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

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Abstract

We uncover a new channel through which financial shocks are transmitted across international borders. Movements in outside investors' flows to developed-country-domiciled global funds force significant changes in these funds' portfolio allocations to emerging markets. These forced portfolio allocation shifts drive temporary movements in emerging market equity returns; correlations between emerging markets; and the betas of emerging markets on developed markets. We calibrate a simple model and find that our results are attributable to performance chasing by outside investors and 'push' effects from their country of domicile, rather than to any private information about emerging market returns.

1. Introduction

Why do asset returns across countries move together, and what drives changes in their co-movement over time? These questions arise naturally when tracing how crises spread from one market to another, or when evaluating the benefits of international portfolio diversification. Correlated changes in fundamentals (such as macroeconomic variables) are an important part of the explanation,[1] but insufficient to explain the full magnitude and variation in international return co-movement. Indeed, in several notable episodes such as the Asian crisis and the recent credit crisis, excess co-movement or 'contagion' has been attributed solely to non-fundamental sources (see Forbes and Rigobon (2001), Karolyi and Stulz (1996), and Karolyi (2003) for useful surveys).

International finance theorists studying excess co-movement have attributed great importance to the role of financial intermediaries.[2] However, empirical evidence on the role played by financial intermediaries has not kept pace with the theory. Kaminsky, Lyons and Schmukler (2004) study a small sample of Latin American-focused investment managers, and Broner, Gelos, and Reinhart (2006) analyze 117 global emerging market funds between 1996 and 2000 to show that relative performance concerns play a role in crisis transmission. Boyer, Kumagai and Yuan (2006) infer the role of financial intermediaries indirectly by contrasting the behavior of investable and non-investable indices during crises, and Kaminsky and Reinhart (2000) investigate cross-market banking lending activity.[3] These papers have used clever approaches to elicit empirical evidence in the face of two considerable obstacles: identification of the transmission mechanism has proven elusive, and data on intermediaries' activities is hard to come by.

Our analysis attempts to plug this gap by bringing a new approach and a new dataset to the analysis of international return co-movement. Our identification strategy follows a growing literature on asset 'fire sales,' beginning with Shleifer and Vishny (1992), which links asset-market liquidity with the funding of financial intermediaries participating in these markets.[4] This channel has found considerable empirical support. For example, Coval and Stafford (2007) show that U.S.

[1] See, for example, Eichengreen, Rose, and Wyplosz (1996), Sachs, Tornell and Velasco (1996), Eichengreen and Rose (1998), Rigobon (1998) and Glick and Rose (1999).

[2] For example, in Calvo's (2005) model, informed, but leveraged investment managers are responsible for elevated cross-country asset return correlations. Pavlova and Rigobon (2008) show that intermediaries' portfolio constraints can amplify price fluctuations as well as cross-market co-movement. 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. Also see Goldstein and Pauzner (2001).

[3] Also see Forbes and Rigobon (2002), and Forbes (2004).

[4] See Gromb and Vayanos (2005), Brunnermeier and Pedersen (2009), and Adrian and Shin (2009)

mutual funds redeem investments as a consequence of funding shocks that originate from their investor base, and that these forced redemptions significantly impact U.S. domestic equity prices.[5] We take these insights to the study of international asset markets, and find significant evidence that such fire sales are important for the study of international stock returns and co-movement.

To conduct our study, we employ a large dataset that captures the (monthly and weekly) capital flows to, and the monthly country-allocations of, global investment managers that invest in emerging markets, obtained from Emerging Portfolio Fund Research (EPFR). The data span the period from 1996 to 2009, and cover over a thousand developed-country-domiciled funds which collectively hold on average 6% (and at maximum, 17%) of the float-adjusted market capitalization of the 25 emerging markets in our sample. Our starting point is to verify that these global funds display the same forced trading behavior documented in the U.S. domestic market. Regardless of the cash buffer that they hold, these funds substantially alter their portfolio allocations in response to funding shocks from their investor base. They do so in a manner that is economically and statistically significant: global funds which experience significant outflows reduce or eliminate their holdings in approximately 73% of the markets in which they invest over the month following the outflows, in contrast with funds experiencing significant inflows, which reduce or eliminate just 27% of their holdings. The behavior is symmetric, in the sense that funds experiencing significant inflows from outside investors increase their holdings in roughly 8 out of 10 of the markets in which they are invested.

Our next step is to connect these fire-sale changes in 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 percentage 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.

Being At-Risk has significant price effects. We sort emerging countries into quintiles each calendar week on the basis of At-Risk, and find that the countries in the top quintile of At-Risk cumulatively outperform those in the bottom quintile by 176 basis points over three weeks. The

[5] Also see Acharya, Schaefer and Zhang (2008), Lou (2009), Ellul, Jotikasthira and Lundblad (2010), and Anton and Polk (2010) These studies verify that fire-sales are important in a range of different asset markets, not just in equities.

top quintile of At-Risk countries exhibit price increases, those in the bottom quintile exhibit price decreases, and these effects are purely temporary, with cumulative returns reverting almost fully over the course of the subsequent 12 weeks. For another measure of the magnitude of the effect, we construct a monthly 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 statistically significant and large, at an annualized level of approximately 16%; it is virtually unchanged when we apply different risk-adjustment methods.

We then turn our attention to international return co-movement, conditioning monthly realized correlations between pairs of emerging markets on At-Risk.[6] We find that these realized correlations increase by approximately 25% if both countries are in either of the extreme At-Risk quintiles. This is not surprising given that we have already documented that fire sales generate significant price impacts on country returns. However the regressions reveal an interesting nuance, namely that the effect is asymmetric – the effect on realized correlations is roughly double for flow-induced *selling* pressure as opposed to *buying* pressure, suggesting that the fire-sale mechanism is important for understanding the well-documented asymmetry of international return correlations (see Boyer, Kumagai, and Yuan (2006), for example). We also find that the beta of emerging markets with the MSCI G-7 index increases by approximately 20% if the emerging market is in either extreme At-Risk quintile. This effect on realized betas displays time-variation – flow-induced buying (selling) pressure is significantly more important during good (bad) times in the developed countries than the opposite.[7] If aggregate flows are 'pushed' by the performance of the G-7 countries in which funds' investors are domiciled (see Griffin, Nardari and Stulz (2004)), we might expect to see such a pattern; we explore this in the context of our model and calibration exercise.

For robustness, and to refine our understanding, we conduct several additional tests. We implement all of our tests using variations of At-Risk that take as inputs *lagged*, and separately, *predicted* *(*rather than realized) flows. These changes leave our comovement results unchanged, but reverse the signs on the calendar-time alphas. This is easily explained when we look at the resulting event time graphs – the reversals that we detect in our event-time analysis occur quickly (as we conduct all of our tests on country return indexes rather than individual stocks). This suggests that in

[6] Realized corrrelations are computed building on the work of Andersen and Bollerslev (1998), and the specifications that we employ are similar to those in Anton and Polk (2010). Related papers explaining international return correlations include Heston and Rouwenhorst (1994), King, Sentana and Wadhwani (1994), Longin and Solnik (2001), Bekaert, Harvey and Ng (2005) and Bekaert, Hodrick and Zhang (2009).

[7] All these results are unaffected by the inclusion of time fixed effects into our panel specifications, ruling out time-varying common factors that may be driving these comovements.

order to take advantage of these fire-sale effects, one would need to trade the reversal in returns rather than the run-up caused by At-Risk in the very short-term. We also 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. This is despite the fact that funds attempt to exercise some discretion in the face of pressure from their outside investors: forced expansions (reductions) of positions occur in relatively more *liquid* markets in the face of inflows (outflows). We then 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.

Finally, we formalize the intuition underlying our empirical results, developing and calibrating a simple model to understand the likely sources of the effects that we detect. In the model, we allow for two classes of motivations for outside investors to direct flows to global mutual funds. One source of these flows is that outside investors receive private signals about returns in specific countries, causing them to direct money towards funds holding these countries. The other, non-informational source encompasses performance-chasing behavior (i.e., investors allocate more capital to high-performing funds), as well as a 'push' factor which relates aggregate flows to the performance of developed stock markets. We model funds' allocations to countries as following the tide of inflows and outflows from outside investors in the short-run, mimicking the behavior that we document in the first part of our empirical analysis. In the longer run, when allocations deviate excessively from target levels, funds rebalance back to these targets, capturing behavior in response to tracking error constraints or a return to preferred country allocation strategies.

When we calibrate this simple model to the data, we find that it is well able to capture a majority of the patterns that we document in our empirical analysis, and provides insights into how the relationship between global funds and their outside investors impacts emerging country returns. The calibration shows that our results cannot be explained by investor flows driven by private information about country return prospects. Moreover, the presence of an explicit 'push' factor is helpful for explaining our results, but not integral. On the other hand, performance-chasing by outside investors is an important feature. This suggests that pure performance-chasing creates an observed 'push,' since significant variations in the returns of global funds can at least partly be traced back to the correlation of their country holdings with returns on the world market.

It is worth mentioning the relationship of our analysis to recent literature connecting foreign portfolio investment flows with local market equity returns. Using different datasets and observational frequencies, Froot, O'Connell, and Seasholes (2001), Bekaert, Harvey, and Lumsdaine (2002), and Froot and Ramadorai (2008) document significant effects of portfolio investment flows *in aggregate* on local market equity returns. Our paper adds another important dimension, focusing on the *cross-section* of funds which direct these portfolio investment flows to emerging markets, and investigating the role played by their funding from outside investors.

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. Section 5 describes our model and calibration exercise, and Section 6 concludes.

2. Data

We employ four main sources of data: Global mutual fund data from Emerging Portfolio Fund Research (EPFR), 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, and the Morgan Stanley Capital International (MSCI) data. Where EMDB country index returns are unavailable, we employ MSCI country index returns; we also use MSCI G-7 index returns in some of our analysis. Over the period from February 1996 to June 2009,[8] the EPFR data covers 1,598 live and dead globally-focused funds, domiciled in the U.S. and Europe, 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. Weekly data for fund flows (but not allocations) are also collected.[9]

Before proceeding to the empirical analysis, we screen the EPFR fund data in a few standard ways (see Appendix 1), resulting in a final sample of 1,175 funds investing in 25 emerging markets. These 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 (46%) in the U.S. The substantial fraction of funds in the data domiciled in the

[8] With the exception of January 2000, for which data is missing for all funds.

[9] 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.

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.[10]

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 42 for Jordan, and as large as 713 for Hong Kong. The funds hold a significant proportion of country market capitalization (2.59% on average across the emerging countries), and the percentage holding varies less over time than across countries, ranging from 0.10 percent in Jordan to 8.58 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 6.47% of float-adjusted market capitalization.[11]

We also investigate the characteristics of the sample funds. TNA varies dramatically across funds (and is highly positively skewed), with the (pooled) average equal to US$ 620.01 million and the (pooled) standard deviation equal to US$ 2.2 billion. 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)).[12]

[10] We also 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)). The cross-country average correlations between the EPFR and TIC ownership change series are 20% for emerging countries.

[11] Two of the countries in our sample (Colombia and Russia) are not covered in their paper.

[12] It is worth noting that the results presented below 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 flow-induced pressure

3.1. Fund flows and re-allocations

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. 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 (this is similar to Coval and Stafford (2007)). Table II 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 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 12.8% (top decile) to -10.8% (bottom) monthly flows as a percentage of assets under management. The second column of Table II shows that the extreme deciles of realized-flow-sorted funds were expected to experience some flow differential.[13] In our subsequent analysis on price effects, we revisit the effects associated with 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 II shows that consistent with the findings of Warther (1995) and Coval and Stafford (2007), funds in the top decile hold, on average, more cash than those in the bottom. As the differences in cash holdings could imply some variability in a fund's ability to manage investor flows, we explore the link between flows, forced re-allocation, and cash holdings below. Finally, the remaining columns show that the funds that appear in the extreme flow deciles

[13] Following Sirri and Tufano (1998), we also estimate a standard flow-performance regression as follows

$$flow_{j,t} = a + \sum_{l=1}^{L} b_l \cdot flow_{j,t-l} + \sum_{l=1}^{L} c_l \cdot R_{j,t-l}, \qquad (3.1)$$

where $flow_{j,t}$ for the capital flows of a sample fund j in a month t and $R_{j,t}$ for its return in the same month. We use $L = 12$ (or one year) for the monthly flows and $L = 13$ (or one quarter) for the weekly flows. We estimate the model using the method of Fama and MacBeth (1973). The details are provided in Appendix Table 1; consistent with the existing literature, we document that both monthly and weekly fund flows are significantly predicted by recent past flows and fund returns.

have comparable country holdings to the average fund and that 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. Figure 1 graphically presents evidence on the degree to which funds re-allocate their holdings in the face of significant realized and expected 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.[14] Panel A demonstrates that realized and expected flow are associated with similar reallocations, although the extremes of realized flow move allocations much more than expected flow. Funds facing the largest inflows expand positions in roughly 50% more markets than those experiencing outflows (17% if we use expected rather than realized flows), while those facing the largest outflows reduce or eliminate positions in roughly 49% (18%) more markets than those experiencing inflows. These percentages are highly statistically significant. Panel B of the figure investigates whether a 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. In all cases, the differences in allocation changes across flow deciles are highly statistically significant. In unreported results, we also split the sample into index and active funds to see whether these trading patterns differ across the two groups. Surprisingly, the two groups of funds do not exhibit statistically different re-allocation behavior. In the next section, we explore whether this forced re-allocation also affects emerging market returns.

3.2. 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

[14] 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. Appendix Table 2 provides additional detail. This differs somewhat from the usual convention in the literature where share holdings are directly observed (at the quarterly frequency). The main difference between the EPFR data and the data employed by, say, Coval and Stafford (2007) is that the Spectrum data contains the number of shares held by financial institutions, whereas EPFR records the fund's USD *value* allocation at the country level (at the monthly frequency).

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 capture 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:

$$\text{At-Risk}_{k,t} = \sum_{j=1}^{N} flow^{*}_{j,t} \cdot allocation_{j,k,t-1} \cdot TNA_{j,t-1} \tag{3.2}$$

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 $t-1$.[15] In our empirical applications we normalize USD At-Risk by the market capitalization of the stock-market of country k at the end of the previous 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.) The next step is to sum the measure across all funds investing in India at the end of January 2008.

Put simply, the At-Risk 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. 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.

[15] 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.

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 the measure for each sample country in each month (and each week for subsequent event studies), and then sort country-months into quintiles.[16] Table III 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* (including the most recent period). In contrast, the bottom quintile captures those countries where invested funds experienced *outflows*. 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 10.6% and 5.2% 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 effects 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 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 will necessarily 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)). In our analysis of how At-Risk relates to emerging market price determination, we compare it with an alternative based solely on funds' aggregate holdings unrelated to their capital inflows and outflows.[17]

[16] We have also computed these statistics for *weekly* At-Risk, and the patterns are virtually the same as for monthly At-Risk. The discussion focuses on the monthly statistics.

[17] We also compared our measure of At-Risk capital to a similar sort variable $PRESSURE\_2$ first proposed by Coval and Stafford (2007). This variable replaces $allocation_{j,k,t-1}$ with $|\Delta allocation_{j,k,t}|$ in equation (3.2) above,

To better understand the dynamics of At-Risk, we also compute the probability that any country will stay in the same quintile over the next month in panel B of the same table. While countries do maintain their positions to some degree, these are far from fixed classifications. Further, 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 quintiles, 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 quintiles.

4. Capital At-Risk and price determination

4.1. Country returns and forced transactions in event time

We document above that (i) global funds, on average, re-allocate their investment positions in the face of sizeable flows and (ii) the potential re-allocation implied by the collective amount of capital At-Risk represents a non-trivial fraction of domestic market trading in these countries. We now turn to an exploration of the price effects associated with forced transactions. To investigate the impact of fire-sale pressure on stock returns, we explore the price effects in the context of an event-time analysis as previously employed by Mitchell, Pulvino, and Stafford (2004) and Coval and Stafford (2007). Figure 2 plots the cumulative abnormal returns (CARs) for an equally-weighted long-short portfolio, long countries in the highest (Q1) At-Risk quintile and short countries in the lowest (Q5). In each calendar week, countries are sorted into quintiles (in month 0) on the basis of actual At-Risk (Panel A), lagged At-Risk (Panel B), and predicted At-Risk (Panel C). We calculate weekly At-Risk by replacing the sum of three monthly flows in equation (3.2) by the current week flow. As the dataset does not capture weekly allocations, we use the end-of-prior-month allocation for all weeks in the current month. Lagged At-Risk is calculated by replacing the current week flow by the lagged flow and predicted At-Risk is calculated by replacing the current week flow by the expected flow from the estimated weekly flow-performance relation discussed above. While some of the results provided in the paper are obtained using monthly data, we employ weekly CARs to provide better resolution on the abnormal price effects associated with flow-induced trading.[18] For each panel, 90% confidence bands computed using a cross-correlation consistent covariance matrix (Rogers (1983, 1993)) are also provided to assess statistical significance.

counting only $flow_{j,t}$ and $\Delta allocation_{j,k,t}$ that are in the same direction. We find that the two measures are very highly correlated, i.e., At-Risk captures the same fire-sale mechanism as $PRESSURE\_2$. We prefer At-Risk, since we wish to avoid any possible contamination that may result from sorting countries using a measure of active changes that employs contemporaneous returns in its construction.

[18] We thank an anonymous referee for this suggestion.

Figure 1 Panel A shows that sorting countries on the size of the potential re-allocation resulting from being At-Risk delivers a large spread in weekly stock returns. Equity markets that are likely associated with significant fund purchases (Q1) and sales (Q5) for a week earn, on average, 118 and -58 basis points in week 0, respectively. The difference of 176 basis points, plotted in the figure, is highly statistically significant. Despite these sizeable effects, questions about their source remain. If forced fund trading simply reflects the information available to 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 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. In Panel A, we indeed observe a significant reversal in abnormal returns over the next twelve weeks, suggesting that much of the initial price effect is driven by temporary liquidity demands and not information-based trading.

Next, Panels B and C provide alternative methods by which we can evaluate the implications of At-Risk for emerging market prices. In both cases, we ensure that the At-Risk determination is known to investors in event time. In Panel B, we simply lag the At-Risk measure by one-week. In Panel C, we employ our estimated flow performance relation to measure predicted At-Risk (as described in Appendix Table 1). In both cases, the peaks of the long-short (Q1-Q5) price effects do precede the event (the sorting of countries into the two quintiles) by one-week. However, we continue to observe statistically significant reversals in emerging market prices over the subsequent weeks, suggesting the critical importance of the price pressure associated with forced trading.

A simple model that we develop below helps to guide the interpretation of these collective findings. We pay particular attention to the potential relative contributions of information and push-induced flows in delivering the patterns associated with these dynamic effects. In particular, we find that these patterns cannot be explained in our model solely based on information-induced flows.

4.2. At-Risk and cross-country correlations

Given that there are significant price effects associated with the forced trading of global mutual funds, a natural question is the degree to which this trading impacts relationships among global markets. This is particularly important given that funds hold (potentially constrained) portfolios spanning a number of markets so that flow-induced trading may simultaneously affect multiple markets. In addition, since funds are domiciled in developed markets and invest in emerging markets, we explore whether significant price movements in developed countries may induce inflows or outflows to emerging market funds thus driving correlations between developed and emerging markets.

We begin by examining the degree to which capital At-Risk explains realized correlations among emerging markets. Our econometric design builds on recent developments in the measurement of *realized* volatility and covariance (see, for example, Andersen and Bollerslev (1998), among many others). Realized correlation between countries $k1$ and $k2$ during month t is computed using daily data, indexed by d, as follows:[19]

$$\text{Realized Correlation}_{k1,k2,t} = \frac{1}{D_t} \frac{\sum_{d=1}^{D_t} r_{k1,d} r_{k2,d}}{\sigma_{k1,t} \sigma_{k2,t}}$$

where D_t is the number of days in month t, $r_{k,d}$ is the USD return of country k's stock market on day d, and $\sigma_{k,t}$ is the daily return standard deviation of country k in month t.

Following Anton and Polk (2010), Table IV regresses these realized correlations (across all possible country pairs) on a constant, indicator variables for inclusion of the country-pair in the extreme quintile of monthly At-Risk, and (in some specifications) time fixed effects. The indicators used in Panel A are based on monthly At-Risk, whereas the indicators in Panel B are based on predicted monthly At-Risk. Both panels of the Table show that the average correlation among emerging markets is about 0.16 to 0.17. However, the first column of each panel shows that the correlation is approximately 25% higher when both countries are in either of the extreme At-Risk quintiles. That is, flow-induced trading induces a statistically significant increase in the degree of realized correlation among emerging market pairs.[20] While the first column of the table shows that markets likely to face elevated flow-induced selling or buying pressure are correlated, the second employs two separate indicators that reflect months for which the two countries are simultaneously in either At-Risk Q1 (correlated buying pressure) or At-Risk Q5 (selling pressure), respectively. Interestingly, both effects are statistically significant, but the effect on realized correlations is roughly double for Q5

[19] We explore these effects at the monthly frequency for two reasons. First, the EPFR monthly data begins in 1996, whereas the weekly data begins in 2001, so the monthly data includes several important emerging market crises. Second, and perhaps most importantly, our measures of realized correlation and betas are built from daily data. Cumulating over five days to measure a weekly quantity delivers a very noisy estimate. In contrast, cumulating twenty–two (on average) daily observations over a month yields a much better estimate of the relevant quantity. Our calibration presented below matches the multiple frequencies in our empirical work.

[20] Estimating correlation effects is known to suffer a potential bias (see Forbes and Rigobon (2001)). However, bias-adjusted estimates that follow their suggestion yield nearly identical effects, so this is not an issue for our panel regressions.

(flow-induced *selling* pressure) as opposed to Q1 (*buying* pressure). The third and fourth columns show that the effects are unaffected by the inclusion of time fixed effects.[21] Finally, the effects in Panel B for predicted At-Risk are similar in that correlated capital At-Risk generates elevated correlations among emerging market pairs, but the asymmetry across buying and selling pressure is no longer evident, suggesting that the predictive model is not good at capturing the extremes of flow-induced selling pressure. Taken together, fire sales by global mutual funds have significant consequences not only for the short-term price effects associated with liquidity consumption, but also cross-market correlations among markets that face this pressure at the same time.

Next, we turn to an examination of the degree to which capital At-Risk affects realized emerging market betas with respect to developed markets. We measure betas with respect to the MSCI G-7 portfolio total return, the value-weighted average of the developed markets that generally reflects the countries of domicile for the global mutual funds in our study.[22] Realized G-7 beta for country k in month t is computed using daily data, again indexed by d, as follows:

$$\text{Realized Beta}_{k,t} = \frac{1}{D_t} \frac{\sum_{d=1}^{D_t} r_{k,d} r_{G-7,d}}{\sigma^2_{G-7,t}}$$

where $r_{G-7,d}$ is the USD return of the MSCI G-7 portfolio on day d, and $\sigma^2_{G-7,t}$ is the daily return variance of the MSCI G-7 portfolio in month t. Table V regresses realized betas in specifications identical to those employed for the cross-emerging-market correlations. Both panels of the table show that the average G-7 daily beta across emerging markets is about 0.49. However, the first and second columns of each panel show that the G-7 beta is approximately 20% higher when the emerging market is in either extreme At-Risk quintile; the effects of flow-induced buying or selling pressure are not significantly different, on average. The third column takes the specification further, estimating an alternative specification that allows for a conditional relationship between the effects of flow-induced trading pressures on betas which depends on the sign of the G-7 portfolio return.

[21] The reported intercepts, in the specifications with time fixed effects, are calculated as the average of the coefficients for all calendar year-month dummies.

[22] 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, the funds in our sample are overwhelmingly domiciled either in the U.S. or in Europe. Anecdotal evidence suggests that there is a high correlation between domicile and fund marketing, leading to the presumption that their investor base is most likely from these economies. Hence, we employ the MSCI G-7 portfolio, despite the MSCI World portfolio being the more natural 'market' portfolio in a typical beta context, since we wish to isolate the correlation of emerging market returns with developed markets. Since this is not exact, we consider two alternatives (as robustness checks) where we replace the G-7 return with either the U.S. or Developed Europe MSCI market index. The results are qualitatively unchanged.

In particular, the estimated effect on realized betas is asymmetric, whereby flow-induced buying (selling) pressure is significantly more important during good (bad) times in the developed countries than the opposite. When the G-7 return is positive, betas are elevated for emerging markets facing flow-induced buying pressure (Q1); however, betas are *even larger* for emerging markets facing flow-induced selling pressure (Q5) when the G-7 return is negative. These effects are robust to the inclusion of time fixed effects (the fourth to sixth columns of the table) or conditioning on predicted At-Risk (Panel B).

To better understand these results, we develop a simple model later in the paper, calibrate it, and explore alternative mechanisms that are capable of generating the entire of set of patterns that we uncover in the data.

4.3. Calendar-time portfolios

The evidence suggests that both emerging market prices and correlations are significantly related to capital At-Risk. To better understand the economic magnitude of the return differences, we put these pieces together by examining the returns of a calendar-time portfolio strategy. Each month, we form a portfolio by going long the highest At-Risk quintile portfolio and going short the lowest At-Risk quintile portfolio. Next, we regress our long-short portfolio returns on the MSCI G-7 excess return (in excess of the USD Treasury bill return). The first column of Table VI reports the regression results. 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 consistent with the price effects documented above. The G-7 beta of this long-short portfolio is effectively zero. This last point requires further exploration given the sizeable differences detected in At-Risk quintile realized betas, conditional on positive and negative developed market returns.

The second column of Table VI corroborates the evidence from the country-level panel regressions that there is a pronounced asymmetry in the betas of the long-short portfolio. We estimate a conditional version of the model in which we allow the loading on the developed market portfolio return to differ between periods in which the G-7 return is positive and negative. Periods of positive and negative developed market returns exhibit significantly different effects on the beta of our long-short portfolio. In the face of positive developed market returns, countries with positive At-Risk capital have significantly larger G-7 betas than do countries with negative At-Risk capital. In sharp contrast, when developed market returns are negative, countries with negative At-Risk capital have significantly larger G-7 betas than do countries with positive At-Risk capital. Also, there appears to be an important interaction between the intercept and the conditional betas.

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 and report comparable calendar-time regression results in the last two columns of Table VI. As can be seen, the alpha in the third column is no longer statistically significant, so it appears that much of the price effect in the first column is associated with the more pronounced forced buying and selling generated by unanticipated funding shocks (recall though that we do show earlier that this price effect significantly and predictably reverses). In the fourth column of Table VI, the conditional version of the G-7 betas does yield significant and similar evidence regarding the different conditional betas of the long-short portfolio based on positive or negative developed market returns (as in Table V). A final comment – it is worth noting that the intercept in the fourth column is actually significantly negative. This simply reflects that fact that the predicted reversal documented above is already taking place over the next month (recall Figure 2). This reversal seems to offset the positive return from the long-short portfolio having pro-cyclical G-7 betas, resulting in the insignificant alpha observed in the third column.

Finally, since At-Risk is a product of both the funds' collective holding in the country as well as the flow the funds face, it is interesting to see whether it is really holding or flow that creates the effects. To address this question, we repeat the analysis 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 in order to isolate the holdings channel. The results are presented in Appendix Table 3, where we observe neither a statistically significant alpha for the long-short portfolio or changing conditional betas. Indeed, countries in which the funds have higher collective holding have significantly higher G-7 betas regardless of the sign of developed market returns. Simply put, holdings alone are not sufficient to infer the conditional beta effects, rather it is the interaction of fund flows and significant holdings that matter for emerging market price determination.

4.4. Additional tests and robustness

4.4.1. Liquidity of the underlying market and At-Risk

Table VII 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. 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 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 5.83 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 2.93 basis point lower per trade than those facing outflows.[23] These differences are statistically significant for both explicit and price impact costs. Statistically significant differences are also evident for expansions versus reductions for funds facing inflow pressure, and the reverse for funds facing outflow pressure. While statistically significant, the results are economically modest. They nevertheless point to attempts by global funds to ameliorate the impacts of the funding pressure that they face by concentrating their flow-induced trading in relatively more liquid markets. This finding might have 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.[24]

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 percentage 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 VIII 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 developed market exposure asymmetry remains statistically significant. While Table VII shows that funds do try to strategically trade in the face of fund flows, the fact that they are sometimes forced to trade in relatively illiquid markets manifests

[23] The former could feasibly be contaminated by correlation between average transaction costs and the size of the underlying market; 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.

[24] Thanks to Ajay Shah for this insight.

itself in a more pronounced return during such periods.[25]

4.4.2. 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. 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. In the next section, we describe a simple model, which we calibrate to match our empirical results.

5. Model and Calibration

5.1. Model

This section presents a simple model of outside investors' flows to global funds and the impact of funds' forced trading behavior on local stock markets. We calibrate the model to the data to match the patterns that we identify in our estimation at the monthly and weekly frequencies. To simplify the model, we write it at the daily frequency, and in our calibration, aggregate the model-implied data to the appropriate frequency to match the empirics. Our goal is to arrive at an accurate description of how country return movements and correlations respond to movements in At-Risk. To do so, we first specify the dynamics of outside investors flows, and funds' trading behavior.

5.1.1. Mutual Fund Flows

We write $f_{i,d}$ for the percentage flows to fund i on day d, and posit that these flows are the sum of a non-information component $p_{i,d}$ and a component $q_{i,d}$ driven by mutual fund investors' information

[25] We also find that when countries are double sorted on At-Risk and transactions costs, both the price effects and the change in conditional betas are concentrated in the relatively less liquid countries despite funds' efforts to lean against the tide. See Appendix Table 4 for these results.

about country-specific return movements:

$$f_{i,d} = p_{i,d} + q_{i,d}. \tag{5.1}$$

The non-information component $p_{i,d}$ constitutes a 'push' factor stemming from the performance of the developed markets in which the investors are domiciled (which we parametrize as linear in the returns on the G-7 index $r_{G-7,d}$); and a component which is linear in L lags of fund returns $r_{i,d}$, to capture performance-chasing by investors. This push factor is a feature of models such as Griffin, Nardari and Stulz (2004), and a robust feature of our data – the time-series correlation between aggregated global fund flows and G-7 returns is 48%.

To account for potential delays associated with investor decision-making and other such frictions, $p_{i,d}$ is modelled as being persistent, again linear in L lags of itself:[26]

$$p_{i,d} = \rho r_{G-7,d} + \sum_{l=1}^{L} \phi_{p,l} p_{i,d-l} + \sum_{l=1}^{L} \phi_{r,l} r_{i,d-l} + \delta_{i,d}. \tag{5.2}$$

For simplicity, we assume that all funds have the same sensitivity to G-7 returns (ρ), and the same loadings on past non-information flow and fund returns ($\phi_{p,l}$ and $\phi_{r,l}$, both linearly declining in l, with sum over L lags less than one for stationarity). Also, $\delta_{i,d} \sim NIID(0, \sigma^2_{\delta,i})$. The aggregate non-information component of flows to country c is given by $P_{c,d} = \left(\sum_{i=1}^{N_F} p_{i,d} A_{i,c,d-1} \right) / M_{c,d-1}$, where $A_{i,c,d-1}$ is the dollar allocation of fund i to country c on day $t-1$ and $M_{c,d-1}$ is the market capitalization of country c on day $d-1$.

When mutual fund investors receive information about country c, they direct flows to funds according to the weight of country c in fund i's portfolio, $\omega_{i,c,d-1}$, so $q_{i,c,d} = a_{c,d}\omega_{i,c,d-1}$,where $a_{c,d}$ is the information-induced flow on day d to a fund 100% invested in country c. The aggregate information-induced flow to fund i is just the sum across countries of $q_{i,c,d}$, i.e. $q_{i,d} = \sum_{i=1}^{N_C} q_{i,c,d} =$

[26] See Froot and Tjornholm-Donohue (2002) for a comprehensive analysis of the persistence of institutional investor flows to emerging markets.

$\sum_{i=1}^{N_C} a_{c,d}\omega_{i,c,d-1}$, and the aggregate percentage information-induced flow to country c is:[27]

$$Q_{c,d} = \left(\sum_{i=1}^{N_F} q_{i,c,d} A_{i,c,d-1} \right) / M_{c,d-1}. \tag{5.3}$$

5.1.2. Mutual Fund Holdings

Implicit in the aggregation of information-induced flow from the fund level to the country level, equation (5.3), is the assumption that mutual funds simply allocate the money that they receive from outside investors in the short-run in proportion to their beginning-of-period holdings of countries. This assumption mimics the findings of Coval and Stafford (2007) and those in the first part of our empirical analysis. Under this assumption, when outside investors allocate information-induced flows to funds, these flows are allocated to *all* the countries that the funds hold, not just the country for which outside investors have information. Consequently, dollar holdings evolve according to:

$$A_{i,c,d} = A_{i,c,d-1}(1 + r_{c,d})(1 + p_{i,d} + q_{i,c,d} + \sum_{k \neq c} p^*_{i,k,d}), \tag{5.4}$$

where $p^*_{i,k,d}$ is the flow that is induced by investors' information about all countries k, other than country c, held by fund i . Note that $p^*_{i,k,d} = q_{i,k,d}$ since an information shock to *any* country held by the fund is proportionally allocated across all country holdings of the fund. This formulation is similar in spirit to Kyle and Xiong (2001), who argue that investors may have to liquidate their positions in other countries when they suffer a large loss in investment in a country undergoing a crisis.In our paper, this channel arises from the constraints faced by mutual funds. Additional motivation is provided in Boyer, Kumagai and Yuan (2005), who assume that margin constraints force liquidations in all assets held by market participants in response to declines in the prices of any single one of the assets held.

Total assets under management for fund i (setting cash to zero for simplicity) is then given by $A_{i,d} = \sum_{c=1}^{N_C} A_{i,c,d}$, where N_c is the total number of countries. We also allow funds to rebalance back to target asset allocation levels, to model the influence of tracking error constraints on funds'

[27] Note that since q flows are the result of information about country returns, we set aggregate information-induced country flows $Q_{c,d}$ in our calibration to various different normalized values first, and then solve for $a_{c,d}$ for each value of $Q_{c,d}$. This is internally consistent, since aggregating dollar flows driven by country c information ($q_{i,c,d} A_{i,d-1} \omega_{i,c,d-1}$) across all funds i gives $Q_{c,d}$ exactly.

country allocation strategies. In particular, if $\bar{\omega}_{i,c}$ is the benchmark percentage holding of country c by mutual fund i, if $|(A_{i,c,d}/A_{i,d})/\bar{\omega}_{i,c} - 1| > \tau$, then $A_{i,c,d} = \bar{\omega}_{i,c} A_{i,d}\ \forall c$, i.e., the fund's country allocations are all re-set.[28]

At the country level, the aggregate of $p^*_{i,k,d}$ across all funds introduces an additional component of non-information-based trading, $P^*_{c,d} = \left(\sum_{k \neq c} \sum_{i=1}^{N_F} p^*_{i,k,d} A_{i,c,d-1} \right) / M_{c,d-1}$. Before we describe country returns, it is worth noting that the sum of the three components of trading in country c, i.e., $Q_{c,d} + P^*_{c,d} + P_{c,d}$ is equivalent to At-Risk in our empirical investigation. Since At-Risk reflects the composite flows, push and/or information-based, to the mutual funds holding these countries, we cannot directly estimate this model. However, our calibrations permit us to evaluate the relative importance of each channel.

5.1.3. Country Returns

Writing $r_{c,d}$ for the excess return of country c on day d, we posit the return-generating process (similar to Hasbrouck (1991), Campbell, Grossman, and Wang (1993), and Pastor and Stambaugh (2003)):

$$r_{c,d} = \beta_c r_{w,d} + \kappa(P_{c,d} + Q_{c,d} + P^*_{c,d}) + \gamma(P_{c,d-1} + P^*_{c,d-1}) + u_{c,d}. \tag{5.5}$$

In equation (5.5) $r_{w,d}$ denotes the excess value-weighted world market return on day d,[29] β_c the 'fundamental' beta of the country return on the world return, κ the price impact of flow-induced trading, γ the continuation or reversal of non-information flows, and $u_{c,d} \sim NIID(0, \sigma^2_{u,c})$.

Substituting for flows from our equations above, writing:

$$\tilde{P}_{c,d} = P_{c,d} - \left(\kappa \sum_{i=1}^{N_F} (\rho A_{i,c,d-1}) / M_{c,d-1} \right) r_{G-7,d},$$

[28] Note that the rebalancing threshold τ could be fund-specific (though we currently set this the same for all funds, at a level of 10%). Note also that *all* country holdings are rebalanced if *any* country goes above the threshold.

[29] We assume $r_{w,d} \sim NIID(\mu_w, \sigma^2_w)$, but demean all returns prior to calibration.

and since $r_{w,d} \approx r_{G-7,d}$ (the correlation over our sample is 0.997), equation (5.5) can be written as:

$$r_{c,d} \approx \left[\boldsymbol{\beta}_c + \kappa \frac{\sum_{i=1}^{N_F} (\rho A_{i,c,d-1})}{M_{c,d-1}} \right] r_{G-7,d} + \kappa \left[\sum_{j=1}^{N_F} \tilde{P}_{c,d} + P^*_{c,d} + Q_{c,d} \right] + \gamma (P_{c,d-1} + P^*_{c,d-1}) + u_{c,d} \quad (5.6)$$

A few points are worth noting. First, in our calibration we set $\gamma = -\kappa$, i.e., we assume full reversal the day after the arrival of non-information flow,[30] ensuring that we are not assuming or hard-wiring the empirical patterns that we uncover in our event-time analysis. Second, inspecting the expression $\boldsymbol{\beta}_c + \kappa \sum_{i=1}^{N_F} (\rho A_{i,c,d-1})/M_{c,d-1}$, it seems that regardless of the size of the push effects ρ, the time-variation in country betas is determined by the (very small) time-variation in aggregate holdings as a percentage of country market capitalization. One insight that this gives us is that the empirically observed conditional beta of the At-Risk calendar portfolio cannot be generated simply from high levels of push flows. The next subsection describes our calibration exercise and compares the results from the calibration to those from our empirical estimation.

5.2. Calibration

Table IX shows which parameters in the model are estimated from the data (as well as their values), and which parameters we set to match the empirical results. We set $N_c = 25$ for the 25 countries in our sample, and $N_F = 498$ to match the number of funds that exist in our data at any point in time in 2008. We also use the average dollar holdings of these 498 funds in 2008 as the starting point. All 'estimated' parameters do not vary across the columns of the table; and columns represent different configurations of the 'set' parameters to explore the roles of the different mechanisms in the model. Going down the rows of the table, $\mu_{\sigma_{r_c}}$ is the cross-sectional mean of the time-series standard deviation of daily country returns; $\mu_{\beta_c}, \sigma_{\beta_c}$ are the cross-sectional mean and standard deviations of estimated country daily betas, which are the sum of the fundamental betas and the G-7 market push effects; ϕ_r and ϕ_p are, respectively, the day 1 flow-performance sensitivity and the persistence of non-information flows. These are set to decline linearly over 60 days.

[30] Given that we are modelling country index returns, this seems an appropriate assumption. See, for example, the empirical literature on the price impact of non-informational trades beginning with Scholes(1972).

Turning to the 'set' parameters, the price impact of flows κ in our baseline calibration that best matches the empirical results is $\kappa = 30$.[31] We maintain this level of κ through the remainder of the comparative statics. Perhaps the most important set parameter in the calibration is the percentage of country idiosyncratic return volatility that arises from informed trading. The baseline value we find that best matches the empirical results is 1%, and we explore values of 0 (the no information case), and 10% (high information) as alternatives. We also explore the role of the push effect, setting $\rho = 0.08$ in our baseline simulation, and setting this parameter to zero in the 'no push' and 'only information' cases. Finally, the 'only information' case sets p and p^* to zero, only allowing q flows.

Figure 3 and Table X show how the calibration matches the estimated moments of the data as we vary the set parameters. The top panel of Figure 3 shows that the baseline calibration is well able to match the observed event study, lying within the 90% confidence intervals at all points. Table X shows that the baseline calibration also matches the other moments of the data, including the calendar-time switching betas, and the coefficients from the regression to explain cross-country correlations. The one set of moments we are unable to match is the calendar-time portfolio betas using predicted At-Risk.

The additional columns of Table X and Panels B and C of Figure 3 provide details on the implications of varying the relative importance of the information and push components. First, information-based trading is not important for explaining the variation in cross-market correlations and G-7 betas. The third column of Table X shows that the results are largely unchanged when information trading is nonexistent. When information-based trading is set to be very high (the fourth column of the table), the cross-market correlations and G-7 betas fail to provide a close match – in particular, the role of the information spillover, $P^*_{c,d}$, becomes too important, generating larger cross-market correlation effects but diminished G-7 betas (since the spillover is unrelated to G-7 returns). In Figure 3 (Panel B), both the absence of information and elevated information-based trading deliver counterfactually small or large CARs, respectively; it appears that a blend of push flows and a modest information component is required to deliver the large event time return followed by a slow reversal that we observe in our empirical estimation.

The fifth column of Table X and Panel C of Figure 3 show the effect of shutting down the

[31] This translates to a 30 basis point increase in returns for a 1 basis point of country market capitalization increase in At-Risk. This is fractionally lower than the estimate of price impact from a cross-border flow shock in Froot and Ramadorai (2008) of 35.

developed market push effect (ρ). This component has limited effect on either the price reversal or the cross-market correlations, relative to the baseline. However, the removal of developed market push effects diminishes the link between At-Risk and variation in G-7 betas. This is consistent with the arguments presented in the discussion of the empirical results that relate to the role of developed market wealth effects or rebalancing needs, although insufficient to explain the full magnitude of the switch. This leads to our investigation in the final column of Table X and Panel C of Figure 3, which shows the effect of shutting down non-information flows, $(P_{c,d} + P^*_{c,d})$, entirely. This alternative delivers completely counterfactual results along all dimensions. Cross-market correlations and G-7 betas are now unrelated to At-Risk, and CARs exhibit a modest event time effect (given the parameter values we set), with no price reversal. One interesting channel that this uncovers is that flow-performance sensitivity generates push-like effects even without the explicit presence of push flows. This accords with intuition, since country returns – and hence fund performance – both load on the world market (equivalent to the G-7), flow-performance sensitivity generates correlation between G-7 returns and fund inflows. In sum, non-informational push effects, regardless of whether they are explicit, or through flow-performance sensitivity, are critical for explaining the various results documented in the paper.

Two additional points should be noted. All versions of the calibration, including the baseline, deliver somewhat more modest link between At-Risk and G-7 variation than is observed in the data. This is not surprising: indeed, the fact that our calibrated model is able to deliver beta variation despite virtually constant fundamental betas for each country, β_c, is a notable finding. To fully explain this variation, it is plausible to envision that fundamental country betas are themselves varying through time (a well documented fact throughout the literature).[32] Hence, we consider an additional version that allows country betas to vary across time with the magnitude of the G-7 return. Specifically, we assume that the G-7 return volatility follows a regime-switching process and that country betas are 20% higher in the high volatility regime compared to those in the low volatility regime. This version delivers a more pronounced link between At-Risk and developed market beta variation. Last, none of the models, including this final version, is able to deliver the link between *predicted* At-Risk and G-7 beta variation. Additional sources of predictability are likely be required to match this final dimension; instead, we have tried to keep this model as parsimonious as possible while still delivering a baseline that is well able to match the main features of the empirical results.

[32] See Harvey (1991) for example.

6. Conclusion

We study the effects of funding shocks experienced by a large set of developed country-domiciled global investment funds on the emerging markets in which they invest. We document several important results. First, global funds, on average, re-allocate their investment positions in the face of sizeable flows. Second, the potential re-allocation implied by the collective amount of capital At-Risk represents a non-trivial fraction of domestic market trading in these countries. Third, fire sale reallocations engender large initial stock price effects in the affected emerging markets that then subsequently reverse. Finally, and most importantly, emerging markets that have significant capital At-Risk from this sort of fire sale activity are both more highly correlated with one-another and with the developed markets from which these funds originate. A calibrated model helps guide the interpretation of these findings – most significantly, non-information-related push effects are very important. We conclude that global investment managers, and the constraints they face, constitute an important transmission channel for financial shocks both between developed and emerging markets and among the emerging markets themselves.

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Table I

Summary Statistics by Country

This table provides descriptive information regarding the EPFR monthly sample, summarized by the emerging country in which the funds invest. The sample period is from February 1996 to June 2009. 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. The holding is also reported as a fraction of the float-adjusted market capitalization, calculated by rescaling market capitalization to adjust for the percentage not closely held as reported in Table 1 of Dahlquist, Pinkowitz, Stulz, and Williamson (2003). The float-adjustment is not available for a few countries.

		Holding (% of Market Capitalization)		
Country	Number of Funds	Mean	Standard Deviation	Mean (Float-Adjusted)
Argentina	273	2.41	2.49	5.10
Brazil	389	3.86	1.17	11.74
Chile	281	1.90	0.71	5.41
China	663	1.32	0.92	4.24
Colombia	153	0.65	0.60	
Czech Republic	270	3.63	2.10	16.59
Hong Kong	713	2.26	0.85	3.94
Hungary	295	8.58	3.66	16.98
India	583	3.62	1.12	6.06
Indonesia	512	3.59	1.41	11.57
Israel	309	1.58	0.82	3.75
Jordan	42	0.10	0.11	0.30
Malaysia	487	1.76	0.87	3.68
Mexico	344	5.54	1.57	7.50
Morocco	60	0.36	0.25	0.71
Pakistan	133	1.15	1.22	5.07
Philippines	365	2.64	1.01	5.39
Poland	276	4.75	2.64	13.29
Russia	392	2.07	1.99	
South Africa	330	1.53	0.57	3.26
South Korea	607	4.66	1.83	7.67
Taiwan	606	2.86	1.44	3.68
Thailand	492	3.70	1.33	8.78
Turkey	313	3.23	1.23	11.10
Venezuela	165	2.26	2.21	5.88
Average	337	2.59	1.26	6.47

Table II

Relation between Fund Flows and Other Fund Characteristics

This table reports descriptive fund characteristics conditional on monthly fund flows. Both fund flows and fund returns are measured as a percentage of the beginning-of-month *TNA*. Fund-month observations 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.

Flow Decile	Flow (%)	E[Flow] (%)	Previous-Month Return (%)	Cash Holding (%)	Number of Countries Invested	Average Market Capitalization Quintile	Average Volume Quintile
1 (Inflow)	12.75	0.99	3.58	4.31	9.52	2.35	2.38
2	3.73	0.45	2.30	3.78	9.54	2.34	2.37
3	1.38	0.07	1.27	3.61	9.82	2.33	2.37
4	0.24	-0.38	0.84	3.55	8.64	2.37	2.38
5	-0.07	-0.67	0.74	3.02	7.83	2.46	2.49
6	-0.67	-0.77	0.27	3.21	9.03	2.33	2.34
7	-1.58	-0.88	0.11	2.96	9.05	2.32	2.34
8	-2.82	-0.80	0.00	2.86	9.39	2.33	2.35
9	-4.71	-0.97	0.05	2.84	9.99	2.33	2.33
10 (Outflow)	-10.85	-1.11	-0.31	2.78	10.23	2.33	2.34
1-10	23.60	2.11	3.90	1.52	-0.72	0.02	0.04
t-statistic	--	(5.50)	(4.98)	(8.31)	(-3.88)	(0.66)	(1.64)

Table III

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 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. 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 June 2009. The average probability of moving from quintile i to quintile j is calculated as the total number of times any country moves from quintile i in period t to quintile j in period 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: Measuring At-Risk

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
1 (Positive)	0.216	10.620	4.703
2	0.048	2.704	2.635
3	0.009	0.611	1.366
4	-0.011	-0.952	1.559
5 (Negative)	-0.106	-5.181	3.776
1-5	0.322	15.801	0.928
t-statistic	--	(19.02)	(5.16)

Panel B: At-Risk quintile transition matrix

From At-Risk Quintile	To At-Risk Quintile 1 (Inflow)	2	3	4	5 (Outflow)
1 (Inflow)	0.703	0.184	0.064	0.023	0.026
2	0.199	0.483	0.236	0.056	0.026
3	0.050	0.238	0.436	0.228	0.048
4	0.031	0.081	0.204	0.494	0.191
5 (Outflow)	0.016	0.022	0.062	0.224	0.676
Steady-State	0.203	0.206	0.203	0.205	0.184

Table IV

Explaining Realized Cross-Country Correlations Using At-Risk

This table reports results from panel regressions of realized correlations on dummy variables for the country pair being in the extreme quintiles of At-Risk. The sample period is from February 1996 to June 2009. Countries are sorted into quintiles on the basis of actual At-Risk (Panel A) and predicted At-Risk (Panel B). Predicted At-Risk is calculated by replacing the current month flow by the expected flows, estimated via the Fama-MacBeth regressions in Panel A of Appendix Table 1. Realized correlation (the dependent variable) is estimated using daily data for each country pair-month. Dummy variables equal one if both countries in the pair are in the extreme quintiles, either Q1 or Q5 as specified, and zero otherwise. The number of country pair-month observations is denoted by *N*. Rogers (1993) standard errors clustered by calendar-month using three leads/lags are in parentheses.

Panel A: At-Risk sort

	(1)	(2)	(3)	(4)
Intercept	0.162***	0.162***	0.162***	0.162***
	(0.018)	(0.018)	(0.001)	(0.001)
At-Risk Q1 or Q5 Dummy	0.039***		0.040***	
	(0.009)		(0.009)	
At-Risk Q1 Dummy		0.027**		0.030**
		(0.012)		(0.012)
At-Risk Q5 Dummy		0.054**		0.052**
		(0.018)		(0.018)
Time (Month) Fixed Effects	NO	NO	YES	YES
N	44508	44508	44508	44508
R-Squared	0.001	0.001	0.173	0.173

Panel B: Predicted At-Risk sort

	(1)	(2)	(3)	(4)
Intercept	0.171***	0.171***	0.171***	0.171***
	(0.019)	(0.019)	(0.001)	(0.001)
At-Risk Q1 or Q5 Dummy	0.034***		0.034***	
	(0.008)		(0.008)	
At-Risk Q1 Dummy		0.035***		0.035***
		(0.014)		(0.014)
At-Risk Q5 Dummy		0.034**		0.033**
		(0.016)		(0.016)
Time (Month) Fixed Effects	NO	NO	YES	YES
N	41407	41407	41407	41407
R-Squared	0.001	0.001	0.173	0.173

Table V

Explaining Realized G-7 Betas Using At-Risk

This table reports results from panel regressions of G-7 betas on dummy variables for the countries that are in the extreme quintiles of At-Risk. The sample period is from February 1996 to June 2009. Countries are sorted into quintiles on the basis of actual At-Risk (Panel A) and predicted At-Risk (Panel B). Predicted At-Risk is calculated by replacing the current month flow by the expected flows, estimated via the Fama-MacBeth regressions in Panel A of Appendix Table 1. For each country-month, G-7 beta (dependent variable) is calculated at daily frequency as the average of country return and MSCI G-7 index return divided by the variance of MSCI G-7 index return. Dummy variables equal one if the country is in the extreme Q1 (high) or Q5 (low) At-Risk quintiles, and zero otherwise. The number of country-month observations is denoted by *N*. Rogers (1993) standard errors clustered by calendar-month using three leads/lags are in parentheses.

Panel A: At-Risk sort

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.492***	0.492***		0.493***	0.493***	
	(0.048)	(0.048)		(0.013)	(0.013)	
At-Risk Q1 or Q5 Dummy	0.080***			0.077***		
	(0.026)			(0.026)		
At-Risk Q1 Dummy		0.090**			0.092**	
		(0.040)			(0.040)	
At-Risk Q5 Dummy		0.067*			0.062*	
		(0.036)			(0.037)	
Positive G-7 Dummy			0.511***			0.512***
			(0.051)			(0.017)
Positive G-7 Dummy * At-Risk Q1 Dummy			0.098***			0.100***
			(0.034)			(0.034)
Positive G-7 Dummy * At-Risk Q5 Dummy			0.017			0.009
			(0.055)			(0.057)
Negative G-7 Dummy			0.467***			0.468***
			(0.059)			(0.020)
Negative G-7 Dummy * At-Risk Q1 Dummy			0.080			0.080
			(0.057)			(0.057)
Negative G-7 Dummy * At-Risk Q5 Dummy			0.136***			0.133***
			(0.035)			(0.035)
Time (Month) Fixed Effects	NO	NO	NO	YES	YES	YES
N	3828	3828	3828	3828	3828	3828
R-Squared	0.003	0.003	0.005	0.216	0.216	0.217

Table V -*continued*

Panel B: Predicted At-Risk sort

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.497***	0.497***		0.497***	0.497***	
	(0.051)	(0.051)		(0.013)	(0.013)	
At-Risk Q1 or Q5 Dummy	0.113***			0.111***		
	(0.030)			(0.030)		
At-Risk Q1 Dummy		0.125***			0.124***	
		(0.043)			(0.043)	
At-Risk Q5 Dummy		0.100***			0.096***	
		(0.036)			(0.038)	
Positive G-7 Dummy			0.519***			0.520***
			(0.055)			(0.018)
Positive G-7 Dummy * At-Risk Q1 Dummy			0.128***			0.129***
			(0.049)			(0.049)
Positive G-7 Dummy * At-Risk Q5 Dummy			0.056			0.051
			(0.053)			(0.056)
Negative G-7 Dummy			0.467***			0.468***
			(0.060)			(0.020)
Negative G-7 Dummy * At-Risk Q1 Dummy			0.120**			0.119*
			(0.061)			(0.061)
Negative G-7 Dummy * At-Risk Q5 Dummy			0.157***			0.154***
			(0.033)			(0.035)
Time (Month) Fixed Effects	NO	NO	NO	YES	YES	YES
N	3561	3561	3561	3561	3561	3561
R-Squared	0.006	0.006	0.008	0.228	0.228	0.229

Table VI

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 G-7 excess return, over the sample period from February 1996 to June 2009. 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 Appendix Table 1. The excess return on the MSCI G-7 index is on the RHS. Positive (negative) G-7 dummy equals one if the G-7 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.

	At-Risk Sort (1)	At-Risk Sort (2)	Predicted At-Risk Sort (3)	Predicted At-Risk Sort (4)
Intercept	0.013***	0.001	-0.004	-0.018**
	(0.005)	(0.007)	(0.005)	(0.008)
G-7 Excess Return	-0.066		-0.089	
	(0.094)		(0.148)	
Positive G-7 Dummy * G-7 Excess Return		0.345*		0.356
		(0.208)		(0.298)
Negative G-7 Dummy * G-7 Excess Return		-0.354***		-0.398**
		(0.133)		(0.198)
N	158	158	147	147
R-squared	0.00	0.03	0.01	0.04

Table VII

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

		Countries Expanded			Countries Reduced or Eliminated			Difference			*t*-statistic		
Flow 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)	12.75	54.11	38.02	16.09	58.76	41.49	17.26	-4.65	-3.47	-1.17	(-8.50)	(-10.74)	(-3.01)
2	3.73	53.77	37.86	15.90	55.74	39.30	16.43	-1.97	-1.44	-0.53	(-5.30)	(-5.72)	(-2.06)
3	1.38	53.86	38.09	15.77	54.79	38.67	16.12	-0.94	-0.58	-0.36	(-2.48)	(-2.12)	(-1.46)
4	0.24	55.21	38.34	16.87	55.95	39.25	16.70	-0.74	-0.91	0.16	(-1.72)	(-3.44)	(0.50)
5	-0.07	55.27	38.56	16.70	55.45	38.77	16.67	-0.18	-0.21	0.03	(-0.41)	(-0.78)	(0.10)
6	-0.67	54.98	38.50	16.48	54.15	38.36	15.79	0.83	0.14	0.69	(2.05)	(0.52)	(2.72)
7	-1.58	54.60	38.05	16.55	52.80	37.36	15.44	1.80	0.69	1.11	(4.30)	(2.63)	(3.80)
8	-2.82	55.59	38.87	16.72	53.47	37.71	15.75	2.12	1.15	0.97	(5.10)	(4.24)	(3.62)
9	-4.71	55.48	38.82	16.66	52.85	37.24	15.61	2.63	1.58	1.05	(5.39)	(5.73)	(3.44)
10 (Outflows)	-10.85	57.08	40.05	17.02	52.92	37.32	15.61	4.15	2.74	1.41	(7.48)	(7.28)	(4.33)
1-10	23.60	-2.96	-2.03	-0.93	5.83	4.18	1.65	--	--	--	-- --	--	--
t-statistic	--	(-3.28)	(-3.19)	(-2.34)	(6.56)	(6.34)	(4.12)						

Table VII *-continued*

Panel B: Equally weighted average

		Countries Expanded			Countries Reduced or Eliminated			Difference			*t*-statistic		
Flow 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)	12.75	56.60	39.88	16.71	60.04	42.51	17.53	-3.45	-2.63	-0.82	(-6.94)	(-8.50)	(-2.32)
2	3.73	55.82	39.47	16.35	57.60	40.76	16.85	-1.78	-1.29	-0.50	(-4.98)	(-5.23)	(-2.10)
3	1.38	55.67	39.60	16.07	56.92	40.37	16.55	-1.25	-0.77	-0.48	(-3.54)	(-3.27)	(-2.07)
4	0.24	56.99	39.76	17.24	58.04	40.70	17.34	-1.05	-0.95	-0.10	(-2.41)	(-3.69)	(-0.31)
5	-0.07	56.96	39.87	17.10	57.59	40.15	17.45	-0.63	-0.28	-0.35	(-1.51)	(-1.10)	(-1.17)
6	-0.67	56.97	40.07	16.90	56.44	40.01	16.43	0.53	0.06	0.48	(1.50)	(0.22)	(2.02)
7	-1.58	56.40	39.42	16.97	55.07	39.00	16.07	1.33	0.43	0.90	(3.46)	(1.78)	(3.35)
8	-2.82	57.42	40.28	17.14	56.14	39.52	16.62	1.28	0.76	0.52	(3.19)	(2.91)	(2.13)
9	-4.71	56.91	40.00	16.91	55.30	38.93	16.36	1.62	1.07	0.55	(3.72)	(3.93)	(2.19)
10 (Outflows)	-10.85	58.31	41.07	17.24	55.81	39.23	16.58	2.50	1.85	0.66	(5.73)	(5.69)	(2.45)
1-10	23.60	-1.71	-1.19	-0.53	4.24	3.29	0.95	--	--	--	--	--	--
t-statistic	--	(-1.77)	(-1.77)	(-1.24)	(4.47)	(4.79)	(2.30)						

Table VIII

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 G-7 excess return, over the sample period from February 1996 to June 2009. 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 flow, estimated via the Fama-MacBeth regressions in Panel A of Appendix Table 1. The G-7 excess return is the excess return on the MSCI G-7 index. Positive (negative) G-7 dummy equals one if the G-7 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 (1)	Liq-Adj At-Risk Sort (2)	Predicted Liq-Adj At-Risk Sort (3)	Predicted Liq-Adj At-Risk Sort (4)
Intercept	0.016***	0.005	-0.002	-0.015*
	(0.006)	(0.008)	(0.006)	(0.007)
G-7 Excess Return	-0.155		-0.014	
	(0.111)		(0.118)	
Positive G-7 Dummy * G-7 Excess Return		0.219		0.412*
		(0.260)		(0.241)
Negative G-7 Dummy * G-7 Excess Return		-0.417***		-0.310*
		(0.137)		(0.160)
N	158	158	147	147
R-squared	0.01	0.03	0.00	0.03

Table IX

Parameters Used in the Simulation

This table lists the model parameters that are used in the simulation at *daily* frequency. Some parameters are estimated directly from the data, hence denoted "estimated", and some are set to match the empirical results or to examine the role of information and push effects, hence denoted "set." $\hat{\beta}_c$ refers to the sum of the fundamental country beta and the push effects. Other symbols are as described in the Model and Calibration section.

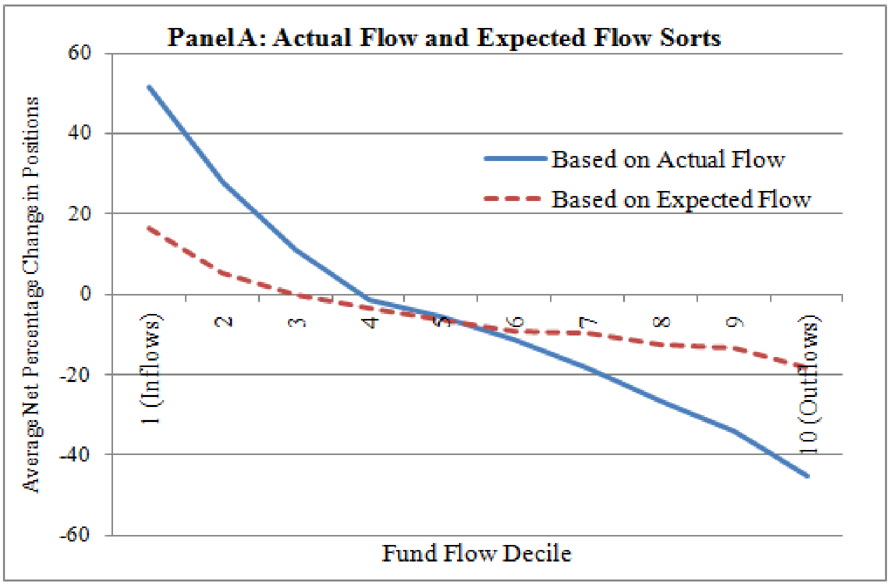
Estimated/ Set	**Parameter**	**Baseline**	**No Info.**	**High Info.**	**No Push**	**Only Info.**
Estimated	μ_w, σ_w	0, 0.011	0, 0.011	0, 0.011	0, 0.011	0, 0.011
Estimated	$\mu_{\sigma_{u,c}}$	0.017	0.017	0.017	0.017	0.017
Estimated	$\mu_{\hat{\beta}_c}, \sigma_{\hat{\beta}_c}$	0.622, 0.370	0.622, 0.370	0.622, 0.370	0.622, 0.370	0.622, 0.370
Estimated	ϕ_r	0.01	0.01	0.01	0.01	0.01
Estimated	ϕ_p	0.01	0.01	0.01	0.01	0.01
Set	κ	30	30	30	30	30
Set	$\frac{\sigma^2(\kappa Q_c)}{\sigma^2(u_c + \kappa Q_c)}$	0.01	0	0.10	0.01	0.01
Set	ρ	0.08	0.08	0.08	0	0
Set	$\mu_{\sigma_{\delta,i}}$	0.011	0.011	0.011	0.011	0

Table X

Matching Results from Simulation

This table reports results of the analyses in Table IV and VI conducted on simulated returns and flows under different assumptions. G-7 returns, innovations of country returns, and innovations of fund flows are randomly generated at daily frequency. From these random realizations, country returns, At-Risk, and fund flows are calculated and then aggregated into monthly variables, as observed in the actual data. The regressions in Table IV and VI are performed on the monthly variables. The empirical estimates are reported in the first column and the comparable estimates from the simulation (averages from 200 runs) are reported in the second to last columns.

	Empirical (1)	Baseline (2)	No Info. (3)	High Info. (4)	No Push (5)	Info. Only (6)	Regime-Dependent Betas (7)
Correlations							
Intercept	**0.162**	0.156	0.153	0.233	0.153	0.115	0.149
At-Risk Q1 Dummy	**0.027**	0.043	0.033	0.059	0.044	-0.009	0.035
At-Risk Q5 Dummy	**0.054**	0.053	0.039	0.076	0.052	-0.012	0.040
Correlations, Predicted							
Intercept	**0.171**	0.156	0.153	0.232	0.152	0.113	0.148
At-Risk Q1 Dummy	**0.035**	0.049	0.048	0.065	0.050	0.033	0.039
At-Risk Q5 Dummy	**0.034**	0.059	0.047	0.083	0.059	0.036	0.047
Calendar-Time Portfolio Betas							
Intercept	**0.001**	0.018	0.012	0.038	0.019	0.019	0.019
Positive G-7 Dummy * G-7 Excess Return	**0.345**	0.204	0.207	0.140	0.166	0.004	0.255
Negative G-7 Dummy * G-7 Excess Return	**-0.354**	-0.238	-0.213	-0.132	-0.170	-0.009	-0.267
Calendar-Time Portfolio Betas, Predictec							
Intercept	**-0.018**	0.000	0.000	0.000	0.000	-0.001	0.000
Positive G-7 Dummy * G-7 Excess Return	**0.356**	-0.035	0.000	0.003	-0.027	0.017	-0.008
Negative G-7 Dummy * G-7 Excess Return	**-0.398**	-0.004	0.008	0.020	0.015	-0.016	-0.018



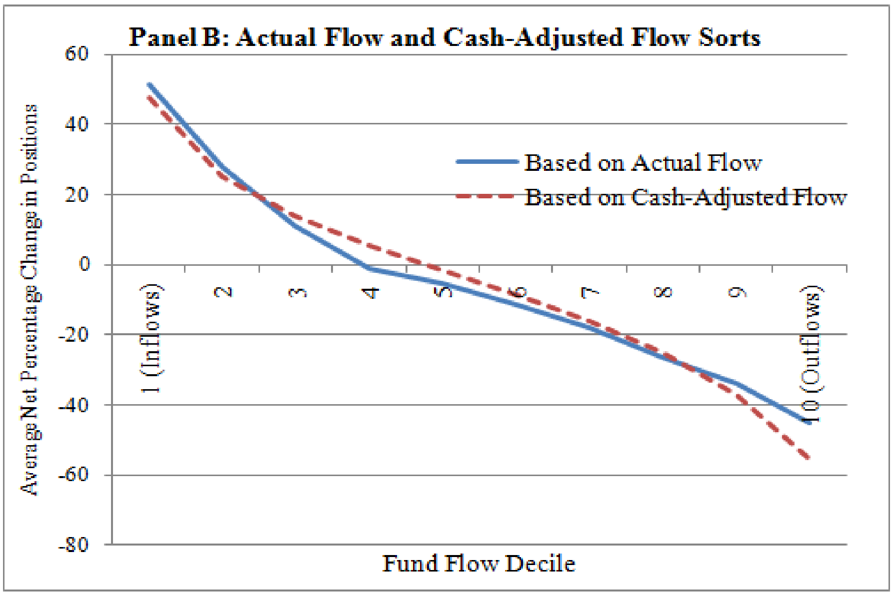


Figure 1. Relation between fund flows and changes in positions. This figure plots the average net percentage changes in positions for funds in different deciles of actual and expected flows (Panel A) and actual and cash-adjusted flows (Panel B). Flows are measured as a percentage of the beginning-of-month *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.

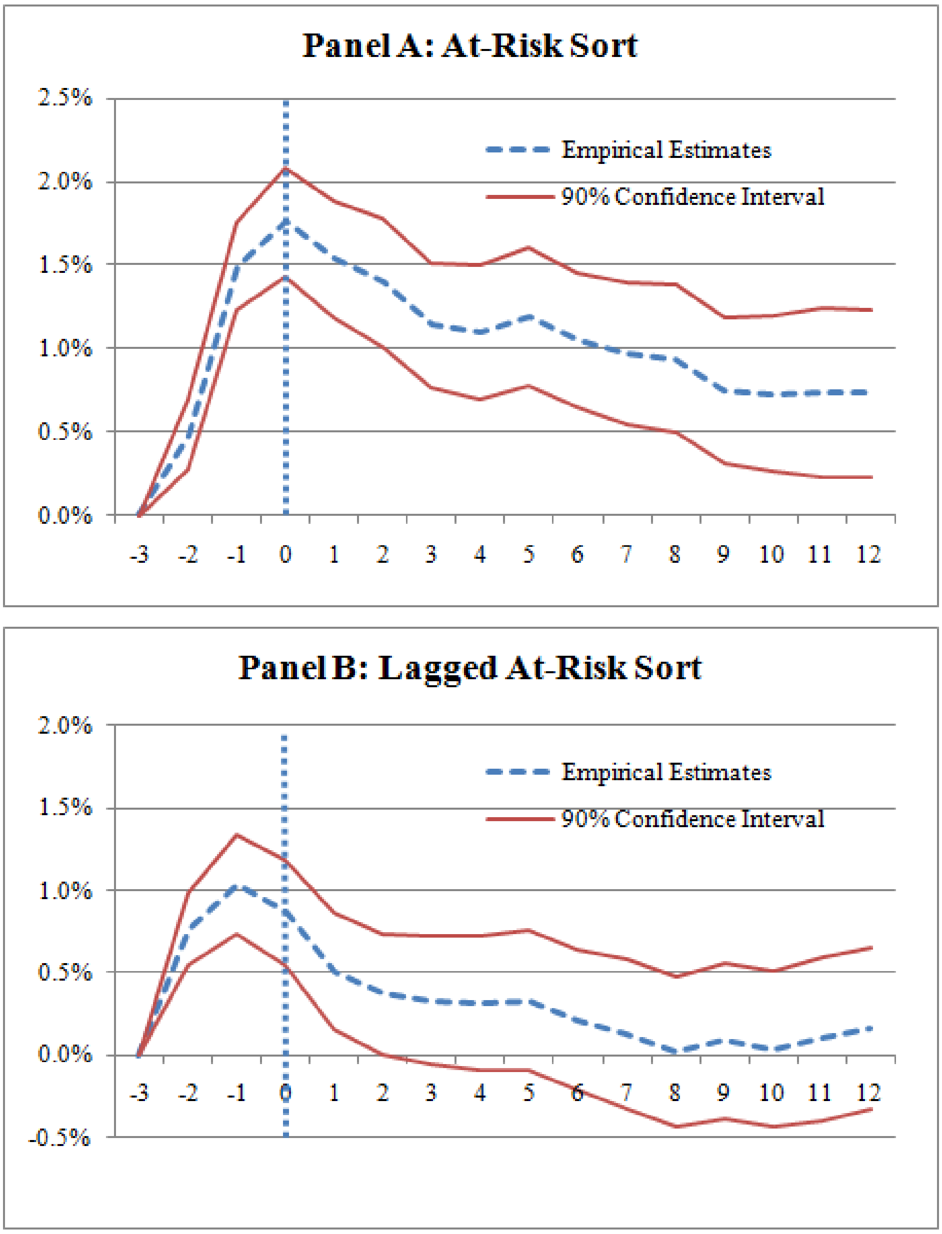


Figure 2. Conditional cumulative abnormal returns. This figure plots the cumulative abnormal returns (*CAR*s) over the period from event weeks -3 to 12 for the equally-weighted long Q1-short Q5 portfolio. In each calendar week, countries are sorted into quintiles on the basis of *weekly* At-Risk (Panel A), lagged At-Risk (Panel B), and predicted At-Risk (Panel C). Lagged At-Risk is calculated by replacing the current week flow by the lagged flow. Predicted At-Risk is calculated by replacing the current week flow by the expected flow, estimated via the Fama-MacBeth regressions in Panel B of Appendix Table 1. Week 0 is the week in which the countries are placed in Q1 and Q5. Abnormal returns (*AR*s) are estimated by regressing weekly country returns on 106 dummy variables for being in Q1and Q5 in each event week from weeks -26 to 26 and the calendar-week fixed effects. *CAR* at event week *t* is calculated as the sum of *AR*s for being in Q1 from event weeks -2 to *t* minus the sum of *AR*s for being in Q5 over the same event period (i.e. normalizing *CAR*s at week -3 to zero). The 90% confidence bands are calculated from the covariance matrix of the regression coefficients, essentially taking into account the correlations in *AR*s across event weeks.

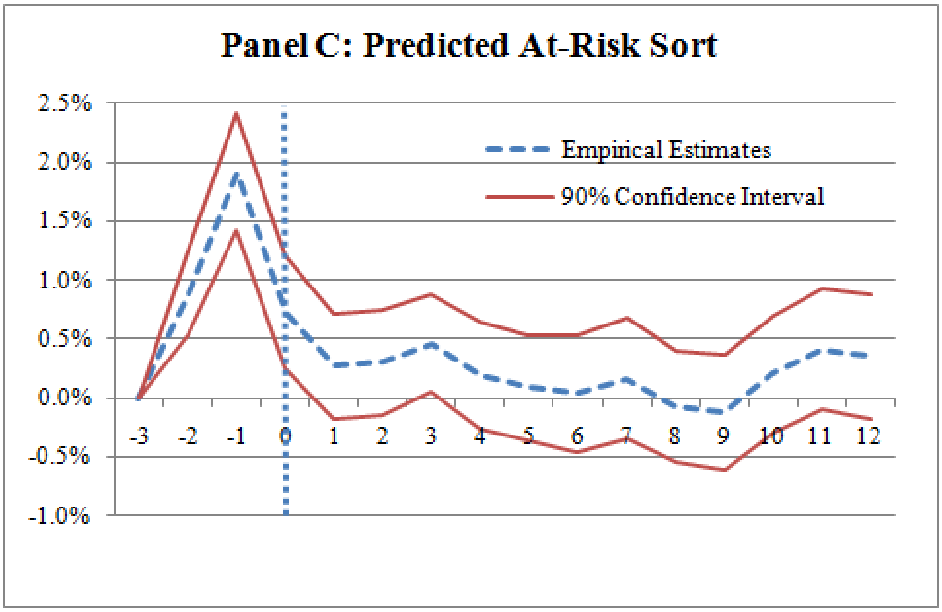


Figure 2 –*continued*

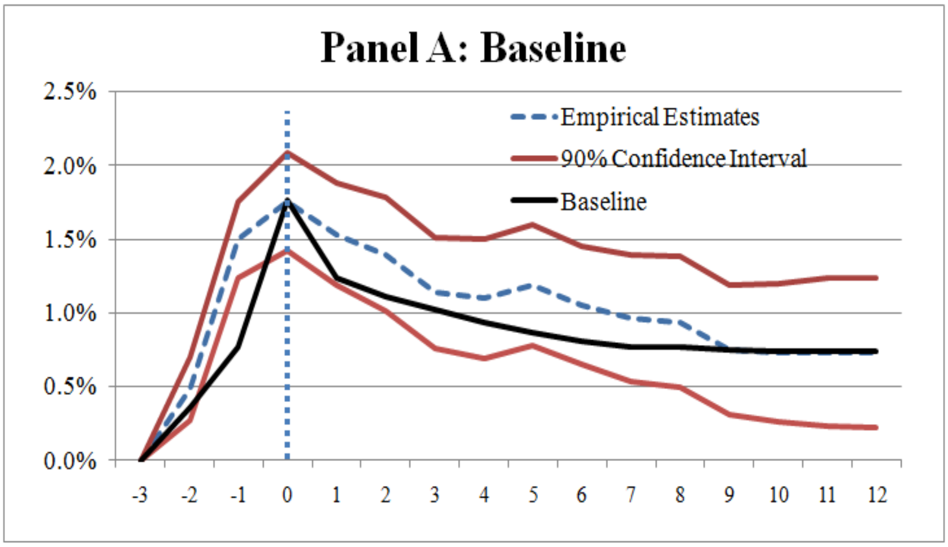
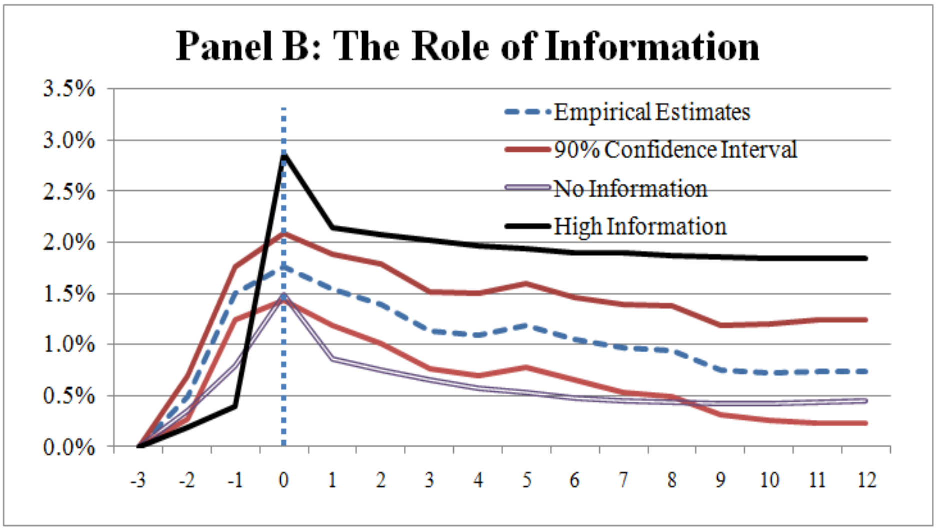


Figure 3. Weekly event studies from simulation. This figure plots the cumulative abnormal returns (*CAR*s) estimated from simulated returns and flows under different assumptions. G-7 returns, innovations of country returns, and innovations of fund flows are randomly generated at daily frequency. From these random realizations, country returns, At-Risk, and fund flows are calculated and then aggregated into weekly variables, as observed in the actual data. *CAR*s are estimated on the simulated weekly variables, as described in Figure 2. Averages from 200 runs are reported. Panel A compares the simulated *CAR*s under the baseline assumptions with the empirical estimates. Panel B examines the simulated *CAR*s under different levels of information. Panel C examines the simulated *CAR*s with vs. without various components of the 'push' effects.



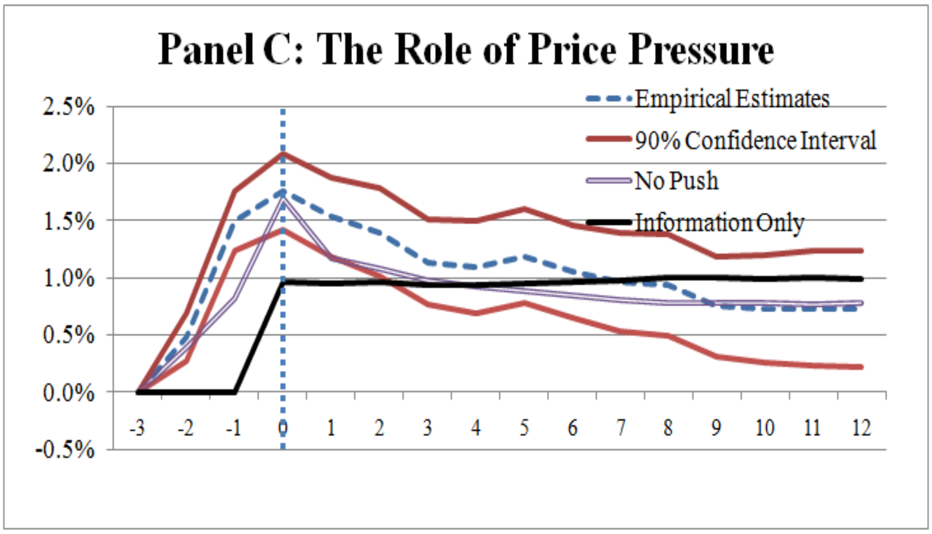


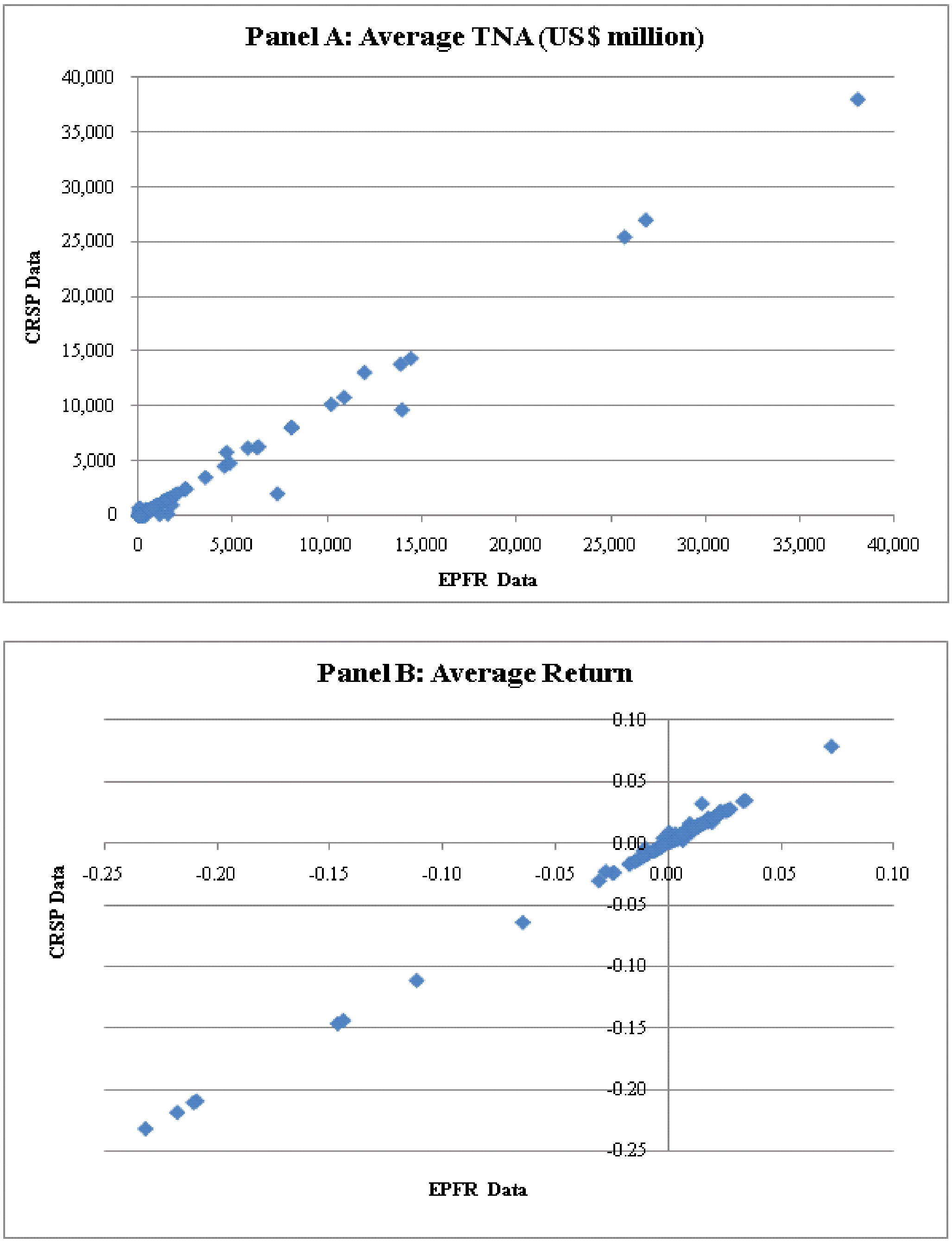
Figure 3 -*continued*

Appendix for “Asset Fire Sales and Purchases and the International Transmission of Financial Shocks”

Appendix 1

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. (We exclude Zimbabwe from the list due to its extremely high inflation.) Second, to avoid data errors, we only include funds once their *TNA*s 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. As this clearly generates data errors, we exclude those months. 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 1,175. 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. We also investigate the reliability of the EPFR data. Appendix Figure 1 below shows the *TNA*s and monthly returns from EPFR and CRSP are virtually identical for funds (around 10% of the overall sample) that we match across databases using a name-matching algorithm.

Appendix Figure 1



Appendix 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, matched by fund name, for the period from February 1996 to September 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*.

Appendix Table 1
Predictive Regressions for Fund Flows

This table reports results from regressions of fund flows on log of beginning-of-period *TNA*, lagged fund flows and lagged fund returns, at monthly and weekly frequencies. The monthly (weekly) sample period is from February 1996 to June 2009 (first week of July 2001 to last week of June 2009). Both fund flows and fund returns are measured as a percentage of the beginning-of-period *TNA*. All variables in the regressions are divided by their own standard deviations. Fama-MacBeth regression coefficients are the time-series average of monthly (weekly) 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. *N* denotes the number of observations, and *t*-statistics are in parentheses.

	Monthly		Weekly	
Variable	Estimate	*t*-statistic	Estimate	*t*-statistic
Intercept	-0.063	(-2.16)	0.013	(1.12)
ln(*TNA*)	-0.006	(-5.46)	-0.001	(-10.68)
Flow_lag1	0.124	(9.31)	0.086	(16.05)
Flow_lag2	0.090	(8.96)	0.071	(16.75)
Flow_lag3	0.073	(7.90)	0.058	(14.98)
Flow_lag4	0.036	(4.16)	0.046	(11.34)
Flow_lag5	0.049	(5.28)	0.031	(9.23)
Flow_lag6	0.029	(2.62)	0.020	(5.64)
Flow_lag7	0.035	(3.78)	0.020	(5.67)
Flow_lag8	0.031	(4.25)	0.026	(8.03)
Flow_lag9	0.019	(1.96)	0.032	(10.02)
Flow_lag10	0.021	(1.91)	0.020	(5.85)
Flow_lag11	0.030	(3.21)	0.018	(5.62)
Flow_lag12	0.030	(3.91)	0.016	(4.89)
Flow_lag13			0.026	(8.32)
Return_lag1	0.171	(8.33)	0.093	(11.66)
Return_lag2	0.058	(3.21)	0.075	(10.12)
Return_lag3	0.029	(0.59)	0.053	(7.54)
Return_lag4	0.104	(1.14)	0.052	(7.46)
Return_lag5	-0.163	(-1.31)	0.031	(4.75)
Return_lag6	0.161	(0.70)	0.027	(3.65)
Return_lag7	0.019	(0.13)	0.024	(3.38)
Return_lag8	-0.059	(-1.03)	0.003	(0.39)
Return_lag9	0.051	(1.83)	0.022	(3.07)
Return_lag10	-0.083	(-1.53)	0.007	(1.05)
Return_lag11	0.072	(0.93)	0.010	(1.58)
Return_lag12	-0.004	(-0.09)	0.008	(1.18)
Return_lag13			-0.004	(-0.65)
R-squared	0.286		0.181	
N	147		404	

Appendix Table 2

Fund Trading Associated with Fund Flows

This table reports how fund holdings change conditional on actual and expected monthly 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 expected fund flow (Panel B), estimated as in Appendix Table 5. 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

Flow Decile	Flow (%)	% Countries Expanded	% Countries Reduced	% Countries Eliminated	Avg. Change in Positions	Change in Cash Holding
1 (Inflows)	12.75	75.78	22.68	1.53	0.22	1.74
2	3.73	63.93	34.46	1.61	0.05	0.54
3	1.38	55.56	43.14	1.30	0.02	0.27
4	0.24	49.37	49.41	1.22	0.00	0.11
5	-0.07	47.34	51.53	1.12	-0.01	0.14
6	-0.67	44.37	54.00	1.63	-0.01	-0.16
7	-1.58	40.91	57.40	1.69	-0.02	-0.22
8	-2.82	36.75	61.29	1.96	-0.04	-0.39
9	-4.71	32.99	65.16	1.85	-0.07	-0.45
10 (Outflows)	-10.85	27.38	69.37	3.25	-0.17	-1.03
1-10	23.60	48.40	-46.69	-1.71	0.39	2.77
t-statistic	--	(44.99)	(-43.64)	(-5.81)	(26.11)	(10.05)

Panel B: Expected flow sort

E[Flow] Decile	E[Flow] (%)	% Countries Expanded	% Countries Reduced	% Countries Eliminated	Avg. Change in Positions	Change in Cash Holding
1 (Inflows)	5.54	58.14	40.37	1.49	0.07	-0.04
2	2.16	52.63	45.78	1.59	0.02	-0.12
3	0.94	50.02	48.59	1.39	0.01	0.10
4	0.18	48.32	50.44	1.24	0.00	0.03
5	-0.36	46.89	51.65	1.46	-0.01	0.01
6	-0.89	45.31	53.03	1.66	-0.01	0.02
7	-1.50	45.13	53.02	1.85	-0.01	0.04
8	-2.27	43.83	54.38	1.79	-0.02	0.13
9	-3.43	43.35	54.39	2.25	-0.03	0.13
10 (Outflows)	-6.74	40.79	56.78	2.43	-0.04	0.24
1-10	12.28	17.36	-16.41	-0.95	0.12	-0.29
t-statistic	--	(10.31)	(-9.72)	(-3.48)	(10.41)	(-1.22)

Appendix Table 3

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 June 2009. 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. The excess return on the MSCI G-7 index is on the RHS. Positive (negative) G-7 dummy equals one if the G-7 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.

	Holding Sort	Holding Sort
Intercept	0.000	0.002
	(0.005)	(0.007)
G7 Risk Premium	0.849***	
	(0.112)	
Positive G7 Dummy * G7 Risk Premium		0.796***
		(0.199)
Negative G7 Dummy * G7 Risk Premium		0.887***
		(0.179)
N	158	158
R-squared	0.34	0.34

Appendix Table 4

Calendar-Time Portfolios: Two Way Sort by At-Risk and Transaction Costs

This table reports average monthly returns and standard deviations of calendar-time portfolios. The sample period is from February 1996 to June 2009. Each month, equally-weighted portfolios are formed by first sorting countries into terciles based on At-Risk as a percentage of country market capitalization. Countries in each At-Risk tercile are then sorted into two groups based on transaction costs. Panels A and B compare the average returns and standard deviations across At-Risk terciles for the low transaction cost and high transaction cost groups, respectively. 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. 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: Low Transaction Cost Group

Quintile Calendar Portfolio	Average Return (%)			Standard Deviation of Return (%)		
	All	G-7 Excess Return > 0	G-7 Excess Return < 0	All	G-7 Excess Return > 0	G-7 Excess Return < 0
1 (Positive)	1.74	5.83	-3.83	8.23	6.28	7.25
2	0.57	4.60	-4.90	7.91	5.73	7.15
3 (Negative)	0.94	4.99	-4.55	8.14	5.62	7.84
1-3	0.80	0.85	0.73	0.08	0.67	-0.59
t-statistic	(1.50)	(1.24)	(1.85)			
F-statistic				(0.08)	(0.84)	(0.49)

Panel B: High Transaction Cost Group

Quintile Calendar Portfolio	Average Return (%)			Standard Deviation of Return (%)		
	All	G-7 Excess Return > 0	G-7 Excess Return < 0	All	G-7 Excess Return > 0	G-7 Excess Return < 0
1 (Positive)	2.02	5.42	-2.60	8.50	7.49	7.59
2	0.45	3.85	-4.17	7.65	6.60	6.48
3 (Negative)	0.74	4.37	-4.20	8.15	6.68	7.35
1-3	1.28	1.04	1.60	0.35	0.81	0.24
t-statistic	(2.02)	(1.32)	(1.68)			
F-statistic				(0.06)	(0.10)	(0.11)