbes and Rigobon (2001) and Karolyi (2003) for useful surveys).

Recent theories explaining non-fundamental or excess co-movement have highlighted the important role of financial intermediaries in transmitting shocks across borders. For example, Calvo (2005) presents a model in which informed, but leveraged investment managers ('Wall Street') are responsible for elevated correlations between asset returns in different countries. More recently, Pavlova and Rigobon (2008) present a model in which portfolio constraints amplify price fluctuations as well as cross-market co-movement.<sup>1</sup> Yet, despite the strong theoretical backing for the role of financial intermediaries in the transmission of financial shocks across borders, empirical evidence on this channel has been suggestive, but not conclusive. The existing evidence has been inferred indirectly by contrasting the behavior of investable and non-investable indices during crises (see Boyer, Kumagai and Yuan (2006)), cleverly extrapolated from the behavior of a small sample of Latin American-focused investment managers (see Kaminsky, Lyons and Schmukler (2004)), or tied to cross-market banking lending activity (Kaminsky and Reinhart (2000)).<sup>2</sup>

<sup>&</sup>lt;sup>1</sup>In other work, Kodres and Pritsker (2002) present a model that generates co-movement through cross-market rebalancing. Also, Kyle and Xiong (2001) and Yuan (2005) show that wealth-constrained investors who lose money may need to liquidate positions in multiple countries, thereby spreading a crisis from one country to others.

<sup>&</sup>lt;sup>2</sup>Also see Forbes and Rigobon (2002), and Forbes (2004).

This paper provides significant, new evidence in support of the theoretically predicted role of financial intermediaries in transmitting shocks across borders. To conduct the analysis, we employ a large dataset on the monthly capital flows to, and country-allocations of, international investment managers that invest in emerging markets, obtained from Emerging Portfolio Fund Research (EPFR). The data span the period from 1996 to the present, and cover over a thousand developed-country-domiciled funds which collectively hold on average 7% (and at maximum, 17%) of the float-adjusted market capitalization of the twenty-five emerging markets in our sample. We find that when these funds experience shocks to their funding, they take actions that significantly impact emerging market equity returns, and change the patterns of co-movement between developed market and emerging market returns. This evidence contributes to the growing literature linking asset-market liquidity with the funding of financial intermediaries. For example, Coval and Stafford (2007), show that U.S. mutual funds redeem investments as a consequence of funding shocks that originate from their investor base, and when such redemptions are correlated across institutions that hold particular stocks, the prices of these stocks fall significantly. Acharya, Schaefer and Zhang (2007) study the Ford and GM credit ratings downgrades in 2005, and identify that the liquidity risk faced by brokers and dealers during that time translated into elevated co-movement between the CDS spreads of GM and Ford, and those of firms in unrelated industries. Theoretical papers in this emerging tradition include Shleifer and Vishny (1992), Brunnermeier and Pedersen (2009), and Adrian and Shin (2009).

Our starting point is to investigate the trading behavior of those global funds that are under financial pressure on account of significant subscriptions or redemptions of capital by their investors. Regardless of the cash buffer that they hold, these funds substantially alter their portfolio allocations in response to funding shocks from their investor base. These changes are economically and statistically significant: Global funds in the bottom decile (which experience significant outflows) reduce or eliminate their holdings in approximately 80% of the markets in which they invest over the month following the outflows. This can be compared to the funds in the top decile, which experience significant inflows, and reduce or eliminate just 21% of their positions. Similarly funds in the top

<sup>&</sup>lt;sup>3</sup>Hau and Rey (2008a, 2008b), using alternative semi-annual data, highlight the importance of an examination of the micro-level activities of individual funds by demonstrating the macro-level implications of their collective actions. While the focus in their work is quite different, we follow this line of thinking using the monthly EPFR flow and allocations data to explore the role that global funds play in international asset return co-movement.

decile expand their holdings in 79% of the markets in which they invest, while those experiencing significant outflows expand just 22% of their positions. However, the funds do seem to exercise some discretion in the face of pressure from their outside investors: We find that forced expansions (reductions) of positions occur in relatively more liquid markets in the face of inflows (outflows).

Our next step is to connect these 'fire-sale' changes in global funds' portfolio allocations to emerging market stock returns. To do so, we construct a measure of emerging market capital that is 'At-Risk.' Specifically, we first take the product of the dollars allocated by each fund to each emerging market with the flows experienced by the fund. We then aggregate the measure across all funds in the sample to obtain total dollars 'At-Risk,' and then normalize the measure in various ways. The measure captures the amount of capital that a particular emerging market could see enter or exit as a result of the inflows and outflows faced by invested funds. When we sort emerging countries into quintiles each calendar month on the basis of At-Risk, we find that the countries in the top quintile of At-Risk outperform those in the bottom quintile by 128 basis points per month on average, or 15.4% on an annualized basis. When we construct a calendar time portfolio that is long the top quintile of At-Risk countries and short the bottom quintile of At-Risk countries, the alpha of the portfolio is virtually unchanged when evaluated using either the excess return on the MSCI G-7 index, or the excess return on the MSCI World index as the systematic risk factor. This large and significant difference between the negative and positive At-Risk country-months suggests that the fire-sale changes in allocations by intermediaries subject to funding pressure have significant impacts on the prices of the markets in which the forced trading occurs.<sup>4</sup>

We then find that these fire-sale actions of global funds increase the co-movement between the returns of the emerging stock markets most subject to this source of pressure and the returns of the developed markets from which the funding shocks emanate. When we allow for betas on the calendar-time portfolio to vary conditional on the sign of the G-7 excess return, the alpha is eliminated. In the face of positive (negative) G-7 returns, emerging markets with positive (negative) At-Risk capital have significantly larger G-7 (and world market) betas than do countries with negative (positive) At-Risk capital. Our explanation for this is as follows: When stock returns in

<sup>&</sup>lt;sup>4</sup>It is worth noting here that the At-Risk measure includes contemporaneous information on capital inflows. Consequently, while these results tell us about price determination in emerging markets, they do not provide an implementable trading strategy.

developed markets are low, funds' investors have incentives to trim their investments in emerging market for at least two reasons. First, they may face margin calls on developed-market asset positions that result in the liquidation of foreign investments, including those undertaken through global funds (see Boyer, Kumagai and Yuan (2006)). Second, the 'denominator effect' (the need for institutional investors such as pension funds to revert to pre-set target asset allocation percentages), causes cuts in emerging market investments as developed market equity holdings shrink in value.<sup>5</sup> These forces cause greater outflows from emerging-market funds at times of low developed market returns, increasing the pressure for forced liquidations by global funds, and generating greater co-movement of stock returns between developed markets and the emerging markets that are negatively At-Risk. The reverse mechanism applies when developed market stock returns are positive. The organizational structure of global funds engenders periods of significant trading pressure that provide the conduit through which shocks can be transmitted and amplified across the many countries in which these funds invest.

We then check whether the actions of the global funds in our sample stem from fundamental or non-fundamental sources. One interpretation of our findings is that the investors in these funds are well-informed about the future fundamentals of the markets in which the funds are invested, and decrease or increase the supply of capital to funds in response to their private signals about these fundamentals. This would mean that our results identify that global funds are a conduit for information transmission between developed market investors and emerging market returns. Another, more resonant with the literature on contagion, is that the shocks to funding experienced by global funds are purely liquidity shocks, and the consequent reductions or increases in global funds' positions generate price pressure (and hence impacts on returns) in the emerging markets in our sample. These should reverse when liquidity returns to these markets. We find that both interpretations find support in the data: During periods of crisis in developed markets, it appears that price pressure arising from the actions of global funds and their investors is the key driver of emerging market returns. These return movements subsequently reverse. Outside of developedmarket crisis periods, we find that information transmission seems to be the main source of emerging market returns arising from the mechanism we identify, as there is less detectable reversal in returns during such relatively calm periods.

<sup>&</sup>lt;sup>5</sup>See "Where the denominator effect lurks," Wall Street Journal, November 12, 2008.

To refine our understanding about the mechanics underlying these return patterns, we conduct several additional tests. First, we implement our tests on a calendar-time portfolio constructed using a variant of At-Risk that takes as an input predicted (rather than realized) flows. We continue to find a significant asymmetry in the betas of this calendar-time portfolio, although the alpha of the portfolio is no longer significant. While this does not directly imply that there are profitable opportunities for front-running the fire sales of global funds, this finding tells us that the co-movement of international asset returns has an important predictable component, and that a portfolio diversification strategy that takes advantage of fire-sale information could help to reduce risk ex-ante. Second, to make sure that we are picking up true crisis periods in the developed markets, we also estimate a regime-switching model in which we allow the mean and variance of the world market return to vary across regimes. When we re-estimate the calendar-time portfolio betas, allowing them to differ across the estimated regimes, our results remain unchanged. Third, we investigate the relationship between the liquidity of the underlying markets and the consequences of fire sales. We find that the most illiquid emerging markets experience the largest return effects from being At-Risk, as we might expect. Finally, we control for emerging market return momentum in our tests, as momentum trading by emerging market investment managers has been noted by Kaminsky, Lyons and Schmukler (2004). Our results are unaffected by the use of this control.

The organization of the paper is as follows. Section 2 describes the data employed in the study. Section 3 relates the variation in the capital flows experienced by global funds to their investment behavior. Section 4 connects the forced reallocations of global funds with underlying emerging market stock returns, and Section 5 concludes.

#### 2. Data

We employ two main sources of data: Global mutual fund and hedge fund data from Emerging Portfolio Fund Research (EPFR), and country index return, market capitalization, and trading volume data from Standard and Poor's Emerging Markets Database (EMDB) and the World Bank's World Development Indicators Database. Over the period from February 1996 to October 2008,<sup>6</sup> the EPFR data covers 1,520 live and dead globally-focused funds, domiciled in the US and Europe,

<sup>&</sup>lt;sup>6</sup>With the exception of January 2000, for which data is missing for all funds.

that invest in equity and bond markets in over 90 developed and emerging markets around the world. For each fund and each month, EPFR collect the total net asset value (TNA) of the fund, the return of the fund, the inflow or outflow from the fund, and the percentage of the fund's assets that are allocated to each country.<sup>7</sup>

Before proceeding to the empirical analysis, we screen the EPFR fund data in a few standard ways. First, given our focus on fund flows and stock returns in emerging markets, we keep only the funds that invest in at least one emerging country (under the current MSCI classification) during the sample period. Second, to avoid data errors, we only include funds once their TNAs hit the US\$ 5 million threshold. Third, in the early part of the sample, we find that several funds have a series of zero returns that persist for a few months. During these months, changes in TNA are all lumped into fund flows by construction which clearly generates data errors, so we exclude them. Fourth, since our analysis requires a significant cross-section of funds, we restrict our sample to those countries in which EPFR has data on at least 30 invested funds. Collectively, these exclusions have almost no impact on our analysis as the excluded funds have negligible dollar holdings and flows compared to the rest of the sample, but they reduce the number of unique funds in our sample to a total of 1,097. Finally, we winsorize fund flows and returns at the -50% and +200% points in order to minimize the influence of potential outliers. This procedure affects less than 1% of the sample.

To investigate the reliability of the EPFR data, we compare the TNAs and monthly returns of a subsample of funds to those in the CRSP mutual fund data. We match the two data sets by fund name, using a scoring system that measures the proportion of common letters in the fund names, and pick funds with a score of 70% or greater on this metric. We then carefully screen out incorrect matches by hand. This process yields 126 funds that appear in both data sets (over 10% of the sample) for comparison purposes. Figure 1 plots the TNAs and monthly returns from EPFR and CRSP mutual fund data sets against one another, and shows that they line up very well. Almost all observations lie on the 45-degree line. In the few cases where we have discrepancies, one of the

<sup>&</sup>lt;sup>7</sup>Chan, Covrig, and Ng (2005) and Hau and Rey (2008a, 2008b) employ data on mutual fund holdings from Thomson Financial Securities. These data provide detail on security level holdings, but are limited to semi-annual observations.

<sup>&</sup>lt;sup>8</sup>We exclude Zimbabwe from the list due to its extremely high inflation.

<sup>&</sup>lt;sup>9</sup>We thank Joey Engleberg for this name-matching program.

two datasets does not capture all the available share classes (which then subsequently come on line, occasionally with a several month lag). This yields minor differences in TNA, despite returns being roughly equal.

Table I reports the descriptive statistics of the EPFR sample by country. The average number of funds investing in each country is as small as 32 for Jordan, and as large as 646 for Hong Kong. The funds hold a significant proportion of country market capitalization (3.02% on average across the emerging countries), and the percentage holding varies less over time than across countries, ranging from 0.11 percent in Jordan to 9.22 percent in Hungary. These holdings percentages are computed using country index market capitalization; however Dahlquist, Pinkowitz, Stulz, and Williamson (2003) show that firms in emerging markets are controlled by large shareholders, so only a fraction of the shares issued in these countries are freely traded by minority portfolio investors such as the foreign domiciled funds considered in this paper. Therefore, we provide an alternative representation of the importance of these funds by scaling these percentages using the float-adjustment factors reported in Table 1 of Dahlquist et al. This raises the average holding of the funds in our sample to 6.82% of float-adjusted market capitalization.<sup>10</sup>

To broadly examine whether funds chase returns and whether fund behavior impacts stock prices, we also calculate the time-series correlations between the active change in dollar holdings, measured as a percentage of the country's market capitalization, and country index returns. The average contemporaneous correlation is 7%, statistically significant at the 5% level. In nineteen of the twenty five sample countries, this correlation is positive. The average correlation between the active change in holdings and the lagged country index return is also 7%, and statistically significant. This suggests that funds tend to increase holdings in the countries that recently experience high returns, similar to the findings in Kaminsky, Lyons and Schmukler (2004). Finally, the average correlation between the lagged active change in holdings and the country index return is 4%, and again statistically significant. This positive correlation, along with the positive contemporaneous correlation, suggests that funds' trading may impact prices both immediately and with some lag.

As we are interested in the behavior of both the flows to funds (i.e., the behavior of the investors in the funds) as well as the behavior of the funds themselves, we conduct a preliminary investigation with the purpose of identifying the location of the ownership base of the funds. The first step in

<sup>&</sup>lt;sup>10</sup>Two of the countries in our sample (Colombia and Russia) are not covered in their paper.

this process is presented in the figures in Appendix 1, which document the location of domicile of the funds in the sample. The figures show that the funds are primarily domiciled in developed market jurisdictions: at the end of 1997, for example, 85% of the funds are domiciled in Ireland, Luxembourg, the U.K. or the U.S., with the lion's share (63%) in the U.S. By the end of 2007, the fraction for these four domiciles is unchanged, remaining at 85%, but with some of the share of funds moving from the U.S. (46%) offshore to Luxembourg (27%). The substantial fraction of funds in the data domiciled in the developed markets, and especially onshore in the U.K. and the U.S. suggests that the investor base of the funds in the sample is predominately located in the developed markets. Second, we compare the data at the country level to data on the net foreign transactions of U.S. investors reported in the Treasury International Capital System (TIC) (see Ahearne, Griever and Warnock (2004)). We first compute the active changes in dollar holdings across all EPFR funds in each country as the aggregate dollar holding of the EPFR funds at the end of the month in the country less the dollar holding at the end of the previous month multiplied by the gross country index return (i.e., the expected dollar holding if all funds follow the buy and hold strategy). We then standardize the active change in dollar holdings by dividing it by the end-of-prior-month country index market capitalization, and cumulate this percentage from the beginning of the sample period in each country, to get an idea of the evolution of EPFR fund ownership in the country. We follow essentially the same procedure with the TIC data, cumulating and standardizing the net transactions of U.S. investors, and plot the EPFR series against the TIC series. (For the purposes of visual inspection, we subtract means and divide by standard deviations to plot the two series on the same scale.) Figure 2 shows the results of this exercise for Hong Kong, Malaysia, Mexico, and Russia. The EPFR and TIC cumulative ownership changes move together closely for all four countries: on a month-to-month non-cumulative basis, the cross-country average correlations between the EPFR and TIC ownership change series are 20% for emerging countries. 11 These pictures appear to verify the conjecture arising from the funds' reported domiciles – that a significant fraction of the investor base is located in the U.S. (comparable statistics to TIC are not available for Europe).

<sup>&</sup>lt;sup>11</sup>Note that the standardization for plotting purposes masks the fact that the TIC flows for Hong Kong are much bigger in magnitude than the active changes in dollar holdings from the EPFR data. For Russia, however, the opposite holds. These differences can be attributed to the inclusion of European-domiciled funds in the EPFR data, and the potentially far broader coverage of US investors in the TIC data.

In Table II, we investigate the characteristics of the sample funds. TNA varies dramatically across funds (and is highly positively skewed), with the (pooled) average equal to US\$ 610.93 million and the (pooled) standard deviation equal to US\$ 2.2 billion. The sample contains both funds which invest exclusively in one country and those which invest in a broad set of countries. On average, the sample funds hold 3.44 percent of their TNAs in cash, broadly in line with the statistics on the mostly U.S. sample reported by Coval and Stafford (2007). The cash holdings don't change much over time, although at the extremes, funds may increase or decrease cash by as much as 12 percent of their TNAs. Consistent with the highly variable emerging market returns, fund returns vary significantly both in the time series and in the cross section (the mean monthly return is 0.71%and the pooled standard deviation is 8.41%). Alphas, measured as an intercept from the time series regression of fund returns on the MSCI world index returns, average 48 basis points per month. The average alpha decreases by more than half under the Fama-French four-factor model, to 21 basis points per month. Most of the decrease is driven by the momentum factor, echoing Carhart (1997). As for fund flows, measured as a percentage of the beginning-of-month TNA, the mean and median are close to zero. The 1st and 99th percentiles of flows are -24.28 percent and 31.70 percent, respectively, indicating that flows are highly variable. This variation is useful in identifying funds and countries that are likely to experience financial pressure. It should also be noted that the EPFR sample includes index funds. Indeed, by 2008, about 50% of the funds in our sample are index funds, identifiable by the relatively low volatility of their percentage allocations to underlying countries. For the purposes of our paper, 'uninformed' index fund demand is just as interesting as the demand of actively managed mutual funds, in the sense that it adds to the literature on how mechanical shifts in portfolio allocations affect asset prices (see Shleifer (1986) and Wurgler and Zhuravskaya (2002)), and consequently we leave these funds in the sample. It is worth noting here that the results are very similar when we split the sample of funds into index and non-index funds and repeat the analysis for each group separately.

### 3. Fund flows and fund behavior

### 3.1. Flows and performance

Our goal is to understand how the funding of managed investment vehicles impacts their allocation decisions, and consequently the stock returns of the markets in which they invest. A necessary first step in this exercise is to decompose the variation in funding into expected and unexpected components. This decomposition will allow us to separately evaluate the distinct roles that are played by shocks to funding versus movements in funding that can be anticipated. To effect this decomposition, we rely on the vast literature that documents a link between capital flows to managed funds and their past performance (see, for example, Sirri and Tufano (1998)). Writing  $flow_{j,t}$  for the capital flows of a sample fund j in a month t and  $R_{j,t}$  for its return in the same month, our model for flows is:<sup>12</sup>

$$flow_{j,t} = a + \sum_{k=1}^{12} b_k \cdot flow_{j,t-k} + \sum_{h=1}^{12} c_h \cdot R_{j,t-h}$$
 (3.1)

We estimate the model in two ways, first, as a pooled regression across all funds and time periods, and second, using the method of Fama and MacBeth (1973), where we estimate a cross-sectional regression for each month in the sample and then calculate the time-series average of the coefficients and the t-statistics using the time-series standard error of the mean.

Table III presents the results from estimating (3.1). First, there is a statistically significant relation between future fund flows and both lagged flows and lagged returns. Specifically, monthly flows are significantly predicted by lagged flows through the first year. While lagged returns also predict future flows, the effect is less pronounced as it appears to be limited to the most recent quarter. Second, the results are broadly comparable across both the pooled and Fama-MacBeth regressions, but the reported  $R^2$  is naturally smaller in the former case as it reflects both cross-sectional and time-series variation in fund flows. These results are largely in line with previous research insofar as they suggest significant predictability in fund flows; however, we should point out that the reported  $R^2$ , 27% in the Fama-MacBeth regression, is somewhat smaller than that which is generally reported elsewhere. It seems the flow-performance relationship is less pronounced for funds investing in emerging equity markets. Finally, given the fitted values implied by the time-

<sup>&</sup>lt;sup>12</sup>Note that we only estimate this specification for funds that ever invest in an emerging market over the sample period.

series average of the coefficients from the estimated Fama-MacBeth regressions in Table III, we measure expected fund flows for each fund at each point in time. We will report various features of expected flows implied by this regression below.

#### 3.2. Fund flows and re-allocations

Our next step is to discover the extent to which movements in fund flows impact funds' allocation decisions and investment behavior. To the extent that fund inflows and outflows put pressure on fund managers to re-allocate, sorting funds along this dimension may help highlight the particular instances in which forced selling (or buying) is taking place.

As a start, we sort fund-month observations into deciles according to fund flows and document the characteristics of the fund-months in each decile. Table IV provides average fund characteristics across different groups of funds sorted by realized monthly flow, where reported statistics are the means for each variable across all fund-months in each decile. The first column of the table presents a simple reiteration of the fact that the funds in our sample indeed experience significant differences in realized flow, with the extreme deciles facing a range of 13.6% (top decile) to -12.6% (bottom) monthly flows as a percentage of assets under management. While this spread is notable, it obtains by construction since this is the exact dimension along which we are sorting. That said, a portion of this difference is associated with predictable expected flows, as constructed in the previous subsection. The second column of Table IV shows that the top and bottom deciles of realized-flow-sorted funds were expected to experience flows of 0.9% and -1.7%, on average, respectively. (We later revisit the effects associated with realized and expected flows). The third column of the table shows that funds experiencing the largest inflows (outflows) also experienced the highest (smallest) prior investment returns, consistent with the evidence in the literature that fund flows are linked to past performance. Finally, two additional observations about the fund characteristics are worth highlighting. The fourth column of Table IV shows that consistent with the findings of Warther (1995) and Coval and Stafford (2007), funds in the top decile hold, on average, considerably more cash than those in the bottom. As the sharp differences in cash holdings could imply some variability in a fund's ability to manage investor flows, we will explore the link between flows, forced re-allocation, and cash holdings in more detail below. Also, the fifth column of Table IV shows that the funds that appear in the extreme flow deciles have relatively fewer country holdings than the average fund; hence, extreme flows in either direction may induce relatively elevated market impact at the country level if funds in those deciles indeed maintain their focused country allocations. Finally, we describe the market capitalization and trading volume of the markets in which the funds are investing. While there are no significant differences in these characteristics across flow deciles, the funds in the EPFR sample are, on average, investing in slightly larger and more liquid markets than the median market.

For fund flows to generate pressure on the equity markets in which the funds are invested, the funds experiencing the flows must adjust their equity positions in response to the flow-exerted pressure. To see whether this is the case, we sort fund-month observations into deciles according to fund flows and calculate the average proportions of countries in which the funds in each decile increase, decrease, or eliminate their holdings. Table V presents evidence on the degree to which funds re-allocate their holdings in the face of significant realized (Panel A) and expected (Panel B) flows. We begin with an examination of the behavior of funds around periods of extreme realized flows. The first column of the table, concerning realized fund flows, is identical to the previous panel to reinforce that this sort is identical to that presented above in Table IV. In the second through fourth columns of Table V, we present a summary of the country allocations that funds in each decile are, on average, expanding, reducing, or eliminating. Before proceeding, the manner in which we measure position changes requires some explanation. As mentioned above, we observe the fund's USD allocation for each country in each month. For each fund-country-month, we compare the USD allocation at the end of the month to the value that would be implied by grossing up the holding using the relevant USD index return for the country given the beginning of month USD allocation. If the actual value is greater (less) than this constructed buy-and-hold benchmark, we say the fund has expanded (reduced) its position; if the USD value is zero, we say the position was eliminated.<sup>13</sup> Funds in the bottom decile (significant outflows) reduce or eliminate around 80% of their positions over the next month. Contrast this with funds in the top decile (experiencing significant inflows), which reduce or eliminate just 21% of their positions over the next month. Similarly funds in the

<sup>&</sup>lt;sup>13</sup>This differs somewhat from the usual convention in the literature where share holdings are directly observed (though at the quarterly frequency). The main difference between the EPFR data and the 13-F filings data employed by Coval and Stafford (2007) and others is that the 13-F data contains the number of shares held by financial institutions, whereas EPFR records the value of the fund's USD value allocation at the country level (though at the monthly frequency).

top decile (inflows) expand 79% of their positions, while those experiencing significant outflows expand just 22% of their positions. These differences across flow deciles are highly statistically significant. The fifth column of Table V demonstrates that the average magnitude of the change in risky positions also exhibits differences across realized fund flow deciles – a movement from extreme inflows to extreme outflows is on average associated with a 0.38% decrease in the allocation to the average country in the portfolio. The final column of the table highlights that cash balances also expand (shrink) for funds that exhibit large inflows (outflows). In sum, it appears that global funds do significantly re-allocate their exposures in emerging markets in the face of investor redemptions and subscriptions.

In unreported results, we also split the sample into index and active funds (based on the timeseries volatility of their percentage country allocations) to see if these trading patterns differ across
the two groups. For index funds, it is unsurprising if allocation changes follow inflows and outflows,
since these funds more or less mechanically allocate capital to underlying stocks with the objective
of minimizing tracking error relative to an index. It would be somewhat more surprising to see
forced trading behavior (especially in the face of inflows) in actively managed funds since these
funds have some discretion to hold the flows in cash and wait for an opportune moment before
investing. Surprisingly, the two groups of funds (index and active) do not exhibit statistically
different re-allocation behavior. (As all of the subsequent results are virtually identical for the two
groups, we elect to simply report the full sample results).

In the next section, we will explore whether this forced re-allocation also affects emerging market returns, and provides a channel through which global market shocks are transmitted to emerging markets. Before moving to this next step, we examine the extent to which re-allocation decisions are linked to variation in expected flows, with the view that such predictability could allow global funds to anticipate and hence manage their activities on the margin. However, if we were to observe comparable variation in re-allocation patterns in the face of expected and realized fund flows, this would suggest that funds face constraints inhibiting them from making adjustments to cushion the effect of movements in flows. Consequently, global funds could collectively act as a mechanism for the transmission of financial shocks across borders even if they can anticipate funding pressure. Panel B of Table V presents the evidence for funds sorted into deciles according to expected fund flows determined from the Fama-MacBeth regressions in equation (3.1). As with the sort based on

realized flow above, the second to the fourth columns of the table reveal a sizeable divergence in the behavior of funds. For instance, funds in the bottom decile of expected flow reduce or eliminate about 61% of their positions over the next month, whereas funds in the top decile reduce or eliminate only 41% of their positions. And again, funds in the top decile of expected flow expand around 59% of their positions over the next month, contrasted with just 39% for those experiencing outflows. While these differences are not as stark as those presented above across realized flow deciles, they are still economically and statistically significant, moreover the fifth column of Table V Panel B shows that the funds do indeed significantly re-allocate the magnitudes of their risky positions. Taken together, the behavior of funds that are expected to experience significant flows is partially predictable. The only notable exception is presented in the final column of Table V Panel B, where we show that funds do not experience significant differences in the change in cash balances across expected flow deciles. This is in contrast to the sizeable difference in cash changes related to (largely unexpected) realized flow, and may be a reflection of the degree to which funds can better manage anticipated flows.

Figure 3 graphically represents the average net change in positions as a function of fund flows. The net change in positions is measured as the proportion of countries in which the fund increases its holdings minus those in which the fund reduces or eliminate its holdings. Panel A of the figure visually represents the findings in Table V, namely that realized and expected flow are associated with similar reallocations, although the extremes of realized flow move allocations much more than expected flow. Panel B of the figure investigates the role that the extent of the cash buffer available to funds plays in their reallocation decisions; the deciles in this figure are computed across fund-months of flows plus cash. The figure shows that accounting for funds' cash buffer does not significantly alter the observed reallocation behavior, especially in the face of outflows.

Table VI investigates whether funds lean against the tide of the funding pressure that they face, by trading in relatively more liquid markets. The table employs quarterly transactions costs data compiled by Elkins/McSherry (see Domowitz, Glen and Madhavan (2001)), on average trading costs as a percentage of trade value for 28 billion shares traded by over 700 active global investment managers. The data is split into explicit costs, namely commissions and fees; and price impact costs, which is the percentage difference between the execution price and a benchmark for buys,

and the reverse for sells.<sup>14</sup> In Panel A, the weight for each country is determined by the estimated amount of each country bought and sold. In Panel B, all countries carry equal weight. The former could feasibly be contaminated by correlation between average transaction costs and the size of the underlying market;<sup>15</sup> this would mechanically deliver a lower average cost among large markets in which funds trade heavily. To the extent that the evidence on transaction costs is comparable across both the value and equal weighting of countries, we can be relatively confident that firms do indeed attempt to trade strategically in the face of these pressures.

The table shows that, regardless of the weighting scheme, reallocations in the face of funding pressure are concentrated in countries with lower transactions costs: For example, funds facing the maximum outflows reduce positions in country-months with total transactions costs that are on average 5.54 basis points lower per trade than those facing inflows, whereas funds in the top decile of inflows expand positions in country-months with total costs that are 5.17 basis point lower per trade than those facing outflows. These differences are statistically significant for both explicit and price impact costs, and statistically significant differences are also evident for expansions versus reductions for funds facing inflow pressure, and the reverse for funds facing outflow pressure. The results clearly point to attempts by global funds to ameliorate the impacts of the funding pressure that they face, by concentrating their fire-sales in relatively more liquid markets. This finding has surprising consequences for emerging market policy: Countries that develop relatively better trading infrastructure might suffer disproportionately from the impacts of fire sales, since better liquidity apparently attracts greater fire-sale volume.<sup>16</sup>

## 4. Flow-induced pressure and equity prices in emerging markets

## 4.1. Capital "At-Risk"

In the previous section, we discovered that global funds experiencing inflows (outflows) are prone to expanding (reducing or eliminating) their emerging market allocations. This naturally leads to the conjecture that these fire-sale reallocations impact prices, since significant discounts are likely to result from these demands for instant liquidity. Of course, the price pressure that forced reallocations

<sup>&</sup>lt;sup>14</sup>This benchmark is computed as the mean of the day's open, close, high and low prices.

<sup>&</sup>lt;sup>15</sup>Say, for example if larger markets are more liquid.

<sup>&</sup>lt;sup>16</sup>Thanks to Ajay Shah for this insight.

are likely to generate in a given country's stock market depends on (i) how much of the market is held by the funds (since liquidating larger stakes will naturally result in larger discounts) and (ii) the aggregate flows that these funds experience (which index the extent of forced redemptions or purchases by the funds). Accordingly, we propose a new measure that reflects the proportion of a country's market capitalization that is 'At-Risk' of forced selling or buying. Specifically, for country k in month t (and with the usual notation that j denotes funds), USD At-Risk is measured as:

$$At-Risk_{k,t} = \sum_{j=1}^{N} flow_{j,t}^* \cdot allocation_{j,k,t-1} \cdot TNA_{j,t-1}$$
(4.1)

where  $flow_{j,t}^* = flow_{j,t} + flow_{j,t-1} + flow_{j,t-2}$ , is the sum of capital flows experienced by fund j over the quarter prior to and including month t, and  $allocation_{j,k,t-1}$  is the percent of fund j's TNA invested in country k at the end of month t-1.<sup>17</sup> In our empirical applications we normalize USD At-Risk by either the market capitalization of the stock-market of country k at the end of the previous year, or by the average monthly volume of the stock market over the prior calendar year.

To provide a concrete example of the construction of At-Risk, imagine a fund at the end of January 2008. Assume that the fund's portfolio allocation to Korea measured at the end of December 2007 is 25%, and the fund's TNA reported at the end of December 2007 is US\$ 100 million. If the fund's total flow over the November-December-January quarter is 10%, this yields US\$ 2.5 million as the fund-country At-Risk dollars at the end of January 2008 (i.e., if flows were proportionally allocated, this is how much they would additionally deploy into the country). (To clarify further, suppose instead that the total flow over the November-December-January quarter was -20%: this would yield US\$ -5 million as the fund-country At-Risk dollars at the end of January 2008.) Put simply, the At-Risk measure captures the quantum of capital that a particular emerging market could see enter or exit as a result of the inflows and outflows faced by invested funds. Since both fund allocations and TNAs are measured at the end of the previous month, the measure is uncontaminated by valuation changes over the same month in which we measure market returns. Thus, the only source of contemporaneous variation in At-Risk is the flow experienced by funds invested in the country.

<sup>&</sup>lt;sup>17</sup>We use flows over the previous quarter in order to alleviate concerns about any potential measurement error as well as to acknowledge that the funds may face increasing pressure based on flows experienced over several months.

To ascertain the impact of being 'At-Risk' on an emerging market, we compute At-Risk for each of the countries each month, and then sort the country-months into quintiles. Table VII Panel A shows summary information on the characteristics of the countries in each of these quintiles. The top quintile captures those countries where invested funds experienced significant inflows over the last quarter (including the most recent month). In contrast, the bottom quintile captures those countries where invested funds experienced outflows over the last quarter. The first two columns of the table present cross-sectional variation in the ratio of At-Risk capital divided by either local market capitalization (the sort variable in this table) or monthly trading activity (volume). While the At-Risk levels are quite small relative to total market capitalization, the levels are a significant portion of average monthly trading volume: For instance, At-Risk capital in quintiles 1 and 5 constitute 8.1% and 3.4% of average monthly trading volume (in absolute terms), respectively. These significant fractions of trading volume suggest that any forced trading induced by flow shocks could have important effect on prices, especially in light of the evidence that emerging markets are plagued by illiquidity and high transaction costs (see Lesmond (2005) and Bekaert, Harvey and Lundblad (2007)). The third column of Table VII Panel A shows that the countries in the extreme quintiles (1 and 5) represent a significantly larger share of the capital invested by the funds in our sample than those in the intermediate quintiles. This is an important by-product of the construction of the At-Risk measure: To have significant capital At-Risk, the country of necessity will represent a significant fraction of global funds' allocations. This automatically reduces concerns that the extreme At-Risk countries are unusual in the sense that they impose investment restrictions, and the attendant concern that any return patterns associated with being At-Risk are a product of such restrictions. However it does raise the concern that any patterns we discover stem from elevated allocations to these countries, especially in light of the extensive evidence on the informational advantage enjoyed by international investors (see Seasholes (2000), Froot, O'Connell and Seasholes (2001) and Froot and Ramadorai (2008)). Consequently, when we explore how being At-Risk relates to emerging market price determination, we compare our measure with an alternative based solely on funds' aggregate holdings unrelated to their capital inflows and outflows.

Finally, the fourth and fifth columns of Table VII Panel A compare our measure of At-Risk capital to a similar sort variable first proposed by Coval and Stafford (2007). This variable,  $PRESSURE\_2$ , is closely related to At-Risk, but different insofar as  $PRESSURE\_2$  measures

funds' actual (rather than potential) trading activity in the face of significant inflows or outflows (i.e., it replaces allocation<sub>j,k,t-1</sub> with  $|\Delta allocation_{j,k,t}|$  in equation (4.1) above, counting only  $flow_{j,t}$ and  $\Delta allocation_{i,k,t}$  that are in the same direction). To measure changes in fund allocations using the EPFR data, we take the difference between observed allocations and those that would result if funds were following a buy-and-hold strategy. Indeed our results in Table V employ this method, and we could easily use these measures of active changes to construct PRESSURE 2. While the use of this method seems reasonable when the goal is to evaluate fund behavior in response to movements in flows (as in Table V), when analyzing the impacts on underlying country prices and returns, we wish to be more careful. Our approach is to avoid any possible contamination that may result from sorting countries using a measure of active changes that employs contemporaneous returns in its construction. Consequently, we prefer our At-Risk measure to PRESSURE 2, and employ it in all our analyses of country returns. 18 Nevertheless, for the sake of comparison, we forge ahead and compute PRESSURE 2, again scaling the quantity either by trading volume or market capitalization. The statistically significant differences in both versions of PRESSURE 2 (scaled by volume in the fourth column and market capitalization in the fifth column of Table VII Panel A) across the At-Risk quintiles suggest that the same countries that face significant At-Risk capital face considerable PRESSURE 2. In other words, At-Risk captures the same fire-sale mechanism identified by Coval and Stafford (2007). In the next section, we turn to an exploration of the pricing implications of significant At-Risk capital.

#### 4.2. Capital At-Risk and price determination

#### 4.2.1. Sorts

To investigate the impact of fire-sale pressure on stock returns, we construct equally-weighted calendar-time portfolios based on At-Risk capital. Each month, we sort countries into quintiles according to At-Risk capital (as a percentage of the country's market capitalization, exactly as in Table VII Panel A) and calculate portfolio returns (in USD) by averaging returns across all countries in the same quintile. We also compute the probability that any country will stay in the same quintile

<sup>&</sup>lt;sup>18</sup>Given the difference between the EPFR data and the 13-F filings mentioned above, we use capital At-Risk rather than the *PRESSURE* measures preferred by Coval and Stafford. The 13-F data contains the number of shares held, whereas EPFR records the value of allocated capital; changes in the latter will be affected by local market returns.

portfolio over the next month in Panel B of Table VII. While countries do maintain their positions to some degree, these are far from fixed portfolios. The steady-state transition probability for countries (computed by taking the transition matrix to a high power) is approximately 20% across each of the five portfolios, i.e., there is about an equal chance for the 25 emerging markets in our sample to end up in any of the five At-Risk portfolios. For comparison purposes, the persistence of stocks in the usual size and book-to-market portfolios is considerably more pronounced.

Panel A of Table VIII reports the time-series mean and standard deviation of each At-Risk quintile portfolio both for the entire sample period and conditional on the contemporaneously realized world market excess return. In Table V we documented that global funds, on average, re-allocate their investment positions in the face of sizeable subscriptions or redemptions. We also showed in Table VII that collectively, the potential re-allocation implied by the amount of capital At-Risk represents a non-trivial fraction of domestic market trading in these countries. Table VIII shows that sorting countries on the size of the potential re-allocation results in a significant spread in stock returns. Equity markets that are likely associated with significant fund purchases (quintile 1) and sales (quintile 5) for a month earn, on average, 191 and 63 basis points per month, respectively. The difference, of 128 basis points per month, is highly statistically significant, and implies an annual return of 15.4% for the zero-investment portfolio created by going long the top quintile of At-Risk countries and short the bottom quintile of At-Risk countries. Figure 4 shows the cumulative returns on this long-short portfolio, also graphing the cumulative return on the world market portfolio in excess of the risk free rate. Clearly, fire-sale re-allocations seem to generate economically significant return movements in emerging markets. However, the figure does demonstrate that there are periods when the long-short At-Risk portfolio underperforms (such as over the 2004-2005 period) suggesting that there are risks embedded in these returns. The figure also shows that some of the largest returns on the portfolio occur during periods of global crisis, which is perhaps unsurprising given that these periods are likely to coincide with the most intense pressure on funds.

The other important finding in Table VIII is that the portfolio returns display a strong link to the sign of the world market return. When the contemporaneous world market return is positive, top quintile At-Risk countries outperform bottom quintile At-Risk countries by 133 basis points per month. However, when the contemporaneous world market return is negative, countries that are in the bottom quintile of At-Risk have far more negative returns (122 basis points per month lower)

than countries which are primarily held by funds facing relatively lower outflows. Our explanation for this pattern is similar to the argument put forward in Boyer, Kumagai and Yuan (2006): Given that the world market return stems primarily from developed markets (it is a value-weighted index), funding pressure from developed country investors on the developed country-domiciled funds in our sample is likely more intense when developed countries have fallen on hard times, i.e., when developed country stock markets are performing poorly, and vice-versa. When stock returns in developed markets are low, investors in those markets face margin calls that result in the liquidation of their foreign investments, including those undertaken through global funds. The 'denominator effect' referred to earlier will also have impacts on institutional allocations to emerging market funds. This means that outflows will be greater at such times of low developed market returns, resulting in more pressure for forced liquidations or 'fire-sales' by global funds. As a result, the correlation of stock returns between developed markets and the emerging markets held most by funds subject to this source of pressure will increase. The reverse of this argument applies when developed market stock returns are positive, generating higher return correlations between positive At-Risk countries and developed markets. If so, the countries held most by funds that face the maximum (minimum) pressure should be hit hardest (least) when developed stock markets are performing poorly. In support of this conjecture, Figure 5 provides graphical evidence that flows into funds that invest in emerging markets are highly correlated with developed equity market returns (the time-series correlation between aggregated global fund flows and G-7 returns is 0.49).

To verify that developed market returns are indeed the source of this pressure, Table VIII Panel B re-estimates the conditional relationship using the return on a portfolio of G-7 countries in place of the world market return. Exactly the same pattern emerges again, suggesting that our posited mechanism is indeed the one in operation (to confirm this, we subsequently explore the implications of this disparity for world market and G-7 betas of a calendar time portfolio). A note on identification is in order here: While it is true that we do not have explicit information about the nationality of the investors that invest in the funds in our sample, our explanation of the asymmetric conditional correlation relies on several important facts. First, the funds in our sample are overwhelmingly domiciled either in the U.S. or in Europe, leading to the presumption that their investor base is most likely from these economies. Second, we find that the aggregated EPFR flows track the U.S. Treasury-recorded net asset flows of U.S. investors quite well over time,

as documented in the Data section. Third, the asymmetry in the correlations that we document here and elsewhere in the paper are just as pronounced when we use the G-7 risk premium in place of the world risk-premium, lending credence to our posited mechanism.

#### 4.2.2. Calendar time portfolios

To understand the economic source of the return differences, we examine the returns of a calendartime portfolio strategy formed by going long the highest At-Risk quintile portfolio and going short the lowest At-Risk quintile portfolio. Given the exposures to the world market portfolio return documented above, we focus on the world CAPM as a benchmark, employing the G-7 portfolio return as an additional control. Specifically, we regress our long-short portfolio returns on the world market risk premium, and we also estimate a conditional version of the model in which we allow the loading on the world market portfolio return to differ between periods in which the worldmarket return is positive and negative. The first two columns of Table IX report the regression results. In the first column, we report the alpha and beta associated with our long-short strategy for the unconditional world CAPM. A portfolio that goes long countries facing significant buying pressure and short countries facing significant selling pressure yields an alpha of 130 basis points per month, which is almost the same magnitude as the return spread presented in Table VIII. The world market beta of this long-short portfolio is effectively zero: Investment re-allocation decisions generated by shocks to global funds' capital flows have significant implications for traded prices but yield negligible exposures to global shocks. This last point requires further exploration given the sizeable differences in At-Risk quintile returns conditional on positive and negative global returns.

The second column of Table IX confirms our initial sort-based finding that there is a pronounced asymmetry in the betas of the long-short portfolio: periods of positive and negative global market returns exhibit significantly different effects on the returns of our long-short portfolio. In the face of positive world market returns, countries with positive At-Risk capital have significantly larger world market betas than do countries with negative At-Risk capital. In sharp contrast, when world market returns are negative, countries with negative At-Risk capital have significantly larger world market betas (in absolute terms) than do countries with positive At-Risk capital. Our explanation for this is the same as that mentioned in the previous section, and again we re-estimate the specification using the G-7 returns in place of the world market returns in Table IX Panel B. The results are

virtually the same, suggesting that our proposed transmission mechanism applies.

Because our At-Risk portfolio sort involves contemporaneous fund flow information, the alpha of 128 basis points per month in Table IX is not indicative of a tradeable strategy, rather it simply speaks to the effects that unexpected forced buying or selling by global funds have on price determination in emerging markets. That said, we also document above that global fund flows are to some degree predictable, and funds appear to re-allocate even in the face of predicted flows. To explore the price effects of predicted flows (and thereby the implementability of the trading strategy), we also sort countries according to predicted At-Risk, calculated by substituting the expected flow ( $E[flow_{j,t}]$ ) based on the model in (3.1) for  $flow_{j,t}$  in (4.1). Comparable world CAPM regression results are presented in the last two columns of Table IX. As can be seen, the alpha in column III is no longer statistically significant, so it appears that much of the price effect in the first column of Table IX is associated with the more pronounced forced buying and selling generated by unanticipated funding shocks. This echoes our finding in Table V Panel B that the observed level of fund re-allocation in the face of expected flow variation is significant but less pronounced. However, in the fourth column of Table IX, the conditional version of the world CAPM does yield significant and similar evidence regarding the different conditional betas of the long-short portfolio based on positive or negative world market (or G-7) returns. In other words, expected flow is useful in predicting betas, and therefore potentially useful in an asset allocation context, although the strategy of providing liquidity to markets based on expected flow is not likely to be profitable.

Since At-Risk is a product of both the funds' collective holding in the country as well as the flows that funds face, it is interesting to see whether it is really the pressure created by fund flows that explains the patterns in Table IX, or simply the fact that global funds disproportionately allocate capital to some of these markets. To address this question, we repeat the analysis in Table IX, with one difference: We sort countries into quintile portfolios based on the beginning-of-month holding (as a percentage of the country's market capitalization) alone. The results are presented in Table X, where we do not observe a statistically significant alpha for the long-short portfolio, or changing conditional betas. The table does show that countries that are held in larger proportion by global funds (quintile 1) appear to have higher betas than those in quintile 5 – they disproportionately gain or lose more when the contemporaneous world market excess return is positive or negative, respectively. These results confirm that it is the combination of high holdings and pressure from fund

inflows and outflows that generates the return patterns and changing conditional betas. Holdings alone are not sufficient to infer these effects.

#### 4.2.3. Country returns and forced transactions in event time

We turn to an additional exploration of the price effects of forced transactions, to separate to what degree the detected price effects arise from price pressure rather than from information transmission. In the previous section, we attempt to control for information arrival by exploring the price effects associated with *predicted* At-Risk. As previously done by Mitchell, Pulvino, and Stafford (2004) and Coval and Stafford (2007), we go further in this section by disentangling price pressure from information effects in the context of an event-time analysis. If forced fund trading reflects the information available to their outside investors, then we should observe an initial price reaction followed by zero subsequent drift in abnormal returns. Alternatively, if fund trading is driven by simply by fluctuations in their investors' desire for liquidity, then we should observe an initial price reaction followed by a period of reversal in the abnormal returns.

Figure 6 displays monthly cumulative abnormal country returns (CARs) for countries in the highest (Q1) and lowest (Q5) At-Risk quintiles. Countries are sorted into quintiles (in month 0) on the basis of actual At-Risk using current-month fund flows. For each event, CARs are measured as average monthly returns of all countries in the quintile in excess of the equal-weighted average return of all emerging countries in the sample. CARs are then averaged across events. Panel A presents the CARs during "crisis" months, i.e., when MSCI G-7 returns are at or below their 10<sup>th</sup> percentile (this corresponds to months in which G-7 returns are less than approximately -5%). The pattern in average abnormal returns during periods in which funds are facing pressures and developed markets are relatively distressed is notable. We document sizeable abnormal returns in the months of presumed forced buying and selling, which subsequently drift in the same direction for close to a year. Most importantly, the pattern in abnormal returns in part reverses once the effects of forced trading subside. This evidence is particularly pronouced for the Q5 portfolio, suggesting that widespread forced selling by funds exerts significant downward price pressure in emerging markets when developed market prices are significantly falling. Information effects would likely not explain the full reversal observed in this portfolio.

In contrast, Panel B repeats these same calculations but for countries in Q1 and Q5 quintiles

during relatively more "normal" months in which the MSCI G-7 returns are larger than -5%. These periods are not associated with extreme price depreciation in the developed markets in which these funds are located. When there is significant flow pressure in periods unrelated to developed market crisis, the reversal in abnormal returns is largely absent in the Q1 portfolio, but still evident (though to a lesser extent) in the Q5 portfolio. While there are significant price effects in emerging markets over the relevant months as funds respond to pressure, the lack of complete reversals suggests that fund pressure (and presumably the altered portfolio demands among their end investors) during relatively more calm periods in the G-7 markets reflect information transmission. To summarize, the coupling of developed market distress with fund pressure appears to be particularly important. These results are indicative of one possible dimension along which contagion effects could be separated from the cross-border transmission of fundamental information.

#### 4.3. Additional tests and robustness

#### 4.3.1. Regime switching model

We reconfirm that our results on changing conditional betas are indeed driven by 'bad times' in developed markets by estimating a regime-switching model, in which both mean returns and variances of return are allowed to vary across regimes. Details about the specification of the model are in Appendix 2. Our estimates of the characteristics of the world market return and volatility indicate that there are two regimes in the data, namely a high return and low volatility regime (regime 1) and a low return and high volatility regime (regime 2). These two identified regimes are consistent with the evidence documented in prior literature (see Boyer, Kumagai, and Yuan (2006), for example). Appendix Figure 2.2 shows that the probabilities of being in regime 2 are high in periods of negative world market returns but the correlation is not perfect. Appendix Table 2.1 shows that the world market beta of the long quintile 1-short quintile 5 At-Risk portfolio is estimated to differ across the two regimes, and a Wald test of the null hypothesis that betas are the same in both regimes rejects the null at the 3% level of significance, indicating that beta is indeed significantly higher in regime 1 than in regime 2. Specifically, in the high return and low volatility regime, the high positive At-Risk capital portfolio has higher beta than the high negative At-Risk capital portfolio. The opposite is true in the absolute value sense in the low return

and high volatility regime. Collectively, the estimates from the regime-switching model echo our earlier findings, and support our proposed mechanism that global funds facing significant outflows constitute an important transmission mechanism for shocks across borders.

#### 4.3.2. Momentum and At-Risk

Given that a number of global funds are known to follow momentum-based strategies and that anticipated fund flows are related to past fund (and hence country) performance, we explore the degree to which our findings are related to the momentum phenomenon. We construct a long-short emerging market momentum portfolio by sorting the countries in our set by past country index returns. In unreported results, we add this emerging market long-short momentum portfolio to the right-hand side of our calendar time regressions to assess whether our At-Risk measure is explained by momentum. The coefficient on the momentum portfolio is not statistically significant, and the other results discussed above are nearly identical (these results are available on request). The country momentum anomaly seems to be a separate issue from the price determination effects associated with the funding pressure of globally-focused funds.

#### 4.3.3. Liquidity of the underlying market and At-risk price effects

In Table VI we showed that in the face of pressure, global funds attempt to soften the blow by expanding or reducing positions in relatively more liquid markets. We therefore investigate whether the price effects of being At-Risk also differ with the liquidity of the market. One possibility is that since funds' fire sale reallocations are concentrated in more liquid markets, greater price impacts will be felt in such markets. Another is the more obvious possibility that funds are not able to completely offset the effects of pressure by moving to relatively more liquid markets, and that relatively more illiquid underlying markets face greater price effects from being At-Risk. In unreported results, we find that when countries are double sorted on At-Risk and transactions costs, that both the price effects and the change in conditional betas are concentrated in the relatively less liquid countries.<sup>19</sup>

To complement these findings, we also consider an alternative construction of the At-Risk measure that directly incorporates transaction costs. We measure the product of At-Risk (as a percent-

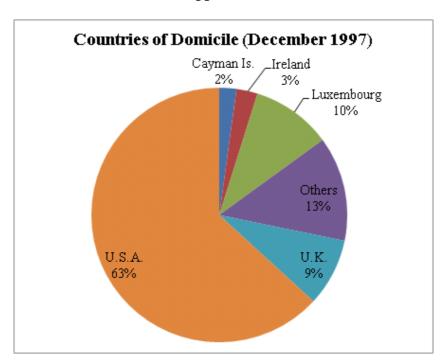
<sup>&</sup>lt;sup>19</sup>This analysis is available on request. Note that double-sorting means that the number of countries in each month is significantly reduced, with a consequent reduction in statistical power.

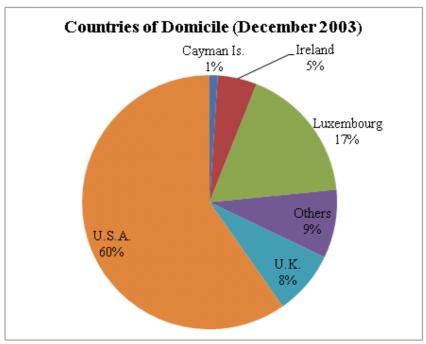
age of market capitalization) for each country constructed as before and the price impact cost for that country. Each month, we sort the countries into quintiles according to the resulting liquidity-modified At-Risk measure. Consistent with the evidence presented above, Table XI shows that the long-short portfolio based on At-Risk sorted in this fashion is associated with a larger average return (1.7% per month). Also, the world market exposure asymmetry is largely unchanged. While Table VI shows that funds do try to strategically trade in the face of fund flows, the fact that they do sometimes have to trade in relatively illiquid markets manifests itself in a more pronounced return during such periods.

#### 5. Conclusion

We find that the funding shocks experienced by a large set of developed country-domiciled global investment funds result in forced portfolio reallocations by these funds in twenty five emerging markets around the world. These fire sale reallocations have an important impact on the average stock returns of the affected emerging markets, which conditionally reverse depending on whether the G-7 markets are currently experiencing significant return declines. Perhaps more importantly, we also find that at times when emerging stock markets are predominately owned by global funds most subject to these funding shocks, they also have significantly elevated correlations with developed stock markets. We conclude that global investment managers, and the constraints they face, constitute an important transmission channel for financial shocks between developed and emerging markets.

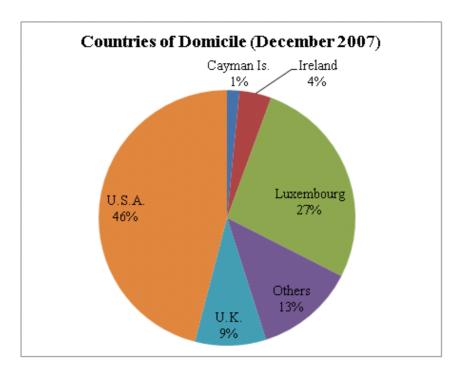
## Appendix 1





**Appendix Figure 1. Distribution of Countries of Domicile.** This figure plots the total net assets (*TNA*) shares for different countries of domicile of the funds in the EPFR sample at the ends of 1998, 2003, and 2007. The *TNA* share is calculated as the sum of *TNA*s of all funds that are domiciled in each country divided by the total TNA of all funds in the EPFR sample on each date. Countries other than Cayman Island, Ireland, Luxembourg, the U.K., and the U.S. have very small shares, and as a result, are grouped together as "others."

(continued)



**Appendix Figure 1** – Continued

### Appendix 2

Conditional on being in state s, at time t the world market risk premium  $R_{W,t}$  is assumed to be normally distributed:

$$(R_{W,t}|s_t = s) \sim N(\mu_s, \sigma_s^2), \tag{5.1}$$

where the unobserved state variable in our model,  $s_t$ , can take on one of the two values,  $s_t \in \{1, 2\}$ . Letting  $\psi_t$  represent all available information through time t, the state variable  $s_t$  is assumed to follow a two-state Markov process:

$$P(s_t = j | \psi_{t-1}) = P(s_t = j | s_{t-1} = i) = p_{ij}$$
(5.2)

resulting in a 2 × 2 transition matrix. This results in 6 parameters to be estimated, namely  $\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, p_{12}$ , and  $p_{21}$ . Once the regime-switching model has been estimated, we then estimate the conditional market model for the long-short calendar time portfolio return as:

$$r_{L-S,t}|s = \alpha + \beta_s R_{W,t} + \varepsilon_t \tag{5.3}$$

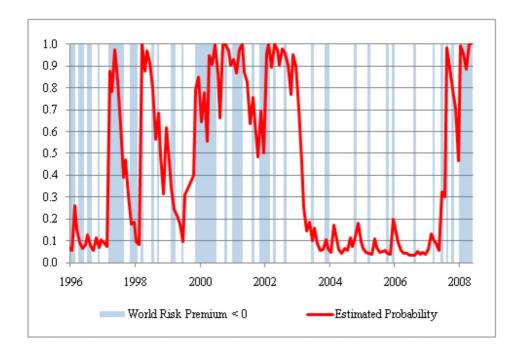
where  $\varepsilon \sim N(0, v^2)$ . This requires another 4 parameters to be estimated, namely  $\alpha, \beta_1, \beta_2$ , and  $v^2$ .

Our estimation of the total of 10 parameters therefore proceeds in two steps. First, we estimate parameters in equations (5.2) and (5.1) by maximum likelihood, using only the world market premium to identify regimes. We then use the first-step parameter estimates and the posterior regime probabilities to estimate parameters of (5.3). Appendix Table 2.1 reports the results, while Appendix Figure 2.2 plots the estimated regime probabilities, along with the periods in which the world market risk premium is less than zero.

## Appendix Table 2.1 Regime-Switching Model Estimation

This table reports parameter estimates of a regime switching model of calendar-time long-short portfolio returns. The sample period is from February 1996 to October 2008. The frequency is monthly. Each month, the portfolio is formed by going long an equally-weighted portfolio of countries in At-Risk quintile 1 and going short those in At-Risk quintile 5. World market premium is measured as the return on MSCI world index minus the one-month U.S. Treasury bill rate. Parameters are estimated by two-step maximum likelihood. In the first step, parameters of the regime-switching model for the world risk premium are estimated. The estimated regime probabilities are then used to estimate parameters of the regime-switching market model for the calendar-time portfolio returns. Standard errors are calculated based on the outer product of the score of the likelihood function. The Chi-squared statistic is based on the Wald test of the hypothesis that loadings on the world risk premium are the same across the two regimes.

Market loading estimates		Market regime estimates	
Intercept	0.842 (0.518)	Mean World Risk Premium (Regime 1)	1.278*** (0.301)
Beta (Regime 1)	0.453* (0.243)	Mean World Risk Premium (Regime 2)	-1.200 (0.914)
Beta (Regime 2)	-0.151 (0.136)	Volatility (Regime 1)	2.559*** (0.251)
Volatility of Residual Returns	5.499 (0.249)	Volatility (Regime 2)	5.585*** (0.790)
		Probability of Staying in Regime 1	0.954*** (0.032)
		Probability of Staying in Regime 2	0.945*** (0.041)
Log likelihood	221	Log likelihood	276
H0: Loadings on world risk premium are the same across regimes			
Chi-squared	4.693**		
<i>p</i> -value	(0.030)		



**Appendix Figure 2.2 Regime probabilities.** The graph plots the probabilities of the regime in which the realized world risk premium is volatile and low, for the period from March 1996 to October 2008. The regimes are estimated based on the mean and volatility of the world market premium, measured as return on MSCI world index minus one-month Treasury bill rate as the risk-free rate.

## References

- [1] Adrian, Tobias and Hyun Shin, 2009, Liquidity and leverage, Journal of Financial Intermediation, Forthcoming.
- [2] Ahearne, A., W. Griever, and F. Warnock, 2004. Information costs and home bias: an analysis of US holdings of foreign equities. Journal of International Economics 62: 313-336.
- [3] Ang, Andrew, and Geert Bekaert, 2002, International asset allocation with regime shifts, Review of Financial Studies 15, 1137-1187.
- [4] Ang, Andrew, and Joseph Chen, 2002, Asymmetric correlations of equity portfolios, Journal of Financial Economics 63, 443-494.
- [5] Bekaert, Geert, Campbell R. Harvey, and Christian Lundblad, 2007, Liquidity and expected returns: Lessons from emerging markets, Review of Financial Studies 20, 1783-1831.
- [6] Bekaert, Geert, Campbell R. Harvey, and Angela Ng, 2005, Market integration and contagion, Journal of Business 78, 1-31.
- [7] Bekaert G., R. Hodrick and X. Zhang. 2008, International stock return comovements, Unpublished working paper.
- [8] Black, Fisher, 1976, Studies in stock price volatility changes, Proceedings of the 1976 Business Meeting of the Business and Economics Statistics Section, American Statistical Association, 177-181.
- [9] Boyer, Brian H., Michael Gibson and Mico Loretan, 1999, Pitfalls in test for changes in correlations, International Finance Discussion Paper 597, Board of Governors of the Federal Reserve.
- [10] Boyer, Brian H., Tomomi Kumagai, and Kathy Yuan, 2006, How do crisis spread? Evidence from accessible and inaccessible stock indices, Journal of Finance 61, 957-1003.
- [11] Brown, Morton B. and Forsythe, Alan B., 1974, Robust tests for equality of variances, Journal of the American Statistical Association, 69, 364–367.

- [12] Brunnermeier, Markus and Lasse Pedersen, 2009, Market liquidity and funding liquidity, Review of Financial Studies, 22(6), 2201-2238
- [13] Calvo, G., 1999, Contagion in emerging markets: When Wall Street is a carrier, working paper.
- [14] Carhart, Mark M., 1997, On persistence in mutual fund performance, Journal of Finance 52, 57-82.
- [15] Chan, Kalok, Vicentiu Covrig, and Lilian Ng, 2005, What determines the domestic bias and foreign bias? Evidence from equity mutual fund allocations worldwide, Journal of Finance 60, 1495-1534.
- [16] Coval, Joshua, and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, Journal of Financial Economics 86, 479-512.
- [17] Dahlquist, Magnus, Lee Pinkowitz, Rene Stulz, and Rohan Williamson, 2003, Corporate governance and the home bias, Journal of Financial and Quantitative Analysis 38, 87-110.
- [18] Domowitz, I., J. Glen and A. Madhavan, 2001, Liquidity, volatility and equity trading costs across countries and over time, International Finance, 4(2), 221-255.
- [19] Eichengreen, Barry and Andrew K. Rose, 1998, Contagious currency crises: Channels of conveyance, in Changes in Exchange Rates in Rapidly Developing Countries (edited by T. Ito and A. Krueger).
- [20] Eichengreen, Barry, Andrew Rose, and Charles Wyplosz, 1996, Contagious currency crises: First tests, Scandinavian Journal of Economics 98, 463-484.
- [21] Fama, Eugene F., and James MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, Journal of Political Economy 91, 607-636.
- [22] Forbes, Kristin J., 2004, The Asian flu and Russian virus: The international transmission of crises in firm-level data, Journal of International Economics 63, 59-92.
- [23] Forbes, Kristin J., and Roberto Rigobon, 2001, Measuring Contagion: Conceptual and Empirical Issues, International Financial Contagion, Kluwer Academic Publishers, edited by Stijn Claessens and Kristin Forbes.

- [24] Forbes, Kristin J., and Roberto Rigobon, 2002, No contagion, only interdependence: Measuring stock market co-movements, Journal of Finance 56, 2223-2261.
- [25] Frankel, Jeffrey and Sergio Schmukler, 1998, Crises, contagion and country funds: Effects on East Asia and Latin America, in Managing Capital Flows and Exchange Rates: Perspectives from the Pacific Basin, Reuven Glick, ed. New York: Cambridge University Press, 232-266.
- [26] Froot, Kenneth A., Paul G. J. O'Connell, and Mark S. Seasholes, 2001, The portfolio flows of international investors, Journal of Financial Economics 59, 151-193.
- [27] Froot, Kenneth A., and Tarun Ramadorai, 2008, Institutional portfolio flows and international investments, Review of Financial Studies 21, 937-971.
- [28] Glick, Reuven and Andrew Rose, 1999, Contagion and trade: Why are currency crises regional?, Journal of International Money and Finance 18, 603-617.
- [29] Hamilton, James D., 1989, A new approach to economic analysis of nonstationary time series and the business cycle, Econometrica 57, 357-384.
- [30] Hamilton, James D., 1990, Analysis of time series subject to changes in regime, Journal of Econometrics 45, 39-70.
- [31] Hau, Harald, and Helene Rey, 2008a, Home bias at the fund level, American Economic Review 98, 333-338.
- [32] Hau, Harald, and Helene Rey, 2008b, Global portfolio rebalancing under the microscope, working paper.
- [33] Heston, S. and K. G. Rouwenhorst, 1994, Does industrial structure explain the benefits of international diversification? Journal of Financial Economics 46, 111-157.
- [34] Kaminsky, Graciela, and Carmen Reinhart, 2000, On crises, contagion, and confusion, Journal of International Economics 51, 145.
- [35] Kaminsky, Graciela, Richard K. Lyons, and Sergio Schmukler, 2001, Mutual fund investment in emerging markets: An overview, World Bank Economic Review 15, 315-340.

- [36] Kaminsky, Graciela, Richard K. Lyons, and Sergio Schmukler, 2004, Managers, investors, and crises: Investment strategies of mutual funds, Journal of International Economics 64, 113-134.
- [37] Karolyi, Andrew, 2003, Does international finance contagion really exist?, International Finance, 179-199.
- [38] Karolyi, Andrew, and Rene Stulz, 1996, Why do markets move together? An investigation of U.S.-Japan stock return co-movements, Journal of Finance 51, 951-986.
- [39] King, Mervyn, Enrique Sentana, and Sushil Wadhwani, 1994, Volatility and links between national stock markets, Econometrica 62, 931-933.
- [40] Kodres, Laura E., and Matthew Pritsker, A rational expectations model of financial contagion, Journal of Finance 57, 769-799.
- [41] Kyle, Albert S., and Wei Xiong, 2001, Contagion as a wealth effect, Journal of Finance 56, 1410-1440.
- [42] Lesmond, David A., 2005, Liquidity of emerging markets, Journal of Financial Economics 77, 411-452.
- [43] Longin, Francois, and Bruno Solnik, 2001, Extreme correlation of international equity markets, Journal of Finance 56, 649-676.
- [44] Newey, Whitney K., and Kenneth D. West, 1987, A simple positive semi-definite, heteroskedasticity and auto-correlation consistent covariance matrix, Econometrica 55, 703-708.
- [45] Pavlova, Anna, and Roberto Rigobon, 2008, The Role of Portfolio Constraints in the International Propagation of Shocks, Review of Economic Studies, 75, 1215-1256.
- [46] Pulvino, Todd C., 1998, Do asset fire sales exist? An empirical investigation of commercial aircraft transactions, Journal of Finance 53, 939-978.
- [47] Rigobon, Roberto, 1998, Informational speculative attacks: Good news is no news, Working Paper, MIT.

- [48] Sachs, Jeffrey, Aaron Tornell, and Andrés Velasco, 1996, Financial crises in emerging markets: The lessons from 1995, Brookings Papers on Economic Activity.
- [49] Seasholes, Mark S., 2000, Smart foreign traders in emerging markets, Working Paper, Harvard Business School.
- [50] Shleifer, Andrei, and Robert W. Vishny, 1992, Liquidation values and debt capacity: A market equilibrium approach, Journal of Finance 47, 1343-1366.
- [51] Sirri, Erik R., and Peter Tufano, 1998, Costly search and mutual fund flows, Journal of Finance 53, 1589-1622.
- [52] Stambaugh, Robert F., 1995, Unpublished discussion of Karolyi and Stulz (1996), National Bureau of Economic Research Conference on Risk Management.
- [53] Warther, Vincent A., 1995, Aggregate mutual fund flows and security returns, Journal of Financial Economics 39, 209-235.
- [54] Yuan, Kathy, 2005, Asymmetric price movements and borrowing constraints: A rational expectations equilibrium model of crisis, contagion, and confusion, Journal of Finance 60, 379-411.

Table I
Summary Statistics by Country

This table provides descriptive information regarding the EPFR sample, summarized by the emerging country in which the funds invest. The sample period is from February 1996 to October 2008. The number of funds is the total number of unique funds that invest in the country at any point in time during the sample period. 'Holding' aggregates dollars held across all funds each month, and divides by the country's latest year-end market capitalization; time-series means and standard deviations are reported. We also report the holding as a fraction of the float-adjusted market capitalization, rescaling market capitalization to adjust for the percentage not closely held as reported in Table 1 of Dahlquist, Pinkowitz, Stulz, and Williamson (2003). There are a few countries for which the float-adjustment is not available. For each country-month, active change in holding is the change in dollar holding net of the country index return in the month, divided by the country's latest year-end market capitalization; time-series correlations are reported with the country index return. Average correlations are calculated using the pooled sample (including all country-months).

	Number	Holding	(% of Market (	Capitalization)		ion (Active	
Country	of Funds	Mean	Standard Deviation	Mean (Float-Adjusted)	(t,t)	(t,t-1)	(t-1,t)
Argentina	248	2.55	2.54	5.39	0.03	-0.02	0.03
Brazil	352	4.00	1.29	12.18	0.15	-0.02	0.10
Chile	253	1.95	0.73	5.57	-0.06	-0.01	-0.10
China	614	1.40	1.02	4.48	-0.21	0.10	0.00
Colombia	139	0.69	0.62		0.12	-0.06	0.08
Czech Republic	246	3.88	2.23	17.73	0.24	-0.12	-0.04
Hong Kong	646	2.30	0.85	4.02	0.16	0.02	0.02
Hungary	275	9.22	3.69	18.25	0.09	0.08	0.12
India	518	3.82	1.28	6.41	0.18	0.23	0.14
Indonesia	461	3.77	1.56	12.17	-0.16	-0.17	0.15
Israel	269	1.62	0.87	3.86	0.04	0.35	0.17
Jordan	32	0.11	0.11	0.31	0.07	0.12	0.18
Malaysia	450	1.83	0.93	3.82	0.25	0.22	0.06
Mexico	315	5.83	1.62	7.90	0.21	0.08	0.02
Morocco	55	0.38	0.25	0.75	0.11	0.09	-0.03
Pakistan	118	1.18	1.27	5.23	-0.02	0.05	0.04
Philippines	348	2.73	1.08	5.59	0.00	-0.01	0.07
Poland	262	5.20	2.65	14.55	0.04	0.09	0.05
Russia	358	3.92	1.32		0.03	0.16	-0.07
South Africa	271	1.59	0.62	3.36	-0.01	0.13	-0.15
South Korea	567	4.98	2.04	8.20	0.09	0.09	-0.06
Taiwan	569	2.88	1.46	3.71	0.30	0.17	0.15
Thailand	468	3.86	1.46	9.15	-0.08	-0.04	-0.09
Turkey	285	3.44	1.53	11.81	0.14	0.12	0.08
Venezuela	151	2.35	2.34	6.11	0.02	0.10	-0.01
Average	307	3.02	1.41	6.82	0.07	0.07	0.04
t-statistic					(4.38)	(4.21)	(2.34)

Table II Fund Summary Statistics

This table provides descriptive information regarding the funds in the EPFR sample. Only funds that invest in emerging countries at any point during the sample period are included. The sample period is from February 1996 to October 2008. The statistics are pooled across fund-months, except for the cross-sectional statistics on alphas. Total net assets (*TNA*) are the total asset value in U.S. dollar at the end of each month. Number of countries invested is the total number of countries, including both developed and emerging countries, in which the fund has non-zero allocation. Allocation to each country and cash holding are measured as a percentage of *TNA*. Month-to-month change in cash holding, fund flows, and fund returns are measured as a percentage of the beginning-of-month *TNA*. Alphas are measured as an intercept from the time-series regression of each fund returns on the MSCI world market returns for the World CAPM or on the world market returns, SMB, HML, and UMD for the Fama-French four-factor model. Alphas are estimated only for funds that exist for at least 12 months.

	Mean	Standard Deviation	1st Percentile	Median	99th Percentile
Total Net Assets (TNA: US\$ million)	610.93	2,200.93	2.80	124.99	10,177.98
Number of Countries Invested	9	8	1	7	31
Allocation to Each Country (%)	30.39	34.63	2.85	12.39	103.74
Cash Holding (%)	3.44	6.14	-9.50	2.39	24.10
Month-to-Month Change in Cash Holding (%)	0.05	4.70	-11.97	0.00	12.50
Flow (%)	-0.06	7.88	-24.28	-0.19	31.70
Return (%)	0.71	8.41	-23.11	1.34	22.19
Alpha (World CAPM, %)	0.48	1.06	-2.47	0.43	2.86
Alpha (Fama-French Four-Factor, %)	0.21	1.02	-3.25	0.22	2.54

Table III
Predictive Regressions for Fund Flows

This table reports results from regressions of fund flows on log of beginning-of-month *TNA*, lagged fund flows and lagged fund returns. The sample period is from February 1996 to October 2008. The frequency is monthly. Both fund flows and fund returns are measured as a percentage of the beginning-of-month *TNA*. All variables in the regressions are divided by their own standard deviations. Fama-MacBeth regression coefficients are the time-series average of monthly cross-sectional regression coefficients, with *t*-statistics calculated as the time-series standard error of the mean. The reported R-squared is the average across all cross-sectional regressions. The pooled regression results are based on OLS. The number of observations is denoted by *N*, and *t*-statistics are in parentheses.

	Poo	oled	Fama-N	MacBeth
Variable	Estimate	<i>t</i> -statistic	Estimate	t-statistic
Intercept	-0.008	(-0.94)	-0.129	(-4.31)
ln(TNA)	-0.002	(-11.16)	-0.001	(-3.30)
Flow_lag1	0.144	(28.22)	0.129	(7.07)
Flow_lag2	0.088	(17.03)	0.076	(6.16)
Flow_lag3	0.058	(11.31)	0.066	(8.16)
Flow_lag4	0.036	(6.94)	0.042	(5.28)
Flow_lag5	0.046	(8.99)	0.051	(6.11)
Flow_lag6	0.031	(5.99)	0.027	(3.06)
Flow_lag7	0.028	(5.32)	0.029	(3.31)
Flow_lag8	0.029	(5.65)	0.033	(4.33)
Flow_lag9	0.019	(3.79)	0.023	(2.48)
Flow_lag10	0.022	(4.42)	0.025	(2.69)
Flow_lag11	0.018	(3.65)	0.026	(3.02)
Flow_lag12	0.028	(6.24)	0.025	(3.23)
Return_lag1	0.098	(19.55)	0.166	(7.16)
Return_lag2	0.042	(8.13)	0.081	(2.88)
Return_lag3	0.022	(4.38)	0.024	(0.66)
Return_lag4	-0.010	(-2.04)	0.065	(1.07)
Return_lag5	0.014	(2.75)	-0.088	(-1.36)
Return_lag6	-0.001	(-0.20)	0.091	(0.92)
Return_lag7	0.004	(0.82)	-0.008	(-0.14)
Return_lag8	-0.008	(-1.62)	-0.020	(-0.54)
Return_lag9	0.003	(0.54)	0.007	(0.27)
Return_lag10	0.008	(1.49)	-0.030	(-0.49)
Return_lag11	-0.017	(-3.41)	0.085	(0.73)
Return_lag12	-0.007	(-2.05)	-0.042	(-0.69)
R-squared	0.114		0.270	
N	38,246		140	

Table IV
Relation between Fund Flows and Other Fund Characteristics

This table reports descriptive fund characteristics conditional on actual fund flows. Both fund flows and fund returns are measured as a percentage of the beginning-of-month *TNA*. Fund-month observations with available flow data are sorted into deciles according to fund flow. Expected flows are estimated via Fama-MacBeth regressions of fund flows on lagged flows and returns. Cash holding is measured as a percentage of the beginning-of-month *TNA*. Number of countries invested is the total number of countries, including both developed and emerging countries, in which the fund has non-zero allocation. For each fund-month, average market capitalization (volume) quintile is the average quintile of latest year-end market capitalization (volume), with 1 being the largest and 5 being the smallest, across all the countries held by the fund at the end of the month. Averages of all fund-months in each decile are reported. Test statistics are for the difference in mean between deciles 1 and 10, based on standard errors clustered by calendar year-month.

Decile	Flow (%)	E[Flow] (%)	Previous- Month Return (%)	Cash Holding (%)	Number of Countries Invested	Average Market Capitalization Quintile	Average Volume Quintile
1 (Inflow)	13.55	0.94	3.43	4.34	7.55	2.41	2.42
2	3.35	0.05	1.93	3.73	9.17	2.34	2.36
3	1.13	-0.41	0.98	3.76	10.46	2.35	2.35
4	0.16	-0.82	0.82	3.70	8.72	2.42	2.40
5	-0.05	-0.89	0.80	3.22	7.47	2.51	2.51
6	-0.54	-1.27	0.31	3.31	10.29	2.31	2.30
7	-1.29	-1.35	0.17	3.05	10.20	2.28	2.28
8	-2.39	-1.56	0.14	3.04	9.06	2.33	2.32
9	-4.41	-1.62	0.27	2.59	8.22	2.36	2.35
10 (Outflow)	-12.61	-1.68	0.13	2.86	7.37	2.44	2.41
1-10	26.16	2.62	3.30	1.48	0.18	-0.03	0.01
t-statistic		(11.70)	(4.49)	(7.66)	(0.90)	(-1.23)	(0.39)

Table V
Fund Trading Associated with Fund Flows

This table reports how fund holdings change conditional on actual and expected flows, measured as a percentage of the beginning-of-month *TNA*. Fund-month observations with available flow data are sorted into deciles according to fund flow (Panel A) and predicted fund flow (Panel B), estimated as in Table III. For each fund-month, countries are considered expanded (reduced) if the end-of-month holdings are greater (smaller) than the beginning-of-month holdings multiplied by the country index returns. These are then reported as fractions of the total number of countries invested in at the beginning of the month. Average change in positions is computed as the cross-country average of the change in dollars invested as a percentage of beginning-of-month *TNA*. Change in cash holding is also measured as a percentage of the beginning-of-month *TNA*. Test statistics are for the difference in mean between all fund-months in deciles 1 and 10, based on standard errors clustered by calendar year-month.

Panel A: Actual flow sort

Decile	Flow (%)	% Countries Expanded	% Countries Reduced	% Countries Eliminated	Avg. Change in Positions	Change in Cash Holding
1 (Inflows)	13.55	78.58	19.91	1.50	0.20	1.63
2	3.35	62.77	35.72	1.50	0.04	0.47
3	1.13	53.95	44.75	1.30	0.01	0.28
4	0.16	47.86	50.97	1.17	-0.01	0.18
5	-0.05	47.47	51.42	1.11	-0.01	0.22
6	-0.54	45.43	52.90	1.67	-0.01	-0.08
7	-1.29	42.38	55.71	1.91	-0.02	-0.23
8	-2.39	37.89	60.29	1.83	-0.03	-0.22
9	-4.41	32.50	65.55	1.95	-0.05	-0.59
10 (Outflows)	-12.61	21.58	75.10	3.31	-0.17	-1.35
1-10	26.16	57.00	-55.19	-1.81	0.38	2.98
t-statistic		(40.36)	(-39.63)	(-5.17)	(30.19)	(13.47)

Panel B: Expected flow sort

Decile	E[Flow] (%)	% Countries Expanded	% Countries Reduced	% Countries Eliminated	Avg. Change in Positions	Change in Cash Holding
1 (Inflows)	4.64	59.09	39.45	1.46	0.07	-0.13
2	1.57	53.17	45.26	1.57	0.02	0.04
3	0.53	50.08	48.61	1.31	0.01	-0.11
4	-0.07	48.44	50.14	1.42	0.00	0.00
5	-0.55	46.00	52.57	1.43	-0.01	0.06
6	-1.05	45.29	52.97	1.74	-0.01	0.06
7	-1.62	44.38	53.85	1.77	-0.02	0.15
8	-2.33	43.23	54.90	1.87	-0.02	-0.06
9	-3.38	41.65	56.07	2.28	-0.04	0.24
10 (Outflows)	-6.35	39.27	58.32	2.40	-0.04	0.05
1-10	10.99	19.82	-18.87	-0.94	0.11	-0.18
t-statistic		(11.66)	(-11.35)	(-4.10)	(9.79)	(-0.91)

Table VI
Trading Costs and Fund Flows

This table reports the average trading costs of countries expanded and countries reduced or eliminated conditional on actual fund flows. Fund flows are measured as a percentage of the beginning-of-month *TNA*. Fund-month observations with available flow data are sorted into deciles according to fund flow. For each fund-month, countries are divided into two groups—those that are expanded and those that are reduced or eliminated. Countries are considered expanded (reduced) if the end-of-month holdings are greater (smaller) than the beginning-of-month holdings multiplied by the country index returns. Trading costs in basis points are first averaged for each group of countries for each fund in each month. In Panel A, the weight for each country is determined by the estimated amount bought and sold. In Panel B, all countries carry equal weight. The average trading costs are then averaged across fund-months in each flow decile. Test statistics are for the difference in mean between deciles 1 and 10 and between the groups of countries expanded and reduced or eliminated, and are calculated using standard errors clustered by calendar year-month.

Panel A: Value-weighted average

		Cour	ntries Expai	nded		Countries Reduced or Eliminated			Difference			<i>t</i> -statistic		
Decile	Flow (%)	Total Trading Costs	Explicit Costs	Price Impact Costs	Total Trading Costs	Explicit Costs	Price Impact Costs	Total Trading Costs	Explicit Costs	Price Impact Costs	Total Trading Costs	Explicit Costs	Price Impact Costs	
1 (Inflows)	13.55 3.35	56.16 55.36	39.87 39.39	16.30 15.97	61.32 57.67	43.41 41.14	17.91 16.52	-5.16 -2.30	-3.55 -1.75	-1.61 -0.56	(-7.41) (-5.50)	(-8.98) (-6.78)	(-3.21) (-2.03)	
3	1.13	55.90	39.67	16.23	56.85	40.42	16.43	-0.95	-0.75	-0.20	(-2.36)	(-2.43)	(-0.77)	
4	0.16	57.63	40.11	17.52	58.39	40.94	17.44	-0.75	-0.83	0.08	(-1.47)	(-2.56)	(0.22)	
5 6	-0.05 -0.54	58.21 56.36	40.61 39.64	17.59 16.72	58.21 55.82	40.68 39.86	17.53 15.96	0.00 0.54	-0.06 -0.22	0.06 0.76	(0.00) (1.30)	(-0.20) (-0.76)	(0.18) (2.57)	
7	-1.29	56.72	40.08	16.64	55.28	39.29	15.99	1.45	0.79	0.66	(3.59)	(2.98)	(2.46)	
8 9	-2.39 -4.41	58.36 58.66	40.84 41.49	17.51 17.18	55.73 56.22	39.40 39.69	16.32 16.53	2.63 2.45	1.44 1.80	1.19 0.65	(4.47) (4.69)	(4.02) (5.36)	(3.45) (1.90)	
10 (Outflows)	-12.61	61.33	42.89	18.44	55.78	39.60	16.18	5.55	3.29	2.26	(7.49)	(6.75)	(5.25)	
1-10 <i>t</i> -statistic	26.16	-5.17 (-4.56)	-3.02 (-4.20)	-2.14 (-3.90)	5.54 (5.65)	3.81 (5.52)	1.73 (3.57)							

Table VI -continued

Panel B: Equally weighted average

	•	Coun	tries Expan	ıded		ries Reduc Eliminated	ed or		Difference			<i>t</i> -statistic	
Decile	Flow (%)	Total Trading Costs	Explicit Costs	Price Impact Costs	Total Trading Costs	Explicit Costs	Price Impact Costs	Total Trading Costs	Explicit Costs	Price Impac Costs	Total Trading Costs	Explicit Costs	Price Impact Costs
1 (Inflows)	13.55	58.86	41.79	17.07	62.40	44.36	18.05	-3.55	-2.57	-0.98	(-5.31)	(-6.47)	(-2.12)
2	3.35	57.35	41.01	16.33	59.88	42.81	17.07	-2.53	-1.79	-0.74	(-6.28)	(-7.01)	(-2.68)
3	1.13	57.98	41.38	16.60	59.18	42.16	17.02	-1.19	-0.78	-0.41	(-3.09)	(-2.86)	(-1.66)
4	0.16	59.55	41.59	17.96	60.50	42.47	18.03	-0.94	-0.87	-0.07	(-1.95)	(-2.83)	(-0.21)
5	-0.05	59.91	41.89	18.02	60.48	42.09	18.39	-0.57	-0.20	-0.37	(-1.11)	(-0.64)	(-0.99)
6	-0.54	58.43	41.24	17.19	58.35	41.63	16.72	0.08	-0.40	0.47	(0.20)	(-1.76)	(1.70)
7	-1.29	58.78	41.64	17.14	57.98	41.18	16.81	0.80	0.47	0.33	(2.06)	(1.76)	(1.29)
8	-2.39	60.49	42.38	18.11	58.77	41.33	17.44	1.72	1.05	0.66	(3.26)	(3.21)	(2.10)
9	-4.41	60.46	42.93	17.53	59.00	41.55	17.45	1.47	1.38	0.09	(2.92)	(4.31)	(0.27)
10 (Outflows)	-12.61	62.54	43.92	18.61	58.65	41.62	17.02	3.89	2.30	1.59	(6.28)	(5.05)	(4.27)
1-10	26.16	-3.68	-2.14	-1.54	3.76	2.73	1.03						
t-statistic		(-3.24)	(-2.89)	(-2.85)	(3.69)	(3.93)	(2.07)						

### Table VII Introducing the At-Risk Measure

Panel A of this table shows At-Risk measured as a percentage of country market capitalization, and connects it with alternative measures of financial pressure. Country-month observations (emerging countries only) with available data are sorted into quintiles according to At-Risk measured as a percentage of country market capitalization. Market capitalizations are the latest year-end numbers. Average monthly volumes are from the previous calendar year. Pressure 2 is calculated based on Equation (5) of Coval and Stafford (2007), henceforth C-S. Since the actual change in fund holding in each country is not observed, it is estimated (for each fund-country-month) as the change in dollar holding net of the country index return in the month. Averages of all country-months in each quintile are reported. Test statistics are for the difference in mean between quintiles 1 and 5, based on standard errors clustered by calendar year-month. Panel B of this table reports the average probabilities of a country currently in a particular At-Risk quintile moving to different At-Risk quintiles next month. The sample period is from February 1996 to October 2008. Each month, countries are sorted into quintiles based on At-Risk as a percentage of country market capitalization. The average probability of moving from quintile i to quintile i is calculated as the total number of times any country moves from quintile i in month t to quintile j at month t+1 divided by the total number of times any country is in quintile i. By definition, the sum of all probabilities across columns in the same row must be one.

Panel A: At-Risk and alternative pressure measures

At-Risk Quintile	At-Risk Measured as % of Market Capitalization	At-Risk Measured as % of Average Monthly Volume	Holding of Sample Funds as % of Market Capitalization	C-S Pressure2	C-S Pressure2 but with Market Capitalization in Denominator
1 (Positive)	0.219	8.055	4.814	0.838	0.024
2	0.049	2.451	2.733	0.309	0.007
3	0.008	0.586	1.380	0.111	0.002
4	-0.012	-0.758	1.624	-0.016	0.000
5 (Negative)	-0.109	-3.375	3.879	-0.206	-0.006
1-5	0.328	11.430	0.935	1.044	0.030
t-statistic		(24.39)	(5.32)	(10.98)	(15.17)

Panel B: At-Risk quintile transition matrix

From At-Risk			To At-Risk Quinti	le	
Quintile	1 (Inflow)	2	3	4	5 (Outflow)
1 (Inflow)	0.70	0.18	0.07	0.02	0.03
2	0.20	0.48	0.24	0.06	0.03
3	0.05	0.24	0.44	0.22	0.05
4	0.03	0.08	0.20	0.50	0.19
5 (Outflow)	0.02	0.02	0.06	0.22	0.67

#### **Table VIII**

### Return and Risk Characteristics of Calendar-Time Portfolios Based on At-Risk Sorted Portfolios

This table reports average monthly returns and standard deviations of calendar-time portfolios. The sample period is from February 1996 to October 2008. Each month, equally-weighted portfolios are formed by sorting countries into quintiles based on At-Risk as a percentage of country market capitalization Time-series averages and standard deviations are reported for the entire sample and separately for the periods of positive and negative excess returns on the MSCI World index (the MSCI G-7 index) in Panel A (Panel B). Tests of difference in mean return and standard deviation of return are between quintile portfolios 1 and 5. Statistics for the test of difference in mean return are calculated based on Newey-West standard errors using three lags. Statistics for the test of difference in the standard deviation (or variance) of return are calculated based on the Brown-Forsythe method.

Panel A: Conditional on the MSCI World Index

Quintile		Average Return (	%)	Standa	Standard Deviation of Return (%)				
Calendar Portfolio	All	World Excess Return > 0	World Excess Return < 0	All	World Excess Return > 0	World Excess Return < 0			
1 (D. 14)	1.01	5.06	2.07	7.07	5.40	7.15			
1 (Positive)	1.91	5.26	-2.97	7.37	5.40	7.15			
2	1.38	4.45	-3.11	6.91	5.99	5.60			
3	0.54	3.62	-3.96	6.62	5.04	6.06			
4	0.63	3.78	-3.97	7.20	4.75	7.71			
5 (Negative)	0.63	3.93	-4.19	7.16	5.13	7.00			
						_			
1-5	1.28	1.33	1.22	0.21	0.27	0.15			
t-statistic	(2.58)	(2.37)	(1.61)						
F-statistic				(0.19)	(0.09)	(0.63)			

Panel B: Conditional on the MSCI G-7 Index

Quintile		Average Return (	%)	Standard Deviation of Return (%)			
Calendar Portfolio	All	G-7 Excess Return > 0	G-7 Excess Return < 0	All	G-7 Excess Return > 0	G-7 Excess Return < 0	
1 (Positive)	1.91	5.35	-2.83	7.37	5.40	7.11	
2	1.38	4.53	-2.98	6.91	6.01	5.59	
3	0.54	3.76	-3.92	6.62	5.01	5.97	
4	0.63	3.82	-3.78	7.20	4.78	7.68	
5 (Negative)	0.63	4.04	-4.09	7.16	5.07	6.97	
						_	
1-5	1.28	1.30	1.26	0.21	0.33	0.14	
t-statistic	(2.58)	(2.37)	(1.62)				
F-statistic				(0.19)	(0.16)	(0.57)	

## Table IX At-Risk Sorted Calendar-Time Portfolio Regressions

This table reports results from time-series regressions of calendar-time long Q1 short Q5 portfolio returns on the world risk premium, over the sample period from February 1996 to October 2008. Countries are sorted into quintiles on the basis of actual At-Risk (first two columns) and predicted At-Risk (last two columns). Predicted At-Risk is calculated by replacing the current month flow by the expected flows, estimated via the Fama-MacBeth regressions in Table III. In Panel A (B), the excess return on the MSCI world index (the MSCI G-7 index) is on the RHS. Positive (negative) world dummy equals one if the world excess return is positive (negative) and zero otherwise. The number of monthly observations is denoted by N, and Newey-West standard errors using three lags are in parentheses.

Panel A: MSCI World Index as the market portfolio

At-Risk Sort	At-Risk Sort	Predicted At- Risk Sort	Predicted At- Risk Sort
0.013**	-0.001	-0.001	-0.017*
(0.005)	(0.008)	(0.006)	(0.009)
0.002		-0.039	
(0.089)		(0.159)	
	0.509***		0.540**
	(0.190)		(0.267)
	-0.319**		-0.401*
	(0.143)		(0.233)
150	150	139	139
0.00	0.04	0.00	0.05
	0.013** (0.005) 0.002 (0.089)	0.013**	At-Risk Sort         At-Risk Sort         Risk Sort           0.013**         -0.001         -0.001           (0.005)         (0.008)         (0.006)           0.002         -0.039           (0.089)         (0.159)           0.509***         (0.190)           -0.319**         (0.143)           150         150         139

Panel B: MSCI G-7 Index as the market portfolio

	At-Risk Sort	At-Risk Sort	Predicted At- Risk Sort	Predicted At- Risk Sort
Intercept	0.013**	-0.001	-0.001	-0.017*
	(0.005)	(0.008)	(0.006)	(0.009)
G-7 Excess Return	0.005		-0.038	
	(0.091)		(0.160)	
Positive G-7 Dummy * G-7 Excess Return		0.510***		0.542**
		(0.191)		(0.261)
Negative G-7 Dummy * G-7 Excess Return		-0.324**		-0.400*
		(0.140)		(0.241)
N	150	150	139	139
R-squared	0.00	0.04	0.00	0.05

# Table X Holding Sorted Calendar-Time Portfolio Regressions

This table reports results from time-series regressions of calendar-time long Q1 short Q5 portfolio returns on the world risk premium, over the sample period from February 1996 to October 2008. Countries are sorted into quintiles on the basis of beginning-of-month holding in the country of all sample funds, measured as a percentage of the country market capitalization. In Panel A (B), the excess return on the MSCI world index (the MSCI G-7 index) is on the RHS. Positive (negative) world dummy equals one if the world excess return is positive (negative) and zero otherwise. The number of monthly observations is denoted by N, and Newey-West standard errors using three lags are in parentheses.

Panel A: MSCI World Index as the market portfolio

	Holding Sort	Holding Sort
Intercept	-0.002	-0.004
	(0.004)	(0.008)
World Excess Return	0.893***	
	(0.134)	
Positive World Dummy * World Excess Return		0.978***
		(0.256)
Negative World Dummy * World Excess Return		0.839***
		(0.194)
N	150	150
R-squared	0.35	0.35

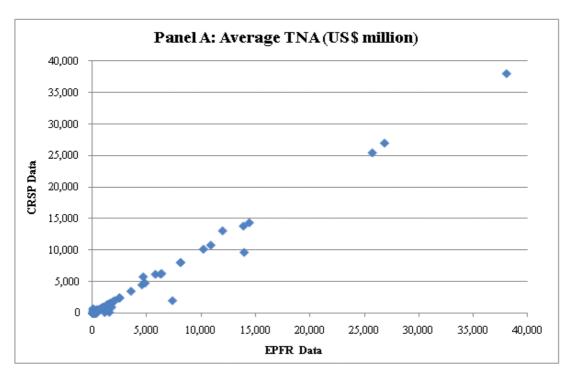
Panel B: MSCI G-7 Index as the market portfolio

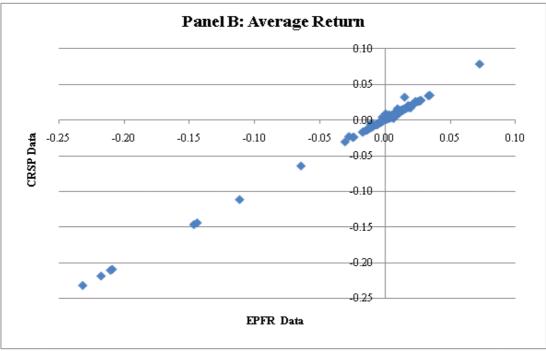
	Holding Sort	Holding Sort
Intercept	-0.002	-0.002
	(0.004)	(0.007)
G-7 Excess Return	0.886***	
	(0.129)	
Positive G-7 Dummy * G-7 Excess Return		0.893***
		(0.241)
Negative G-7 Dummy * G-7 Excess Return		0.881***
		(0.195)
N	150	150
R-squared	0.33	0.33

Table XI
Liquidity Adjusted At-Risk Sorted Calendar-Time Portfolio Regressions

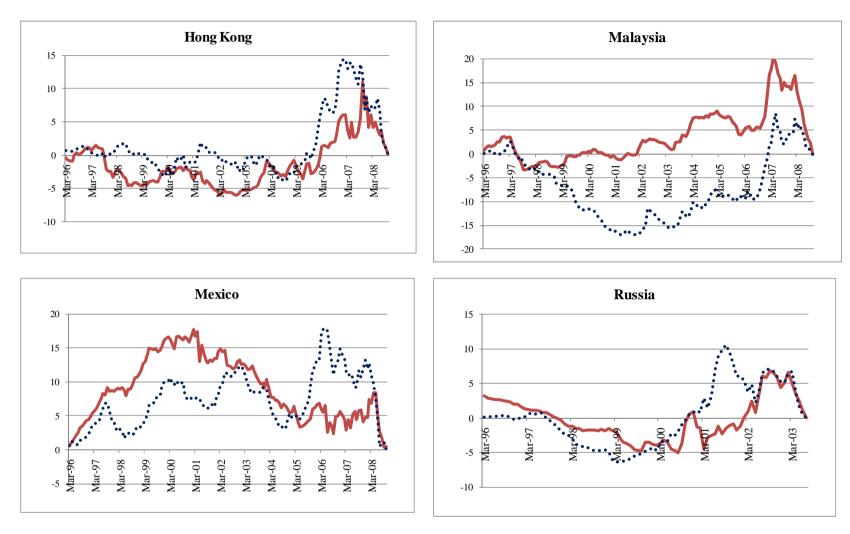
This table reports results from time-series regressions of calendar-time long Q1 short Q5 portfolio returns on the world risk premium, over the sample period from February 1996 to October 2008. Countries are sorted into quintiles on the basis of actual liquidity-adjusted At-Risk (first two columns) and predicted liquidity-adjusted At-Risk (last two columns). For each country-month, liquidity-adjusted At-Risk is calculated as the product of At-Risk and the corresponding price impact costs. For country-months with missing price impact costs, the time-series average price impact costs for the country are used. Predicted At-Risk is calculated by replacing the current month flow by the expected flows, estimated via the Fama-MacBeth regressions in Table III. The world excess return is the excess return on the MSCI world index. Positive (negative) world dummy equals one if the world excess return is positive (negative) and zero otherwise. The number of monthly observations is denoted by N, and Newey-West standard errors using three lags are in parentheses.

	Liq-Adj At-Risk Sort	Liq-Adj At-Risk Sort	Predicted Liq-Adj At-Risk Sort	Predicted Liq-Adj At-Risk Sort
Intercept	0.017***	0.003	0.006	-0.014
	(0.006)	(0.008)	(0.005)	(0.009)
World Risk Premium	-0.094		0.001	
	(0.110)		(0.146)	
Positive World Dummy * World Risk Premium		0.418*		0.686**
		(0.236)		(0.324)
Negative World Dummy * World Risk Premium		-0.419***		-0.428***
		(0.147)		(0.142)
N	150	150	139	139
R-squared	0.00	0.04	0.00	0.06

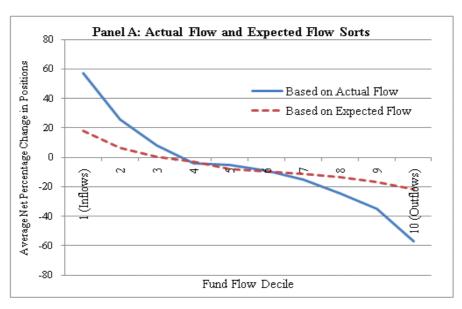


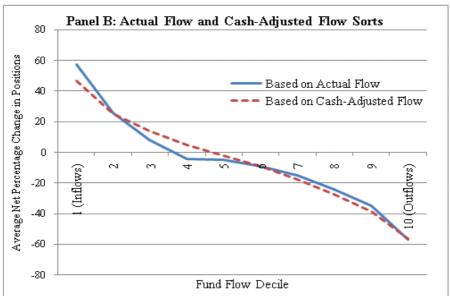


**Figure 1. Comparison between EPFR and CRSP mutual fund data.** For a subset of funds, this figure compares the average *TNA*s and the average monthly returns from the EPFR and CRSP mutual fund data. The two data sets are matched by fund name. The sample period is from February 1996 to October 2008. Panel A plots the (time-series) average *TNA*s. The *TNA* for each fund-month is measured as the sum of reported *TNA*s of all share classes from the same portfolio. Panel B plots the (time-series) average monthly returns. The return for each fund-month is measured as the sum of US\$ return of all share classes from the same portfolio divided by the portfolio *TNA*.

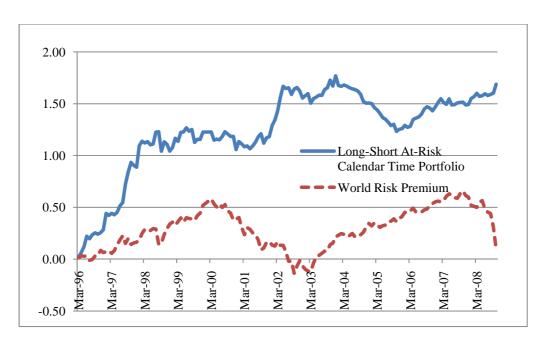


**Figure 2. Comparison between EPFR and TIC data.** This figure compares the cumulative standardized change in dollar holding of all funds in the EPFR data with the cumulative standardized net transactions in foreign stocks (by U.S. investors) from the TIC data for four countries: Hong Kong, Malaysia, Mexico, and Russia. The sample period is from February 1996 to October 2008. The change in dollar holding and the net transactions in stocks for each country are standardized by subtracting their own means and dividing by their own standard deviations. The red solid lines represent the EPFR data. The blue dotted lines represent the TIC data.

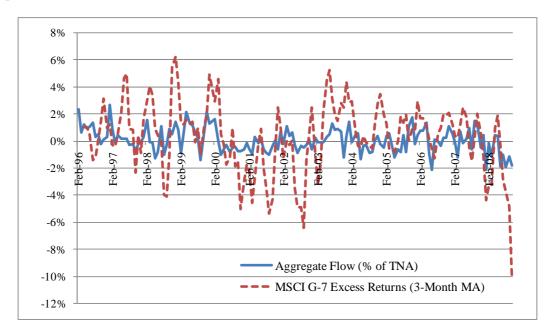




**Figure 3. Relation between fund flows and changes in positions.** This figure plots the average net percentage changes in positions for funds in different deciles of actual and expected flows (Panel A) and actual and cash-adjusted flows (Panel B). Flows are measured as a percentage of the beginning-of-month *TNA*. Expected flow is estimated via Fama-MacBeth regressions of flows on lagged flows and returns, where coefficients are the time-series average of periodic cross-sectional regression coefficients. Cash-adjusted flows are calculated as the sum of flows and cash holdings at the beginning of the month. For each fund-month, the net percentage change in positions is calculated as the percentage of countries in which the fund increases its holding during the month minus the percentage of countries in which the fund reduces or eliminates its holding. Each country holding is considered increased (reduced) if the end-of-month dollar holding is the country is greater (less) than the beginning-of-month dollar holding multiplied by the country index return. All fund-months observations are sorted into deciles according to the fund's actual and expected flows for the month. The average of net percentage change in positions is reported for each flow or expected flow decile.

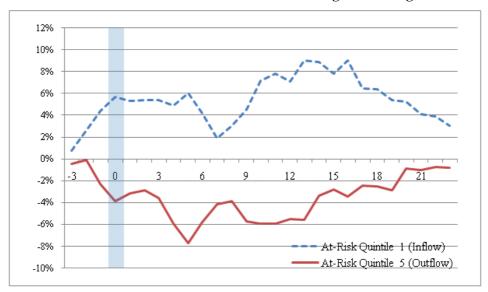


**Figure 4. Cumulative logged returns.** This figure plots the cumulative logged returns of the calendar-time long Q1/short Q5 portfolio (blue solid line) and the cumulative excess return on the MSCI world index (red dashed line). The sample period is from February 1996 to October 2008. Each month, countries are sorted into quintiles on the basis of At-Risk as a percentage of the country market capitalization. The portfolio is then constructed by going long the equally-weighted portfolio of countries in the top At-Risk quintile and going short the equally-weighted portfolio of countries in the bottom At-Risk quintile.

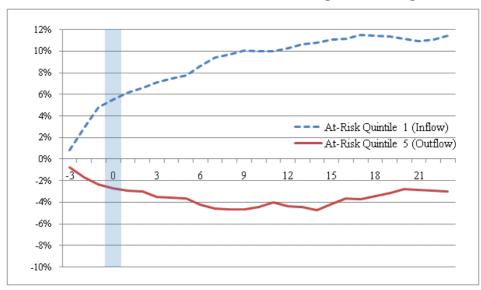


**Figure 5. Aggregate flows and G-7 returns.** This figure plots aggregated dollar flows to the funds in the EPFR sample (blue solid line) and the 3-month moving average excess returns on the MSCI G-7 portfolio (red dashed line). The correlation between the two series is 49%.

Panel A: Cumulative Abnormal Returns During "Crisis Regime"



Panel B: Cumulative Abnormal Returns During "Normal Regime"



**Figure 6. Conditional cumulative abnormal returns.** This figure plots the cumulative abnormal returns (*CARs*) for countries in the highest (Q1) and lowest (Q5) At-Risk quintiles, conditional on the contemporaneous MSCI G-7 returns. Countries are sorted into quintiles on the basis of At-Risk. Month 0 is the month in which the countries are placed in Q1 and Q5. For each event, *CARs* are measured as average monthly returns of all countries in the quintile in excess of the equally weighted average return of all emerging countries in the sample. *CARs* are then averaged across events. Panel A (Panel B) presents the *CARs* for countries in Q1 and Q5 during months in which the MSCI G-7 returns are less than or equal to (greater than) the 10<sup>th</sup> percentile during the sample period.