Asset Fire Sales and Purchases and the International Transmission of Funding Shocks.*

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Abstract

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1. Introduction

An important new strand of the literature in financial economics shows that asset market liquidity can be significantly affected by the funding available to intermediaries (see Brunnermeier and Pedersen (2009) and Adrian and Shin (2009)). In a recent paper, Coval and Stafford (2007) present evidence that this channel is empirically important for price determination in U.S. stocks. Their methodology relies on the insight that mutual funds and hedge funds are often forced to redeem investments as a consequence of funding shocks that originate from their investor base. Using data on fund inflows and outflows in combination with mandatory disclosures of fund holdings, they find that when such forced redemptions (or 'fire sales') are correlated across institutions that hold a particular stock, they cause the price of the stock to fall significantly. While temporary, these price effects last on average for long periods of time (several months or a year) until capital flows back into the assets, alleviating the funding-generated pressure.

Our contribution in this paper is to show that this line of reasoning yields a rich set of findings with important implications for the debate surrounding "contagion," the term given to the transmission of shocks between country financial markets, over and above any links between the underlying fundamentals of the economies. While a large body of literature in finance and economics has been devoted to understanding contagion,[1] there is an ongoing discussion in the literature about the sources of contagion, and much debate on the magnitude of the impacts of contagion on emerging economies in particular. We find that the funding shocks experienced by a large set of developed country-domiciled funds are transmitted to twenty five emerging markets around the world through the forced portfolio reallocations of these funds, with important impacts on the average stock returns of the emerging markets. Perhaps more importantly, we also find that at times when emerging stock markets are predominately owned by funds most subject to funding shocks, they also have significantly elevated correlations with G-7 stock markets. This finding helps to provide evidence on the sources of the transmission of shocks across borders that has hitherto been inferred in the literature either indirectly (see Boyer, Kumagai and Yuan (2006)), or cleverly extrapolated from the

[1] See Kodres and Pritsker (2002) for a model that generates contagion through cross-market rebalancing. 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 crisis from one country to others. For empirical work, see Longin and Solnik (2001), Forbes and Rigobon (2002), Forbes (2004), and Boyer, Kumagai, and Yuan (2006).

behaviour of a small sample of investment managers (see Kaminsky, Lyons and Schmukler (2004)).

To conduct our investigation, we employ a new data source from Emerging Portfolio Flow Research (EPFR) on the monthly capital flows to, and country-allocations of, global investment managers that invest in emerging markets. These data cover over a thousand funds that collectively hold on average 3% (and at maximum, 9%) of the capitalization of the emerging markets in our sample. The funds are overwhelmingly domiciled in developed markets (the U.S. and Europe). Using these data, we investigate the forced trading behavior of those international mutual and hedge funds that are financially distressed on account of significant redemptions of capital by their investors. In the absence of a sufficiently large cash buffer, we find that these financial intermediaries change their portfolio allocations to the markets in which they invest in response to funding shocks from their investor base. These changes are economically and statistically significant: 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 over the next month. Similarly funds in the top decile expand their holdings in 79% of the markets in which they invest, while those experiencing significant outflows expand just 22% of their positions.

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 in the EPFR data to each emerging market with the flow 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 country-months by capital At-Risk, we find that the country-months 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 the world market risk-premium 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.[2]

Finally, we find that the fire-sale actions of global funds increase the correlation 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 to vary conditional on the sign of the world market risk-premium, the alpha is eliminated. In the face of positive (negative) world market returns, countries with positive (negative) At-Risk capital have significantly larger world market betas than do countries with negative (positive) At-Risk capital.[3] Our explanation for this echoes Boyer, Kumagai and Yuan (2006): when stock returns in developed markets are low, investors face margin calls that result in the liquidation of foreign investments, including those undertaken through global funds. This means that outflows will be greater at such times of low developed market returns, resulting in more pressure for forced liquidations 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.

To confirm our intuition, we conduct several robustness checks. First, we re-estimate the specification using the returns on a portfolio of the G-7 countries in place of the world market returns, and find virtually unchanged results. Second, we implement the regression for portfolios sorted by our At-Risk measure created using *predicted* (rather than realized) flows, and continue to find the asymmetry in betas. Finally, to ensure that our results are not driven by a conditional bias in the correlation estimate, potentially induced by splitting the data according to the realized returns (Forbes and Rigobon (2002)), 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 portfolio betas, allowing them to differ across regimes, the documented results remain unchanged.

[2]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.

[3]Bekaert, Harvey, and Ng (2005) measure contagion as the residual correlations from a two-factor model that already allows for time variation in beta.

In sum, the finding that there are increased (and asymmetric) correlations between developed markets and the emerging markets most held by distressed intermediaries constitutes robust evidence of an important transmission mechanism underlying contagion.

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 behaviour. Section 4 connects the forced reallocations of global funds with underlying emerging market stock returns, and Section 5 concludes.

2. Data

We use two main sources of data: (i) data on international mutual and hedge funds from Emerging Portfolio Fund Research (EPFR) and (ii) 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. The EPFR data covers globally-focused funds, domiciled in the US and Europe, that invest in equity and bond markets in over 90 industrialized and emerging countries around the world. The specified fields provided, for each fund and each month are: 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. The sample period spans February 1996 to October 2008.[4] There are 1,520 unique funds during the sample period, although the number of funds present on any given month fluctuates as funds are born or die. At the end of 2007, for example, the sample contains 938 funds with US$ 943,589 million worth of assets under management. On average, the funds in the sample collectively hold approximately 2 percent of country equity market capitalization across all the 90 (emerging and developed) countries .

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.[5] We then carefully screen out incorrect matches by hand (see details in Appendix A). This process yields 126 funds that appear

[4] The data for January 2000 is missing for all funds.

[5] We thank Joey Engleberg for the name-matching program that we use in this paper.

in both data sets (a little less than 10% of the sample used in this study). 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 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.

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 this process is presented in the figures in the Appendix, 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). 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.[6] In terms of size, at the end of 2007, funds in the EPFR sample collectively hold 3.73 percent of an average emerging country's total market capitalization. The same statistic is 9.95 percent for all U.S. investors as captured by TIC. These statistics 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).

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.[7] 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. 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. 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, and as mentioned before, the funds hold a significant proportion of country market capitalization (3.02% on average across the emerging countries). This percentage holding does not vary much over time (with time-series standard deviation less than half of the mean) but varies significantly across countries, ranging from 0.11 percent in Jordan to 9.22 percent in Hungary. This variation is useful in helping us distinguish the effects of fund flows from those of fund holdings in general.

[6] 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.

[7] We exclude Zimbabwe from the list due to its extremely high inflation.

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. 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.

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. Some funds invest exclusively in one country while others 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. In all, the characteristics of global funds that invest in emerging markets are broadly in line with the evidence presented elsewhere in the literature for other funds, and the EPFR data do not appear to be different from other common data sources along these dimensions.

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:[8]

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

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. Finally, the results are also 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

[8] Note that we only estimate this specification for funds that ever invest in an emerging market over the sample period.

that which is generally reported elsewhere. The flow-performance relationship is less pronounced for funds investing in emerging equity markets.

Finally, given the fitted values implied by the time-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-allocation

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 to some extent linked to past performance, and the motivating factor behind specification (3.1). 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 likely 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.[9]

[9]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).

Funds in the bottom decile (significant outflows) reduce or eliminate around 78% of their positions over the next month. Contrast this with funds in the top decile (experiencing significant inflows), who reduce or eliminate just 21% of their positions over the next month. Similarly funds in the 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 sharp 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 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 may be 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. To present this graphically, Figure 3 displays 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. 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.

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 forced ‘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 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:

$$\text{At-Risk}_{k,t} = \sum_{j=1}^{N} flow^{*}_{j,t} \cdot allocation_{j,k,t-1} \cdot TNA_{j,t-1} \tag{4.1}$$

where $flow^{*}_{j,t} = flow_{j,t} + flow_{j,t-1} + flow_{j,t-2}$, is the sum of capital flows experienced by a 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 $t-1$.[10] 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 100 MM USD. If the fund's total flow over the November-December-January quarter is 10%, this yields 2.5 MM USD 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 -5 MM USD 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.

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 VI 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

[10] 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.

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 VI 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 will 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 VI 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 $allocation_{j,k,t-1}$ with $\Delta allocation_{j,k,t}$ in equation (4.1) above). 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.[11] 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 VI) 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 global funds 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 (exactly as in Table VI) and calculate portfolio returns (in USD) by averaging returns across all countries in the same quintile. Panel A of Table VII 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 VI 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 VII 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. Clearly fire-sale re-allocations seem to generate economically

[11] 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.

significant return movements in emerging markets.

The other important finding in Table VII 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. This is because 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. 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.

To verify that developed market returns are indeed the source of this pressure, Table VIII 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 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.

Since At-Risk is a product of both the funds' collective holding in the country as well as the flows the funds face, it is interesting to see whether it is really the pressure created by fund flows that explains the patterns in Panel A of Table VII and Table VIII or simply the fact that global funds disproportionately allocate capital to some of these markets. To address this question, we repeat the same analysis, but sort countries into quintile portfolios based instead on the beginning-of-month holding (as a percentage of the country's market capitalization) alone. The results are presented in Panel B of Table VII, where we do not observe a statistically significant difference in returns between the portfolios at the two extremes when sorted by holdings. The pattern we observe in the first column of Panel A suggests that both holdings and fund flows are required to observe return effects from potential forced trading. That said, countries that are held in larger proportion by global funds (Quintile 1) appear to have higher betas – they disproportionately gain or lose more when the contemporaneous world market excess return is positive or negative, respectively. These differences are highly significant, with t-statistics exceeding 4. This suggests that some portion of the beta effects documented in Table VII may be driven by the holdings – although it is worth noting that the bottom quintile of At-Risk sorted portfolios have higher downside betas than the top quintile of At-Risk sorted portfolios despite the fact that the countries in the latter are significantly more highly held than the those in the former (see the third column of Table VI). Finally, we also find that countries which are most highly held by global funds are significantly more volatile.

4.2.2. Calendar time portfolios

To understand the economic source of return differences, we examine the returns of a calendar-time 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, but in some specifications we use 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 world-market 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 128 basis points per month, which is almost the same magnitude as the return spread presented in Panel A of Table VII. The world market beta of this long-short portfolio is effectively zero: investment reallocation 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 VIII 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 VIII 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, although the strategy of providing liquidity to markets based on expected flow is not likely to be profitable.

Table X formalizes our test in Table VI Panel B, in that we repeat the world CAPM estimation with the long-short portfolio of countries sorted according to the funds' holding as a percentage of the country's market capitalization, rather than by At-Risk. These results are reported in Table X, and 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.

4.3. Global regimes

Several papers find that market correlations vary over time, and are generally higher during bear markets than during bull markets (see Longin and Solnik (2001), Ang and Bekaert (2002), and Ang and Chen (2002), for example). The same goes for volatility, as we re-confirm in Table VII. Stambaugh (1995), Boyer, Gibson, and Loretan (1999), and Forbes and Rigobon (2002) note that calculating correlations conditional on realized high (low) returns, or high (low) volatility, induces a conditional bias in the correlation estimate.[12]

To make sure that this source of bias does not affect our results, we follow Boyer, Kumagai,

[12]If realized country-level returns or volatility vary systematically with fund flows, our conditional beta estimates for the At-Risk portfolio could also be subject to bias arising from this source. While possible, this is unlikely for two reasons. First, our At-Risk measure is constructed by using the cross-sectional variation in flows, and changes in this cross-sectional distribution over time (rather than the systematic time-varying component of flows). Second, as Table VII shows, neither the unconditional or conditional variance differ significantly across At-Risk quintile portfolios (despite the fact that volatility is, on average, higher during global market downturns consistent with the usual leverage effect argument (see Black (1976)).

and Yuan (2006) and estimate a regime-switching model, in which both mean returns and variances of return are allowed to vary across regimes. Conditional on being in state s, at time t the world market risk premium $R_{W,t}$ is assumed to be normally distributed:

$$(R_{W,t}|s_t = s) \sim N(\mu_s, \sigma_s^2), \tag{4.2}$$

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

$$P(s_t = j|\psi_{t-1}) = P(s_t = j|s_{t-1} = i) = p_{ij} \tag{4.3}$$

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:

$$r_{L-S,t}|s = \alpha + \beta_s R_{W,t} + \varepsilon_t \tag{4.4}$$

where $\varepsilon \sim N(0, \upsilon^2)$. This requires another 4 parameters to be estimated, namely α, β_1, β_2, and υ^2.

Our estimation of the total of 10 parameters therefore proceeds in two steps. First, we estimate parameters in equations (4.3) and (4.2) 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 (4.4). Table XI reports the results, while Figure 4 plots the estimated regime probabilities.

Our estimates of the characteristics of the world market return and volatility indicate that Regime 1 is a high return and low volatility regime while Regime 2 is a low return and high volatility regime. These two identified regimes are consistent with the evidence documented in the regime-switching literature (see Boyer, Kumagai, and Yuan (2006), for example). Figure 4 shows that the probabilities of being in Regime 2 are high in periods of negative world market returns but the correlation is not perfect. The estimates of the world market beta appear to be different in the two regimes, +0.453 in Regime 1 and -0.151 in Regime 2. Although these estimates are only significant at the 10% level, they are of the same sign and only slightly smaller in magnitudes compared to those reported in Table IX.[13] We also perform a Wald test of the null hypothesis that betas are the same in both regimes. The test 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.

5. Conclusion

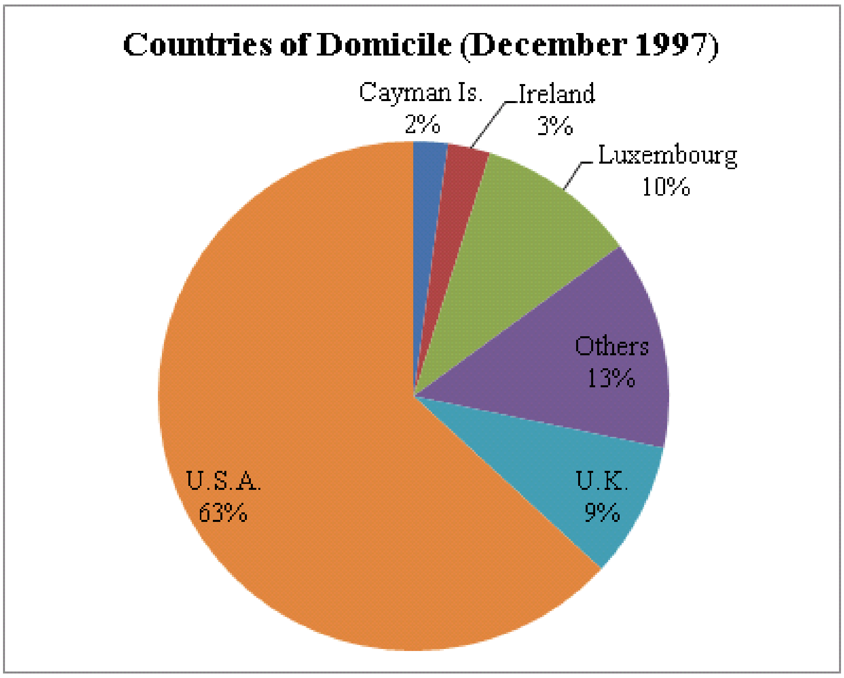
Using new data from Emerging Portfolio Flow Research (EPFR) on the capital flows to and allocations of global investment managers, we demonstrate that the forced reallocation mechanism first identified by Coval and Stafford (2007) has important implications for the debate surrounding contagion. In particular, we find that global investment managers in financial distress constitute an important transmission channel for financial shocks between developed markets and emerging markets. We document both the forced trading behavior of those globally-focused funds that face significant capital flows and the implications of their actions for price determination in the emerging markets in which they are invested.

Specifically, we find that funds facing significant outflows reduce or eliminate their holdings in approximately 78% of the markets in which they invest, whereas funds facing inflows reduce or eliminate just 21% of their positions. Similarly, funds facing sizeable inflows expand their holdings in 79% of their positions, while those experiencing sizeable outflows expand just 22% of their positions. Using our measure of managed capital 'At-Risk', capturing 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, we also find that the emerging markets in the top quintile of At-Risk significantly outperform

[13] This is a result of the persistence of the regimes which are identified using Bayesian inference using past and current data. As shown, the regime probabilities do not coincide perfectly with periods of positive or negative returns. In particular, negative (positive) return months that occur during a long span of positive (negative) returns are often identified as still being in the high return and low volatility (low return and high volatility) regime.

those in the bottom quintile. In other words, flows into and out of globally focused mutual and hedge funds force them to engage in fire sales which in turn generate significant price pressure in the emerging markets in which they are heavily invested. Finally, we find that periods during which global funds are facing pressure to reallocate their emerging markets investments are also associated with elevated correlations between equity returns in emerging and developed markets. Taken together, we conclude that an understanding of the international contagion effect requires an appreciation for the role played by forced reallocation among global funds facing funding shocks.

APPENDIX



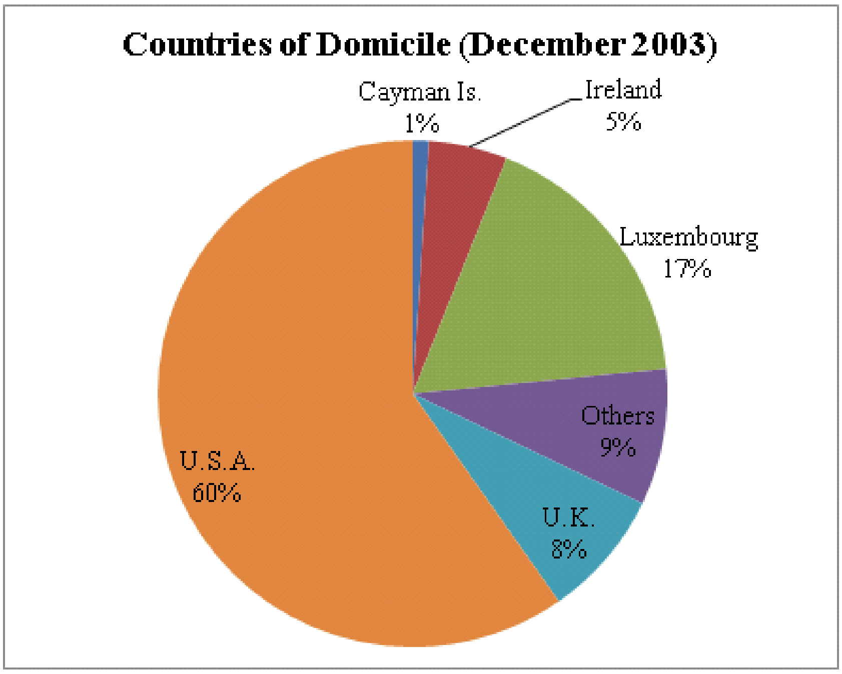


Figure Appendix 1. Distribution of Countries of Domicile. This figure plots the total net assets (*TNA*) shares for different countries of domicile of the funds in the EPFR sample at the ends of 1998, 2003, and 2007. The *TNA* share is calculated as the sum of *TNA*s of all funds that are domiciled in 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)

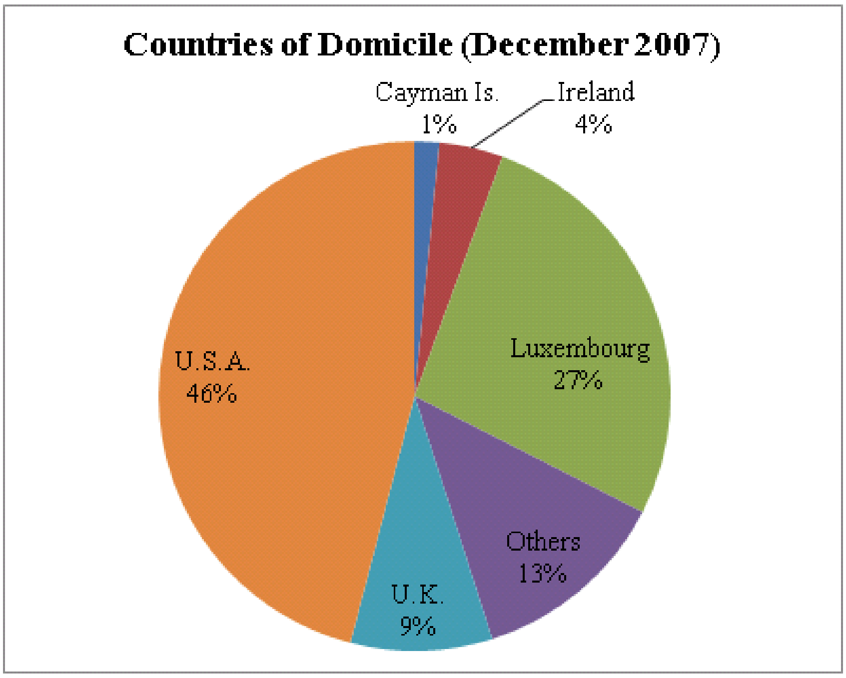


Figure Appendix 1 -- *Continued*

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Table I

Summary Statistics by Country

This table provides descriptive information regarding the EPFR sample, summarized by country in which the funds invest. The sample period is from February 1996 to October 2008. Only emerging countries (excluding Zimbabwe) under MSCI classification are included. 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 is measured as the total dollar holding in the country of all funds in the EPFR data in a particular month, divided by the country's latest year-end market capitalization. Time-series averages and standard deviations are reported. 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 between active change in holding and country index return are reported. Average correlations are calculated using the pooled sample (including all country-months).

		Holding (% of Market Capitalization)		Correlation(Active Change in Holding, Index Return)		
Country	Number of Funds	Mean	Standard Deviation	(t,t)	(t,t-1)	(t-1,t)
Argentina	248	2.55	2.54	0.03	-0.02	0.03
Brazil	352	4.00	1.29	0.15	-0.02	0.10
Chile	253	1.95	0.73	-0.06	-0.01	-0.10
China	614	1.40	1.02	-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	0.24	-0.12	-0.04
Hong Kong	646	2.30	0.85	0.16	0.02	0.02
Hungary	275	9.22	3.69	0.09	0.08	0.12
India	518	3.82	1.28	0.18	0.23	0.14
Indonesia	461	3.77	1.56	-0.16	-0.17	0.15
Israel	269	1.62	0.87	0.04	0.35	0.17
Jordan	32	0.11	0.11	0.07	0.12	0.18
Malaysia	450	1.83	0.93	0.25	0.22	0.06
Mexico	315	5.83	1.62	0.21	0.08	0.02
Morocco	55	0.38	0.25	0.11	0.09	-0.03
Pakistan	118	1.18	1.27	-0.02	0.05	0.04
Philippines	348	2.73	1.08	0.00	-0.01	0.07
Poland	262	5.20	2.65	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	-0.01	0.13	-0.15
South Korea	567	4.98	2.04	0.09	0.09	-0.06
Taiwan	569	2.88	1.46	0.30	0.17	0.15
Thailand	468	3.86	1.46	-0.08	-0.04	-0.09
Turkey	285	3.44	1.53	0.14	0.12	0.08
Venezuela	151	2.35	2.34	0.02	0.10	-0.01
Average	307	3.02	1.41	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.

	Pooled		Fama-MacBeth	
Variable	Estimate	*t*-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

Relations 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. 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 (Panel A) and expected fund flow (Panel B). Expected flows are estimated via Fama-MacBeth regressions of fund flows on lagged flows and returns. 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. Fractions of countries expanded, reduced, and eliminated are calculated by dividing the numbers of countries expanded, reduced, and eliminated, respectively, by the total number of countries invested in at the beginning of the month. For each fund-month, average change in positions is the cross-country average of the changes in dollar invested in each country as a percentage of the beginning-of-month *TNA*. Change in cash holding is also measured as a percentage of the beginning-of-month *TNA*. 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.

Panel A: Actual flow sort

Decile	Flow (%)	% Countries Expanded	% Countries Reduced	% Countries Eliminated	Average Change in Positions (% of Beginning *TNA*)	Change in Cash Holding (% of Beginning *TNA*)
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)

(*continued*)

Table V--*Continued*

Panel B: Expected flow sort

Decile	E[Flow] (%)	% Countries Expanded	% Countries Reduced	% Countries Eliminated	Average Change in Positions (% of Beginning TNA)	Change in Cash Holding (% of Beginning TNA)
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

Relations between At-Risk and Other Measures of Financial Pressure

This table reports the relations between At-Risk measured as a percentage of country market capitalization and other 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.

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)

Table VII

Return and Risk Characteristics of Calendar-Time Portfolios Based on At-Risk and Holding Sorts

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 (Panel A) and holding of sample funds as a percentage of country market capitalization (Panel B). Time-series averages and standard deviations are reported for the entire sample and separately for the periods of positive and negative world market premium (measured as the return on MSCI world index minus the one-month U.S. Treasury bill rate). Tests of difference in mean return and standard deviation of return are between quintile portfolios 1 and 5. S.e.'s 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 standard deviation (or variance) of return are calculated based on the Brown-Forsythe method.

Panel A: At-Risk sort

Quintile Calendar Portfolio	Average Return (%)			Standard Deviation of Return (%)		
	All	World Premium > 0	World Premium < 0	All	World Premium > 0	World Premium < 0
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: Holding sort

Quintile Calendar Portfolio	Average Return (%)			Standard Deviation of Return (%)		
	All	World Premium > 0	World Premium < 0	All	World Premium > 0	World Premium < 0
1 (Positive)	1.47	5.49	-4.38	8.16	5.53	7.85
2	1.34	5.20	-4.29	8.04	5.53	7.82
3	0.56	3.81	-4.20	7.32	5.49	7.08
4	0.35	3.25	-3.89	6.44	5.45	5.35
5 (Negative)	1.53	3.22	-0.93	4.83	4.17	4.70
1-5	-0.06	2.27	-3.45	3.33	1.36	3.16
t-statistic	(-0.12)	(4.04)	(-4.43)			
F-statistic				(23.67)	(3.21)	(7.30)

Table VIII

Return and Risk Characteristics of Calendar-Time Portfolios Based on At-Risk and Holding Sorts

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 (Panel A) and holding of sample funds as a percentage of country market capitalization (Panel B). Time-series averages and standard deviations are reported for the entire sample and separately for the periods of positive and negative G7 risk premium (measured as return on MSCI G7 index minus one-month U.S. Treasury bill rate). 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: At-Risk sort

Quintile Calendar Portfolio	Average Return (%)			Standard Deviation of Return (%)		
	All	G7 Premium > 0	G7 Premium < 0	All	G7 Premium > 0	G7 Premium < 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)

Panel B: Holding sort

Quintile Calendar Portfolio	Average Return (%)			Standard Deviation of Return (%)		
	All	G7 Premium > 0	G7 Premium < 0	All	G7 Premium > 0	G7 Premium < 0
1 (Positive)	1.47	5.62	-4.25	8.16	5.52	7.77
2	1.34	5.20	-3.99	8.04	5.59	7.89
3	0.56	3.96	-4.15	7.32	5.46	6.97
4	0.35	3.33	-3.77	6.44	5.48	5.31
5 (Negative)	1.53	3.33	-0.95	4.83	4.07	4.73
1-5	-0.06	2.29	-3.30	3.33	1.45	3.04
t-statistic	(-0.12)	(4.04)	(-4.23)			
F-statistic				(23.67)	(3.25)	(6.85)

Table IX

At-Risk Sorted Calendar-Time Portfolio Regressions

This table reports results from time-series regressions of calendar-time portfolio returns on world risk premium. 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 quintile 1 and going short those in quintile 5. Countries are sorted into quintiles on the basis of actual At-Risk (first two columns) and predicted At-Risk (last two columns) as a percentage of country market capitalization. Predicted At-Risk is calculated by replacing the current month flow by the expected flows, estimated via Fama-MacBeth regressions of fund flows on lagged flows and returns. In Panel A, the world market premium is measured as return on MSCI world index minus one-month U.S. Treasury bill rate. Positive (negative) world dummy equals one if the world risk premium is positive (negative) and zero otherwise. In Panel B, the G7 risk premium is measured as return on MSCI G7 index minus one-month Treasury bill rate as the risk-free rate. Positive (negative) G7 dummy equals one if the G7 risk premium 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
Intercept	0.013**	-0.001	-0.001	-0.017*
	(0.005)	(0.008)	(0.006)	(0.009)
World Risk Premium	0.002		-0.039	
	(0.089)		(0.159)	
Positive World Dummy * World Risk Premium		0.509***		0.540**
		(0.190)		(0.267)
Negative World Dummy * World Risk Premium		-0.319**		-0.401*
		(0.143)		(0.233)
N	150	150	139	139
R-squared	0.00	0.40	0.00	0.05

(*continued*)

Table IX--*Continued*

Panel B:MSCI G7 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)
G7 Risk Premium	0.005		-0.038	
	(0.091)		(0.160)	
Positive G7 Dummy * G7 Risk Premium		0.510***		0.542**
		(0.191)		(0.261)
Negative G7 Dummy * G7 Risk Premium		-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 portfolio returns on the world risk premium. 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 quintile 1 and going short those in quintile 5: Countries are sorted into quintiles based on the beginning-of-month holding in the country of all sample funds, measured as a percentage of the country market capitalization. World market premium is measured as the return on the MSCI world index minus one-month U.S. Treasury bill rate. Positive (negative) world dummy equals one if the world risk premium 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 Risk Premium	0.893***	
	(0.134)	
Positive World Dummy * World Risk Premium		0.978***
		(0.256)
Negative World Dummy * World Risk Premium		0.839***
		(0.194)
N	150	150
R-squared	0.35	0.35

Table X--*Continued*

Panel B:MSCI G7 Index as the market portfolio

	Holding Sort	Holding Sort
Intercept	-0.002	-0.002
	(0.004)	(0.007)
G7 Risk Premium	0.886***	
	(0.129)	
Positive G7 Dummy * G7 Risk Premium		0.893***
		(0.241)
Negative G7 Dummy * G7 Risk Premium		0.881***
		(0.195)
N	150	150
R-squared	0.33	0.33

Table XI

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	Mean World Risk Premium (Regime 1)	1.278***
	(0.518)		(0.301)
Beta (Regime 1)	0.453*	Mean World Risk Premium (Regime 2)	-1.200
	(0.243)		(0.914)
Beta (Regime 2)	-0.151	Volatility (Regime 1)	2.559***
	(0.136)		(0.251)
Volatility of Residual Returns	5.499	Volatility (Regime 2)	5.585***
	(0.249)		(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**		
p-value	(0.030)		

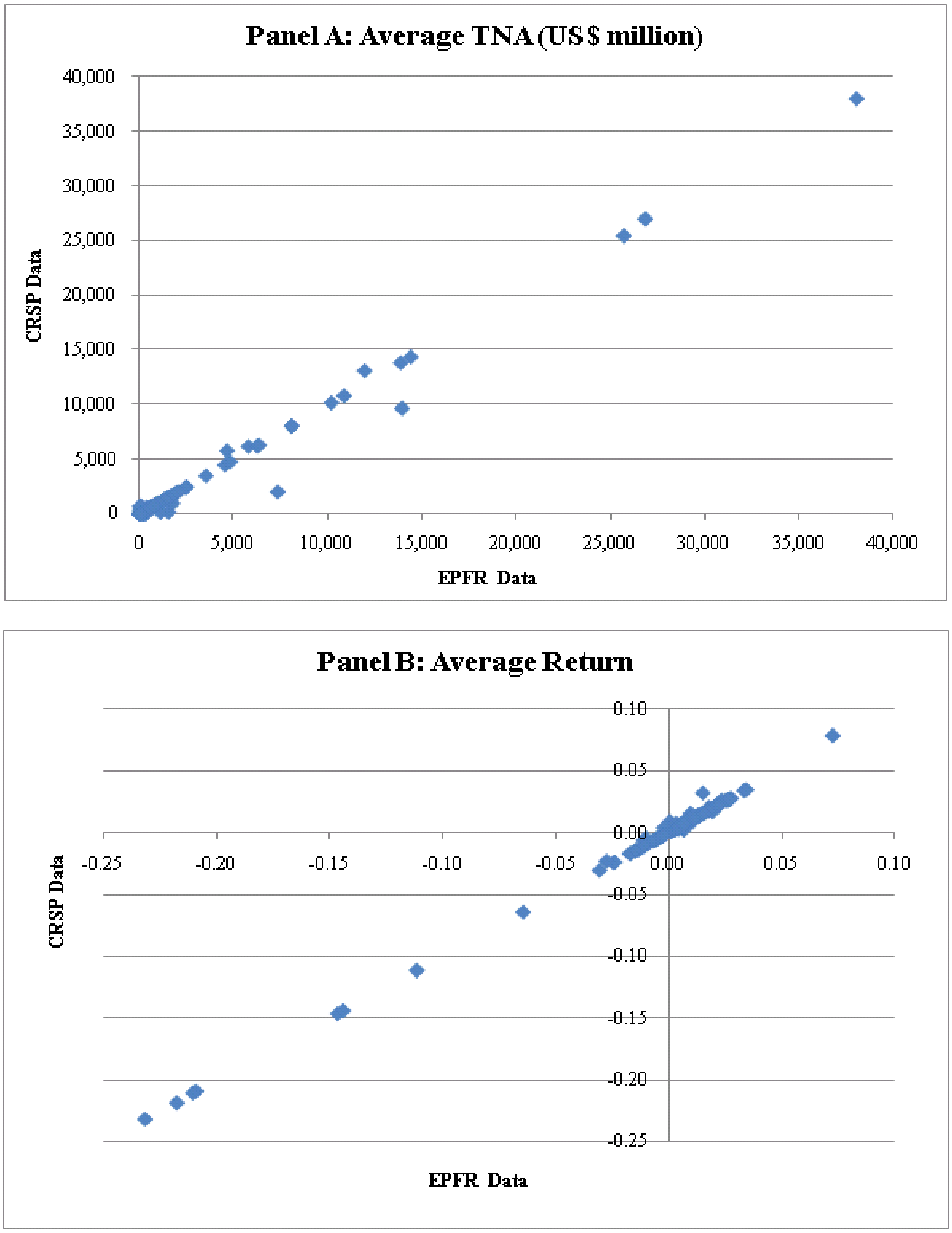

Figure 1. Comparison between EPFR and CRSP mutual fund data. For a subset of funds, this figure compares the average TNAs and the average monthly returns from the EPFR and CRSP mutual fund data. The two data sets are matched by fund name. The sample period is from February 1996 to October 2008. Panel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

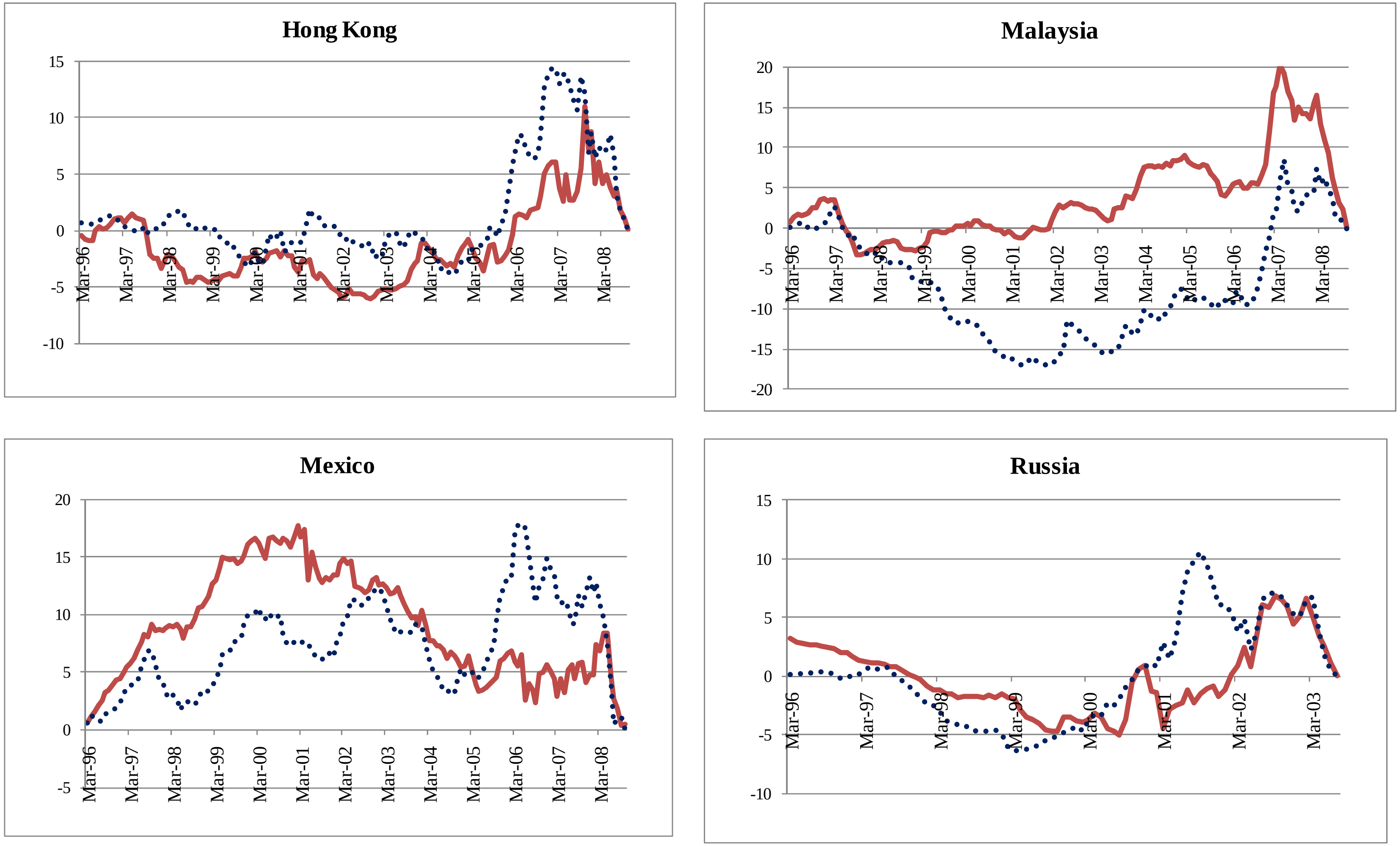

Figure 2. Comparison between EPFR and TIC data. This figure compares the cumulative standardized change in dollar holding of all funds in the EPFR data with the cumulative standardized net transactions in foreign stocks (by U.S. investors) from the TIC data for four countries: Hong Kong, Malaysia, Mexico, 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.

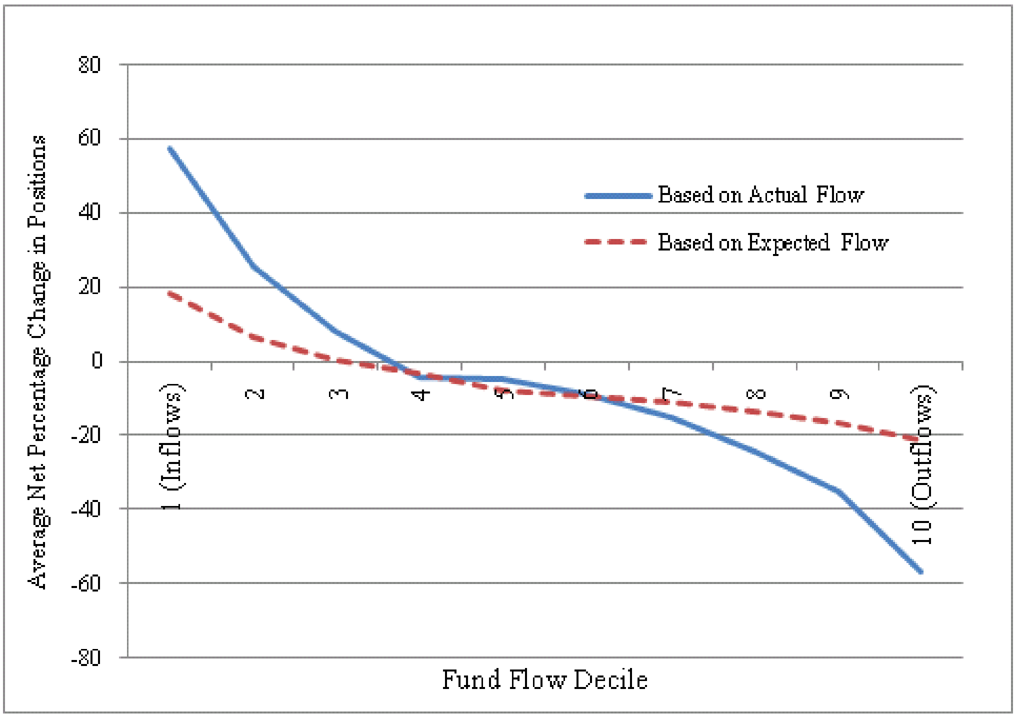

Figure 3. Relation between fund flows and changes in positions. This figure plots the average net percentage changes in positions for funds in different deciles of actual and expected flows. Flows are measured as a percentage of the beginning-of-month TNA. Expected flow is estimated via Fama-MacBeth regressions of flows on lagged flows and returns, where coefficients are the time-series average of periodic cross-sectional regression coefficients. 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.

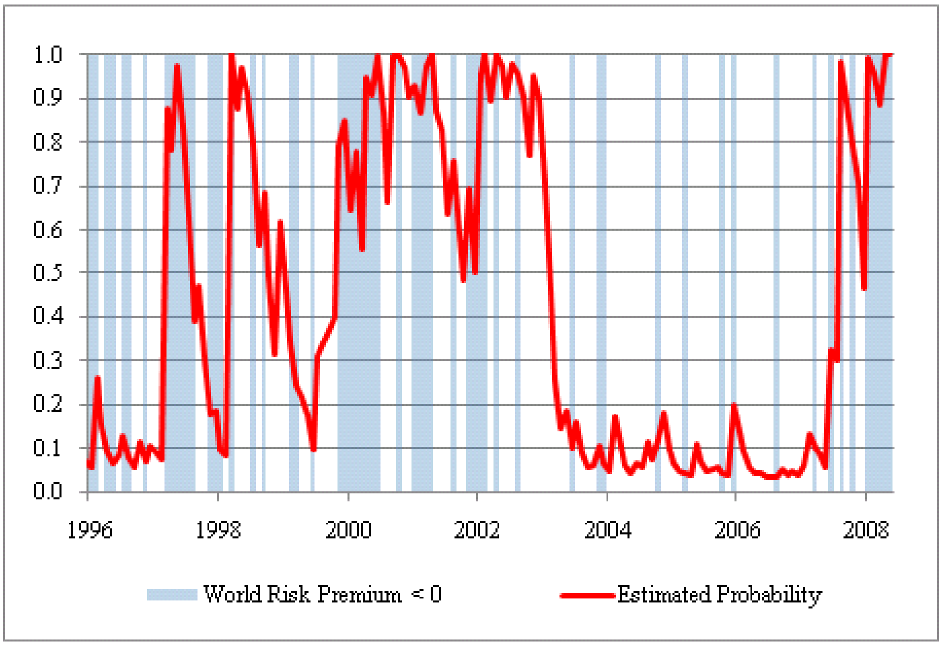

Figure 4. Regime probabilities. The graph plots the probabilities of the regime in which the realized world risk premium is volatile and low, for the period from March 1996 to October 2008. The regimes are estimated based on the mean and volatility of the world market premium, measured as return on MSCI world index minus one-month Treasury bill rate as the risk-free rate.