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The flow-performance relationship around the world

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ABSTRACT

We use a new dataset to study how mutual fund flows depend on past performance across 28 countries. We show that there are marked differences in the flow-performance relationship across countries, suggesting that US findings concerning its shape do not apply universally. We find that mutual fund investors sell losers more and buy winners less in more developed countries. This is because investors in more developed countries are more sophisticated and face lower costs of participating in the mutual fund industry. Higher country-level convexity is positively associated with higher levels of risk taking by fund managers.

1. Introduction

There are numerous papers that study how flows depend on past performance using US mutual fund flow data (e.g., Ippolito, 1992; Sirri and Tufano, 1998; Del Guercio and Tkac, 2002). Most concur that flows are highly dependent on past performance and that US investors chase winners more intensely than they sell poorly performing funds.

The interest in the flow-performance relationship stems from three main sources. First, fund flows determine the assets under management of fund management companies and hence their fees; this means that the flow-performance relationship is paramount for fund families to understand. Second, the literature also highlights that a convex flow-performance relationship may encourage fund manager risk taking to increase the likelihood that they are winners. Finally, the way flows respond to past performance also matters as it has implications for fund persistence. This is because the flow-performance relationship will determine the degree to which fund size is affected by past performance which conditions how a fund performs in the future (Berk and Green, 2004).

The mutual fund industry has been influential in the US financial market for some time, and this is also now the case in many other countries around the world (Khorana et al., 2005).[1] The far-reaching influence of the mutual fund industry in most economies suggests that the dependence of flows on past performance will have implications for the risk and return that investors experience in stock and bond markets. Yet we have little idea of how this dependence varies around the world, as there is scant work on mutual fund flows beyond the US. We aim to fill this void and to provide new insights into the flow-performance relationship around the world, in particular, to understand what determines the shape that we observe.[2]

We use a worldwide sample of mutual funds to investigate why the intensity with which investors buy past winners and sell past losers differs across countries. The focus is the role of economic, financial, and mutual fund industry development in shaping the flow-performance relationship around the world. Relating the nature of this relationship to the diverse development levels across countries in our sample is important, because this sheds light on its likely evolution within countries. This would be difficult to

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[1] At the end of 2007, the world mutual fund industry managed financial assets exceeding $26 trillion (including over $12 trillion in stocks), more than four times the $6 trillion of assets managed at the end of 1996 (Investment Company Institute, 2009). The number of mutual funds has also grown dramatically to more than 66,000 funds worldwide at the end of 2007. The world share of assets under management outside the US grew from 38% in 1997 to 54% in 2007.

[2] There are a limited number of studies on fund flows outside the US Dahlquist et al. (2000) study Sweden, while Keswani and Stolin (2008) study the UK.

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see using individual country data rather than a sample of countries at different stages of development.

There are several possible explanations for why flow-performance sensitivities differ across countries, and these can be related to levels of development. Investors may chase past favorable performance because they put more weight on the latest fund performance information or fail to sell losers because they tend to shade the latest performance information when a fund they have purchased underperforms (Goetzmann and Peles, 1997). Investors may also buy into past winners and not sell past losers because fund families tend to advertise funds that have recently outperformed rather than drawing attention to poorly performing funds (Sirri and Tufano, 1998).[3] This suggests that investor sophistication can explain the levels of flow-performance sensitivities observed as more sophisticated investors will be less behaviorally biased and will not be persuaded by advertising. Indeed, the US literature shows that not chasing winners and selling losers is a sensible thing for fund investors to do (Hendricks et al., 1993; Brown and Goetzmann, 1995; Carhart, 1997). We confirm this is also the case in our worldwide sample of mutual funds.[4]

We expect mutual fund investors in more developed countries to be more familiar with financial products owing to the greater development of their financial markets. In addition, these investors should also have a better understanding of mutual funds, not only because the mutual fund industry is typically older but also because it is larger and more pervasive in their countries. Khorana et al. (2005) find larger fund industries in countries with wealthier and more educated populations. Finally, we expect investors in countries with higher education levels and more advanced development to be more able to process the information when dealing with mutual funds. For these reasons mutual fund investors in more developed countries are likely to be more sophisticated and we expect to see a less convex flow-performance relationship.[5]

Huang et al. (2007) discuss the role of mutual fund participation costs in shaping the flow-performance relationship. They argue that the higher the participation costs (whether transaction or information costs) the higher the rate of return a fund must earn before a large number of investors choose the fund. As a result, funds with higher participation costs will have a more convex flow-performance relationship at the upper end of the performance scale.

Translating these ideas from the fund level to the country level, when we compare countries with different levels of participation costs, we could expect to see more convexity in countries with higher average participation costs. Huang et al. (2007) show that convexity has declined over time for US mutual funds. They argue this is a result of a decline in participation costs due to investors becoming better informed. Thus, the aggregate flow-performance relationship in a given country may be explained by the average level of participation costs. This is the intuition we apply in our work.

How do we expect participation costs to vary with development? Khorana et al. (2009) show that mutual fund fees are lower in more developed countries. In addition, we might expect that in more developed markets, the convenience of obtaining information concerning mutual funds is higher.[6] This would suggest lower costs of participating in the mutual fund industry for investors in more developed countries. At the mutual fund industry level, this would suggest that more developed countries will have a less convex flow-performance relationship.

In summary, investor sophistication and participation costs arguments suggest a less convex flow-performance relationship in more developed countries than in less developed countries.[7] In our analysis below we choose to model their influence separately on the flow-performance relationship for two reasons. First, they capture different elements of fund trading decisions. Investor sophistication captures the ability of investors to process fund information while participation costs capture the informational and transactional costs of trading funds. Second, investor sophistication is expected to influence the top and bottom of the flow-performance relationship while participation costs are expected to be more influential for the middle and top of the flow-performance relationship. As a result it makes sense to model their impact on the way flows respond to past performance separately.

To examine these issues we use a large sample of equity mutual funds. The sample consists of more than 16,000 open-ended and actively managed equity funds in 28 countries over 2001–2007. We find that there are marked differences in the flow-performance relationship across countries, suggesting that US findings to date do not apply directly to other countries.

We test the hypothesis that investors from more developed countries will show lower convexity in their flow-performance relationship due to their higher sophistication and the lower participation costs they face. We find that measures of economic, financial and mutual fund industry development aimed at capturing these factors explain cross-country differences in convexity. Our findings support the view that development reduces convexity levels. We also show that our results are robust to other explanations of the flow-performance relationship such as taxes (Ivkovic and Weisbenner, 2009), market volatility and dispersion of fund manager ability (Kim, 2010).

We go onto demonstrate that differences in convexity across countries have implications for levels of fund manager risk taking. Specifically, we investigate whether fund managers respond to different levels of convexity in the flow-performance relationship in their countries. Chevalier and Ellison (1997) argue that greater flow sensitivity to performance is associated with greater fund manager risk taking as fund managers stand to gain significant flow if they do well but do not lose significantly if they perform poorly. We find that country-level convexity is positively and significantly associated with risk taking by fund managers.

We make several contributions to the mutual fund literature. We believe we are the first study on mutual fund flows to use a worldwide sample. While there are mutual fund cross-country studies covering topics such as industry size (Khorana et al., 2005), fees (Khorana et al., 2009), and performance (Ferreira et al., forthcoming), there are no cross-country studies on mutual

[3] There are other explanations for why investors do not sell underperformers. Lynch and Musto (2003) argue that investors may be reluctant to sell poorly performing funds because they expect failing funds will change their managers or their investment strategy.

[4] We sort funds in each country into quintiles based on risk-adjusted performance and calculate the returns to buying prior year winners and losers. We find that in most countries that buying the prior year's winners does not lead to positive and significant risk-adjusted returns while buying the past year's losers results in significantly negative abnormal returns. This suggests that buying winners does not pay off while selling losers does.

[5] As countries develop, the cohort of mutual fund investors may widen and reduce the average level of investor sophistication. This may limit the positive impact of country development on sophistication. We investigate this possibility in our tests.

[6] In more developed fund industries we expect a greater number of funds. It might be argued that this could make the informational participation costs of investing in mutual funds actually greater in more developed countries (Carlin and Manso, 2011). We investigate this empirically and find little evidence that the number of funds behaves like a participation cost.

[7] An additional reason why development levels and convexity might be related is given to us by Berk and Green (2004). They argue that competitive equilibrium in the fund management industry is characterized by investors chasing winners and limited persistence in top fund performance. However, in transition to equilibrium before fund flows have reduced persistence, there will be greater performance persistence and winner chasing. This suggests that fund industries that are younger and further away from their long-run steady state will have investors that chase winners more intensely.

fund flows. Second, our worldwide sample of funds allows us to explore the role of economic, financial, and mutual fund industry development in shaping the flow-performance relationship around the world. Our results suggest that flow-performance convexity is likely to decline as countries develop. Finally, we show how convexity differences across countries influence the levels of risk taking we observe. To the best of our knowledge, we are the first to relate country-level convexity to the degree of risk taking in fund management. This finding suggests that regulators and investors should exert greater effort in monitoring mutual funds in less developed countries, where mutual fund industries are less developed and participation costs are higher.

The paper is structured as follows. The next section describes the dataset and the variables constructed to enable cross-country comparison of the sensitivity of mutual fund flows to performance measures. Section 3 presents our results on the shape of the relationship between flows and performance, and in Section 4 we investigate the role of a country's development in influencing that relationship. In Section 5 we study the implications of the flow-performance relationship across countries for the risk taking behavior of fund managers. Section 6 reports the results of several robustness checks, and Section 7 concludes.

2. Data and methodology

Our survivorship bias-free data on mutual fund sizes and returns are drawn from the Lipper Hindsight database. Lipper collects these data from fund management companies directly. We begin by eliminating multiple share classes to avoid double-counting funds and use the share class that Lipper identifies as the primary one.[8] Although multiple share classes are listed as separate funds in Lipper, they have the same holdings, the same manager, and the same returns before expenses and loads. The initial sample includes 37,910 primary equity funds (both active and dead funds) in the 2001–2007 period. It includes both domestic funds (funds that invest primarily in stocks of the country of domicile) and international funds (funds that invest primarily in stocks of countries different from the country of domicile). We restrict the sample to actively managed equity funds and exclude funds-of-funds, closed-end, index tracking, and offshore funds which reduces the sample to 25,110 funds.[9]

We use aggregate statistics on mutual funds from the Investment Company Institute (2009) (ICI) to check the coverage of funds by Lipper. At the end of 2007, Lipper and ICI reported respectively, 26,800 and 26,950 equity funds. As of December 2007, ICI reported total net assets (TNAs) of equity funds summed across all share classes of $12.5 trillion, while the Lipper database reported a corresponding figure of $10.9 trillion. Thus, our initial sample of equity funds covers 87% of the total net assets of worldwide equity funds, despite some variation in coverage across countries and years. In some countries, including Canada, Germany, Sweden, the UK, and the US, the coverage is above 90%, while the coverage in Australia and France is about 60% and in Japan only 40%.

We use quarterly data for fund sizes and monthly data for returns. A minimum of 24 monthly observations of fund returns are required for inclusion in the final sample. This is to ensure that we have sufficient observations to calculate risk-adjusted performance measures. To be able to draw meaningful conclusions from our analysis for different countries, we impose a minimum of ten funds per quarter in each country which leads to a final sample of 16,135 open-ended actively managed equity funds in 28 countries over 2001–2007. Table 1 presents the number of funds and TNA across countries at the end of 2007.

Table 1
Number and average size of mutual funds by country. This table presents the number of funds and total net assets (TNA) by country at the end of 2007. The sample is restricted to open-end and actively managed equity funds. Off-shore funds are excluded. A minimum of 24 continuous monthly observations for returns per fund and a minimum of 10 funds per quarter in each country are required for inclusion in our sample.

Country	Number of funds	TNA ($ million)
Australia	1477	178,495
Austria	260	24,164
Belgium	197	29,326
Canada	1472	419,754
Denmark	183	35,991
Finland	138	21,585
France	1099	263,602
Germany	409	152,527
Hong Kong	28	5213
India	112	22,869
Indonesia	18	2498
Ireland	80	21,229
Italy	289	76,634
Japan	613	52,648
Malaysia	138	5626
Netherlands	166	65,775
Norway	150	31,283
Poland	23	10,674
Portugal	54	4535
Singapore	195	15,299
South Korea	147	17,935
Spain	406	32,122
Sweden	241	108,866
Switzerland	169	41,014
Taiwan	209	15,293
Thailand	96	1641
UK	1009	536,400
US	2629	4,508,814
All countries	12,007	6,701,814

One can see considerable variation in the number of funds and TNA across countries in our sample. As of the end of 2007 there are 12,007 funds. The US has the highest number of funds. US funds represent 22% of the total number of funds and 67% of TNA in our sample of equity funds. Australia and Canada have the second and third highest number of funds, each representing about 12% of the total number of funds in the sample. Indonesia is the country with the lowest number of funds.

2.1. Fund flows

Following Chevalier and Ellison (1997), Sirri and Tufano (1998), and others, we define the new money growth rate as the net growth in total net assets (TNAs), not due to dividends and capital gains on the assets under management but to new external money. Fund flow for fund i in country c at quarter t is calculated as:

$$Flow_{i,c,t} = \frac{TNA_{i,c,t} - TNA_{i,c,t-1}(1 + R_{i,c,t})}{TNA_{i,c,t-1}}, \quad (1)$$

where $TNA_{i,c,t}$ is the total net asset value in local currency of fund i in country c at the end of quarter t, and $R_{i,c,t}$ is fund i's raw return from country c in quarter t. Eq. (1) assumes flows occur at the end of each quarter, as we have no information regarding the timing of new investment.[10] To ensure that extreme values do not drive our results, we winsorize fund flows by country at the bottom and top 1% level of the distribution.

[8] The primary fund is typically the class with the highest total net assets. The primary class represents more than 80% on average of the total assets across all share classes.

[9] Offshore funds consist of funds registered for sale in offshore centers such as Luxembourg, Dublin, and the Cayman Islands.

[10] Sirri and Tufano (1998) show that results are not sensitive to this assumption. Our results do not change whether flows are assumed to occur at the beginning or middle or continuously throughout the period.

Table 2
Descriptive statistics of fund flows by country. This table presents mean, standard deviation, percentiles of quarterly money growth rates in percentage across funds within each country from 2001 to 2007. Flows are winsorized by country at the 1st and 99th percentiles. *N* is the number of fund-quarter observations.

Country	Mean	Standard deviation	Percentiles					*N*
			10th	25th	50th	75th	90th	
Australia	1.48	15.44	−10.44	−5.24	−0.84	4.59	15.11	3417
Austria	−0.53	13.82	−11.12	−5.09	−1.20	1.78	9.35	4715
Belgium	−1.56	13.74	−12.31	−5.93	−2.21	0.99	9.24	4435
Canada	−0.23	11.33	−9.03	−5.14	−1.79	2.28	9.26	14,227
Denmark	6.04	45.72	−9.55	−4.67	−0.59	4.53	16.19	3125
Finland	2.49	18.25	−11.25	−4.97	−0.41	4.73	17.15	2141
France	0.47	14.99	−11.20	−4.49	−0.66	2.89	12.10	24,458
Germany	−2.38	12.28	−12.10	−6.19	−2.15	0.86	6.51	9758
Hong Kong	4.72	14.73	−5.64	−1.12	1.74	9.41	24.30	58
India	2.75	44.73	−23.77	−11.13	−3.54	6.22	32.98	1769
Indonesia	17.46	59.40	−28.85	−10.96	0.19	26.90	73.66	213
Ireland	1.25	22.37	−15.64	−6.51	−0.94	3.95	15.38	991
Italy	−2.66	12.95	−13.42	−8.18	−4.03	0.43	8.11	8171
Japan	−3.74	9.97	−12.33	−6.80	−3.29	−0.57	3.93	13,753
Malaysia	−2.71	11.85	−15.20	−7.42	−1.95	1.18	7.96	2254
Netherlands	−0.47	9.44	−8.10	−4.27	−1.12	1.63	6.23	3032
Norway	0.01	18.72	−12.74	−6.13	−2.13	2.20	13.20	3170
Poland	15.98	41.00	−13.53	−2.99	6.58	18.27	49.80	396
Portugal	1.00	14.45	−10.87	−5.04	−1.30	4.38	17.12	914
Singapore	−1.16	13.67	−11.90	−6.93	−2.57	1.56	11.28	4201
South Korea	−12.48	21.92	−40.94	−24.44	−8.74	−0.56	6.65	4432
Spain	0.15	18.61	−13.39	−7.11	−2.34	2.40	14.89	8445
Sweden	1.22	11.36	−7.28	−2.79	−0.40	3.17	11.13	5235
Switzerland	−2.19	11.52	−11.92	−5.91	−2.43	1.33	7.97	3814
Taiwan	6.37	38.88	−16.97	−10.03	−3.68	6.41	34.31	1261
Thailand	−2.71	10.40	−10.59	−4.37	−1.73	−0.30	1.80	1761
UK	−0.21	14.73	−9.18	−3.81	−1.03	2.07	9.28	16,480
US	1.26	14.64	−9.27	−4.68	−1.10	3.68	13.25	66,725
All countries	−0.17	16.37	−11.27	−5.45	−1.56	2.41	11.17	213,351

Table 2 presents descriptive statistics on flows measured as money growth rates by quarter for funds within each country and region during the sample period. Indonesia and Poland enjoy by far the highest average quarterly flows during the period, while South Korea has the lowest average quarterly outflows averaged across funds. The average money growth rate across the European countries in our sample is −0.16%; for Asian countries, the average quarterly fund growth rate is −3.03%. The US enjoyed growth rates of 1.26% per quarter on average. Overall, the average quarterly fund growth rate is about zero across all countries.

2.2. Performance measurement

Mutual fund performance is measured using raw returns and risk-adjusted returns in local currency. The calculation of total returns assumes that dividends are immediately reinvested. As in US studies, our raw returns are gross of taxes and net of total expenses (annual fees and other expenses).

Risk-adjusted performance is calculated using two approaches: (1) Jensen's alpha, and (2) four-factor alpha model using market, size, value, and momentum factors. Jensen's alpha is calculated in different ways for domestic and international funds. For domestic funds we first regress the previous 36 months of fund excess returns on the local (fund domicile) market excess returns, and store the estimated beta. We then use the estimated beta and the realized excess market return to predict the return of the fund in the next quarter. The quarterly alpha is the difference between the predicted return and the realized fund return.[11]

For international funds, we calculate alphas the same way except that we use the investment region market excess return factor in the regressions (calculated as the value-weighted average of market excess returns for all countries in the region in which the fund invests). Like Bekaert et al. (2009), to avoid the inclusion of a large number of country factors for each fund, we take a region-based rather than country-based approach to risk adjustment. The fund investment region is based on the Lipper geographic focus field, which can be a single country, a geographic region, or global. We map the geographic focus into four regions (Europe, Asia–Pacific, North America, Emerging Markets), plus the World for global funds.

We calculate four-factor alphas for domestic funds the same way we calculate Jensen's alpha, except that we use the market, size, value, and momentum factors instead of a single market factor. For international funds, we calculate size, value, and momentum factors for each region. Size, value, and momentum factors are calculated as value-weighted averages of the corresponding factor for all countries in the region. The Appendix A in the paper explains in detail how we calculate the risk factors for each country in our dataset.

Panel A of Table 3 contains fund performance statistics by country. Hong Kong, India, and Indonesia turned in the highest average raw returns, and France, Germany, and Italy the lowest. The average Jensen's alphas and four-factor alphas in Table 3 provide us with a better understanding of the value of active management in each country. We can see that in Spain and Austria managers have most underperformed the market, while in Hong Kong and Taiwan managers have outperformed the most. The average one-factor alpha in our sample is −0.47% per quarter and the average four-factor alpha is −0.60%. Asia–Pacific countries, on average, performed better than the other regions according to the three measures of performance. Overall, the fund performance figures here are consistent with evidence in other studies that fund managers

[11] We use at least 24 monthly observations to estimate fund alphas if fewer than 36 monthly return observations are available. The risk-free rates of return are calculated using interbank middle rates for each country, with the exception of the US for which we use US T-bill rates from the US Federal Reserve. Data on interbank middle rates are drawn from Datastream. Countries' market returns are given by Datastream country return indices.

Table 3
Fund variables. Panel A presents fund level variables averaged across fund quarters by country for the period 2001–2007. Panel B presents pairwise correlations among these variables. Performance measures include: the average raw returns in the past four quarters; one-factor alpha and four-factor alpha both calculated based on average alpha in the past four quarters. Control variables include: fund size, measured by fund's TNA in millions of US dollars at the end of each quarter (*Size*); fund age in years at the end of each quarter (*Age*); percentage annual fee (*Fees*); percentage front-end load (*Front-end loads*); percentage rear load (*Back-end loads*); geographic investment style dummy variable (*Geographic dummy*), that equals zero if the fund is a domestic fund or one if the fund is an international fund; number of countries where a fund is registered to sell (*Number of countries fund sold*); loadings on the small minus big size factor (*SMB*); and loadings on the high minus low book-to-market factor (*HML*).

Country	Raw returns (%)	One-factor alpha (%)	Four-factor alpha (%)	Size ($ million)	Fund age (years)	Fees (%)	Front-end loads (%)	Back-end loads (%)	Geographic dummy	Number of countries fund sold	Family size ($ million)	SMB	HML
Panel A – Average fund variables by country													
Australia	4.22	−0.96	−0.51	138	6.52	1.46	2.07	0.06	0.46	1.03	24,700	0.21	0.01
Austria	2.00	−1.48	−1.48	47	7.33	1.52	4.53	0.00	0.96	1.99	8810	−0.06	−0.03
Belgium	1.40	−1.22	−0.96	102	7.44	1.08	2.62	0.02	0.88	3.77	9440	−0.18	−0.24
Canada	3.15	−1.34	−1.16	186	9.16	1.49	1.87	3.04	0.65	1.00	32,100	0.01	−0.16
Denmark	2.90	−0.75	−0.70	104	9.64	1.35	2.12	0.69	0.88	1.80	5350	−0.14	−0.20
Finland	3.17	−0.38	−0.04	110	6.78	1.51	1.14	0.94	0.79	1.46	7410	−0.15	−0.19
France	0.97	−1.22	−1.36	137	10.76	1.63	2.94	0.24	0.73	1.14	14,000	−0.04	−0.02
Germany	0.75	−1.38	−1.30	292	11.84	1.33	4.38	0.00	0.83	1.92	24,400	−0.04	−0.06
Hong Kong	8.60	2.09	1.78	149	7.55	1.08	3.40	0.25	0.83	1.36	57,900	0.27	−0.02
India	9.75	1.38	0.84	44	6.85	1.24	2.12	0.60	0.00	1.44	15,100	0.12	0.06
Indonesia	8.29	0.35	0.13	47	8.06	1.76	1.33	1.67	0.00	1.06	5550	0.02	0.00
Ireland	3.11	−1.32	−1.36	162	5.60	1.19	4.55	0.36	1.00	6.20	17,600	0.02	−0.16
Italy	0.65	−1.43	−1.33	262	8.61	1.92	2.45	0.78	0.82	1.00	17,900	−0.08	−0.10
Japan	1.87	0.40	0.38	64	8.13	1.43	2.24	0.12	0.34	1.00	28,400	0.04	−0.02
Malaysia	2.60	−0.59	−0.41	43	10.11	1.56	6.23	0.18	0.01	1.06	2140	0.00	−0.03
Netherlands	1.49	−1.27	−1.15	335	10.01	1.17	1.15	0.60	0.85	1.25	12,400	−0.08	−0.17
Norway	3.40	−1.22	−1.74	106	8.67	1.61	2.53	0.48	0.63	1.34	4880	−0.10	−0.06
Poland	5.04	0.51	−0.43	157	6.10	3.58	4.04	0.59	0.24	1.00	22,700	0.01	−0.02
Portugal	2.58	−0.88	1.28	52	7.67	1.90	0.26	1.98	0.67	1.11	3660	−0.04	−0.09
Singapore	2.89	−0.26	0.31	38	7.36	1.19	4.69	0.00	0.94	1.12	16,800	0.20	−0.05
South Korea	4.89	0.85	1.03	19	5.26	2.70	0.04	0.00	0.00	1.00	10,200	−0.07	−0.05
Spain	1.48	−1.68	−1.66	65	7.23	1.94	0.00	0.92	0.78	1.02	4190	−0.11	−0.11
Sweden	1.93	−0.80	−0.83	278	10.70	1.38	0.26	0.37	0.59	1.19	12,000	−0.14	−0.11
Switzerland	1.58	−0.39	−0.49	197	14.03	1.47	4.17	0.71	0.72	2.01	14,600	−0.10	0.03
Taiwan	6.70	2.30	2.58	57	8.69	1.59	1.96	0.77	0.24	1.00	27,000	−0.55	−0.43
Thailand	5.11	0.79	0.26	10	9.01	1.39	0.78	0.45	0.01	1.00	844	0.08	0.06
UK	1.45	−0.90	−0.74	348	14.93	1.38	4.29	0.01	0.63	2.03	35,200	−0.05	−0.12
US	1.95	0.36	−0.20	952	12.63	0.71	1.78	0.78	0.20	1.05	46,500	0.31	0.10
All countries	2.07	−0.47	−0.60	403	10.61	1.29	2.38	0.64	0.51	1.31	27,500	0.07	−0.03

		1	2	3	4	5	6	7	8	9
Panel B – Pairwise correlations among fund variables										
Log size	1	1								
Log age	2	0.40***	1							
Fees	3	−0.25***	−0.14***	1						
Front-end loads	4	0.02***	0.07***	0.10***	1					
Back-end loads	5	0.02***	−0.02***	0.18***	0.00	1				
Geographic dummy	6	−0.09***	−0.13***	0.22***	0.14***	0.04***	1			
Number of countries fund sold	7	0.11***	0.06***	0.05***	0.18***	−0.09***	0.17***	1		
SMB	8	0.08***	0.03***	−0.17***	−0.04***	0.04***	−0.17***	−0.07***	1	
HML	9	0.08***	0.07***	−0.08***	−0.03***	−0.01***	−0.09***	−0.03***	0.36***	1

*** 1% significance level.

do not have the ability to beat the market after fees (e.g., Malkiel, 1995; Gruber, 1996).

It is informative to measure degrees of performance persistence by country. To examine this, we sort funds in each country into quintiles based on one-factor and four-factor alphas, and then we calculate the equally weighted return of the bottom and top quintiles over the next year. We then rebalance these portfolios each year. Using the generated time series of returns for the bottom and top quintiles, we regress these monthly returns on appropriate risk factors. The top and bottom fund quintile portfolios formed here for each country contain both domestic and international funds. We therefore calculate their one factor alpha using the market factor for the country concerned together with the world market factor. We do likewise for four factor alpha and use the domestic four factors plus the world four factors to risk adjust performance.

The intercepts, representing monthly abnormal returns, generated for the bottom and top quintile regressions and their associated *t*-statistics are presented in Table 4. We find that buying past winners does not result in statistically significant abnormal returns measured using either one-factor alpha or four-factor alpha for any country. In 16 countries out of 28 using one-factor alpha and in 17 countries using four-factor alpha, we find statistically significant negative abnormal performance to buying past losers suggesting that selling past losers is generally advisable for countries in our dataset.

2.3. Control variables

The literature shows that non-performance-related variables are also important in explaining flows and their sensitivity to performance, so we introduce a large number of non-performance-related fund attributes. Larger funds are expected to capture more money, and hence we include fund size as an explanatory variable (Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Barber et al.,

Table 4
Performance persistence by country.

Country	One-factor alpha				Four-factor alpha			
	Bottom quintile		Top quintile		Bottom quintile		Top quintile	
	Coefficient	*t*-stat.	Coefficient	*t*-stat.	Coefficient	*t*-stat.	Coefficient	*t*-stat.
Australia	−0.172	−0.38	−0.930**	−2.13	−1.113**	−2.05	−2.062***	−3.70
Austria	−1.052***	−3.93	−0.258	−0.99	−0.938***	−3.53	−0.357	−1.19
Belgium	−0.792***	−4.16	0.043	0.22	−0.686***	−3.25	−0.024	−0.11
Canada	−0.488	−1.24	−0.446	−1.29	−0.654	−1.55	−0.488	−1.53
Denmark	−0.697***	−3.29	0.232	0.79	−0.609***	−2.76	0.167	0.46
Finland	−0.673***	−2.96	0.105	0.36	−0.575**	−2.42	0.156	0.41
France	−0.945***	−4.89	−0.208	−1.10	−1.023***	−4.76	−0.358*	−1.76
Germany	−0.976***	−5.32	−0.356**	−2.48	−0.810***	−4.03	−0.325**	−2.30
Hong Kong	0.024	0.07	−0.278	−0.64	0.082	0.23	−0.014	−0.03
India	0.071	0.09	0.754	0.80	0.121	0.13	0.791	0.76
Indonesia	−0.512	−0.53	0.797	1.07	−1.083	−1.19	0.324	0.40
Ireland	−0.689***	−3.01	−0.049	−0.19	−0.705***	−2.90	0.062	0.19
Italy	−0.840***	−6.54	−0.280	−1.59	−0.713***	−5.01	−0.124	−0.60
Japan	−0.512**	−2.32	0.357	1.21	−0.542***	−2.73	0.432	1.33
Malaysia	0.493	0.77	1.163	1.17	−0.316	−0.23	0.666	0.32
Netherlands	−0.827***	−3.50	−0.043	−0.18	−0.767***	−3.15	−0.125	−0.44
Norway	−0.352	−1.27	0.366	1.11	−0.387	−1.32	0.204	0.64
Poland	0.482	0.93	0.720	0.66	0.634	0.58	0.638	0.28
Portugal	−0.697***	−3.26	0.149	0.43	−0.225	−0.66	0.024	0.06
Singapore	−0.328*	−1.69	0.075	0.29	−0.301	−1.57	−0.210	−0.79
South Korea	−0.696	−1.23	−0.571	−1.13	−1.118*	−1.93	−1.029*	−1.94
Spain	−0.718***	−4.62	−0.164	−0.80	−0.663***	−3.47	−0.177	−0.88
Sweden	−0.820***	−2.83	0.058	0.25	−0.768***	−2.92	0.003	0.01
Switzerland	−0.479**	−2.26	0.035	0.14	−0.592**	−2.54	−0.182	−0.70
Taiwan	−0.114	−0.25	−0.236	−0.54	0.113	0.24	0.037	1.46
Thailand	−0.679	−0.72	−0.339	−0.33	0.420	0.35	1.878	1.46
UK	−0.757***	−3.11	−0.275*	−1.66	−0.826***	−2.80	−0.335*	−1.66
US	−0.159	−1.21	0.228	1.09	−0.220**	−2.11	−0.190	−1.64

This table presents absolute performance persistence statistics by country. We first sort funds in each country into quintiles based on one-factor alpha and then we calculate the equally weighted return of the bottom and top quintiles over the next year. We then rebalance these portfolios each year. Using the generated time series of returns for the bottom and top quintiles, we regress these monthly returns on the appropriate risk factors. In the case of one factor alpha we use the market factor for the country concerned together with the world market factor. In the case of four factor alpha we use the domestic four factors plus the world four factors. The intercepts generated for the bottom and top quintile regressions and their associated *t*-statistics are presented.
* 10% significance level.
** 5% significance level.
*** 1% significance level.

2005). Most of these studies also use fund age to explain flows. We also use fund annual fees as a control variable, as many authors show that these fees explain fund flows, including Barber et al. (2005), Huang et al. (2007), and Gil-Bazo and Ruiz-Verdú (2009). We also include front-end and back-end loads as control variables.

We include several additional control variables that are particular to this study. First, to capture the impact of geography, we introduce a dummy variable that equals zero if the fund is a domestic fund or one if the fund is an international fund. International funds are expected to offer wider investment diversification opportunities to their investors, and this may lead to higher flows. Second, we control for the number of countries where a fund is registered to sell. We include this variable to control for the possibility that an increase in the number of countries where a fund is sold may influence the flows that it attracts. Third, as the style of funds may affect the flows they receive, we also estimate the loadings on SMB and HML factors in each fund quarter and include these loadings as additional control variables (for domestic funds we use the domestic SMB and HML, and for international funds we use the region specific SMB and HML factors).[12] Finally, to control for the level of aggregate flows in each country in our flow-performance regressions we also include the average percentage flow across all funds in the prior quarter in each country.

Panel A of Table 3 presents summary statistics of control variables by country averaged across fund quarters. As we would expect, funds in more developed countries (particularly the US and the UK) are the oldest and also the largest, on average. Fees are lowest in the US and highest in Poland. Malaysia and Singapore charge the highest front-end loads and Canada and Portugal the highest back-end loads. Spain and South Korea have the lowest front-end loads, while Austria, Germany, Singapore, and South Korea are countries where funds tend not to charge back-end loads. Funds from India, Indonesia, and South Korea invest only in their own market in our dataset, while all funds from Ireland are international funds. Irish funds are registered to sell in by far the greatest number of countries. Funds in Canada, Italy, Japan, Poland, South Korea, Taiwan, Thailand, and the US sell generally only in their own country. The table also indicates that there is substantial variation in average SMB and HML loadings across countries.

The pairwise correlation matrix among fund control variables is presented in Panel B of Table 3. Multicollinearity among these variables does not appear to be a serious concern as most correlation coefficients are low, suggesting that these variables may be included together in our flow-performance regressions.

3. The flow-performance relationship

In this section we measure how differently flows in each country respond to past performance.

[12] We imply fund styles by using loadings on SMB and HML factors because we do not have access to fund style information for many of the countries in our dataset.

Table 5
The flow-performance relationship across all countries.

	Raw returns				One-factor alpha				Four-factor alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Low $t-1$	0.038	0.062^{**}	0.053^{**}	0.042^{*}	0.086^{***}	0.122^{***}	0.111^{***}	0.097^{***}	0.076^{***}	0.088^{***}	0.083^{***}	0.072^{***}
	(1.39)	(2.39)	(2.14)	(1.67)	(3.32)	(4.95)	(4.88)	(4.16)	(2.80)	(3.23)	(3.32)	(2.91)
Mid $t-1$	0.057^{***}	0.068^{***}	0.062^{***}	0.058^{***}	0.041^{***}	0.048^{***}	0.044^{***}	0.041^{***}	0.038^{***}	0.047^{***}	0.042^{***}	0.040^{***}
	(7.92)	(8.81)	(8.54)	(8.29)	(5.59)	(6.13)	(6.13)	(5.76)	(5.18)	(5.93)	(5.73)	(5.55)
High $t-1$	0.317^{***}	0.305^{***}	0.253^{***}	0.255^{***}	0.362^{***}	0.356^{***}	0.300^{***}	0.303^{***}	0.300^{***}	0.296^{***}	0.248^{***}	0.251^{***}
	(7.06)	(6.36)	(6.30)	(6.14)	(7.04)	(6.52)	(6.29)	(6.10)	(5.84)	(5.32)	(5.19)	(5.07)
Log Size $t-1$		-0.007^{***}	-0.008^{***}	-0.006^{***}		-0.007^{***}	0.008^{***}	-0.006^{***}		-0.006^{***}	-0.008^{***}	-0.005^{***}
		(−5.28)	(−6.77)	(−4.49)		(−5.02)	(−6.57)	(−4.34)		(4.65)	(−6.28)	(−4.14)
Log Age $t-1$		-0.012^{***}	-0.008^{***}	-0.007^{***}		-0.011^{***}	0.007^{***}	-0.006^{***}		-0.011^{***}	-0.008^{***}	-0.007^{***}
		(−5.32)	(−4.08)	(−3.41)		(4.89)	(−3.70)	(−3.03)		(4.91)	(−3.70)	(−3.15)
Fees $t-1$		−0.005	−0.004	−0.002		−0.003	−0.003	−0.002		−0.002	−0.002	−0.001
		(−1.42)	(−1.40)	(−0.71)		(−0.98)	(−0.96)	(−0.48)		(−0.76)	(−0.74)	(−0.40)
Front-end loads $t-1$		−0.001	−0.001	0.001		−0.001	−0.001	0.001		−0.001	−0.001	0.001
		(−0.80)	(−0.90)	(1.33)		(−0.82)	(−0.92)	(1.25)		(−0.70)	(−0.80)	(1.31)
Back-end loads $t-1$		0.006^{*}	0.005^{*}	0.005^{**}		0.006^{*}	0.005^{*}	0.006^{**}		0.006^{*}	0.005^{*}	0.006^{**}
		(1.67)	(1.73)	(2.43)		(1.70)	(1.76)	(2.48)		(1.68)	(1.75)	(2.46)
Number of countries fund sold		0.005^{***}	0.004^{***}	0.002^{**}		0.005^{***}	0.005^{***}	0.002^{***}		0.005^{***}	0.005^{***}	0.002^{***}
		(4.37)	(4.70)	(2.49)		(4.73)	(5.11)	(2.78)		(4.89)	(5.29)	(2.95)
Geographic dummy		0.012^{***}	0.010^{***}	0.007^{***}		0.011^{***}	0.009^{***}	0.006^{**}		0.010^{***}	0.008^{***}	0.005^{**}
		(4.36)	(4.16)	(2.65)		(3.80)	(3.61)	(2.28)		(3.40)	(3.17)	(2.08)
Flows $t-1$			0.129^{***}	0.134^{***}			0.129^{***}	0.134^{***}			0.133^{***}	0.137^{***}
			(9.18)	(9.30)			(9.09)	(9.21)			(9.38)	(9.46)
SMB $t-1$				-0.007^{***}				-0.006^{**}				-0.009^{***}
				(−2.91)				(−2.45)				(−3.99)
HML $t-1$				0.004^{***}				0.004^{***}				0.008^{***}
				(2.92)				(2.58)				(5.06)
Average country flow $t-1$				0.625^{***}				0.622^{***}				0.619^{***}
				(11.27)				(11.17)				(11.14)
Country fixed effects	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.067	0.077	0.092	0.077	0.067	0.077	0.092	0.077	0.063	0.073	0.089	0.075
Number of observations	213,351	213,351	213,351	213,351	213,351	213,351	213,351	213,351	213,351	213,351	213,351	213,351
Wald test High = Low (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001

This table presents the results of panel regressions examining the aggregate flow-performance relationship with funds pooled across 28 countries. Weighted least squares is used where each fund is weighted by the inverse of the number of funds in each country-quarter. The dependent variable is fund *flows* and the independent variables are past performance and control variables. A piecewise linear regression is used to define three linear segments in the flow-performance relationship. In each quarter, by country, fractional performance ranks ranging from zero to one are assigned to funds according to their average raw returns in the past four quarters, their one-factor alpha and their four-factor alpha. This procedure designates three performance variables: $Low_{i,c,t-1} = min(0.2, Rank_{i,c,t-1}), Mid_{i,c,t-1} = min(0.6, Rank - Low_{i,c,t-1})$, and $High_{i,c,t-1} = Rank - (Low_{i,c,t-1} + Mid_{i,c,t-1})$. Refer to equation (2) for variable definitions. Control variables include: fund size, measured by the natural log of fund's TNA in US dollars lagged by one quarter (*Log Size*$_{t-1}$); the natural log of fund age lagged by one quarter (*Log Age*$_{t-1}$); annual fee lagged by one quarter (*Fees*$_{t-1}$); front-end load lagged by one quarter (*Front-end loads*$_{t-1}$); rear load lagged by one quarter (*Back-end loads*$_{t-1}$); flow lagged by one quarter (*Flow*$_{t-1}$); geographic investment style dummy variable (*Geographic dummy*), that equals zero if the fund is a domestic fund or one if the fund is an international fund; the number of countries where fund is registered to sell (*Number of countries fund sold*); small minus big factor loadings lagged by one quarter (*SMB*$_{t-1}$); high minus low factor loadings lagged by one quarter (*HML*$_{t-1}$); and the average fund flow by country lagged by one quarter (Average country flow$_{t-1}$). Robust t-statistics clustered by fund are reported in parentheses. p-values from a Wald test of the equality of top and bottom performance quintile coefficients for each regression specification are reported in the last row of the table.

* 10% significance level.
** 5% significance level.
*** 1% significance level.

3.1. Measuring worldwide convexity

We first measure the level of convexity across all countries in the sample. Our aim is to measure the relationship between favorable fund performance and flows and between poor fund performance and flows. We use a piecewise-linear specification in the manner of Sirri and Tufano (1998) and others, which allows for different flow-performance sensitivities at different levels of performance. We allow slopes to differ for the lowest quintile, middle three quintiles, and the top quintile. The slopes are estimated separately for the bottom quintile (*Low*), the three middle quintiles (*Mid*), and the top quintile (*High*) of the fractional fund performance ranks.

In each quarter and for each country fractional fund performance, ranks ranging from zero (poorest performance) to one (best performance) are assigned to funds according to their past performance in the past year (measured by raw returns, one-factor alpha or four-factor alpha). The coefficients on these piecewise decompositions of fractional ranks represent the marginal fund-flow response to performance. This procedure assigns performance ranking variables for each of the three performance measures:

$$Low_{i,c,t-1} = \min(0.2, Rank_{i,c,t-1})$$

$$Mid_{i,c,t-1} = \min(0.6, Rank - Low_{i,c,t-1})$$

$$High_{i,c,t-1} = Rank - (Low_{i,c,t-1} + Mid_{i,c,t-1}). \quad (2)$$

We pool the data across countries and regress quarterly fund flows on piecewise past performance as well as control variables. We could use the Fama–Macbeth approach to run our regressions but we are prevented from doing so as we only have 28 countries in our dataset. We use weighted least squares, weighting each fund by the inverse of the number of funds in that country-quarter. This is to avoid giving excessive weight to countries in

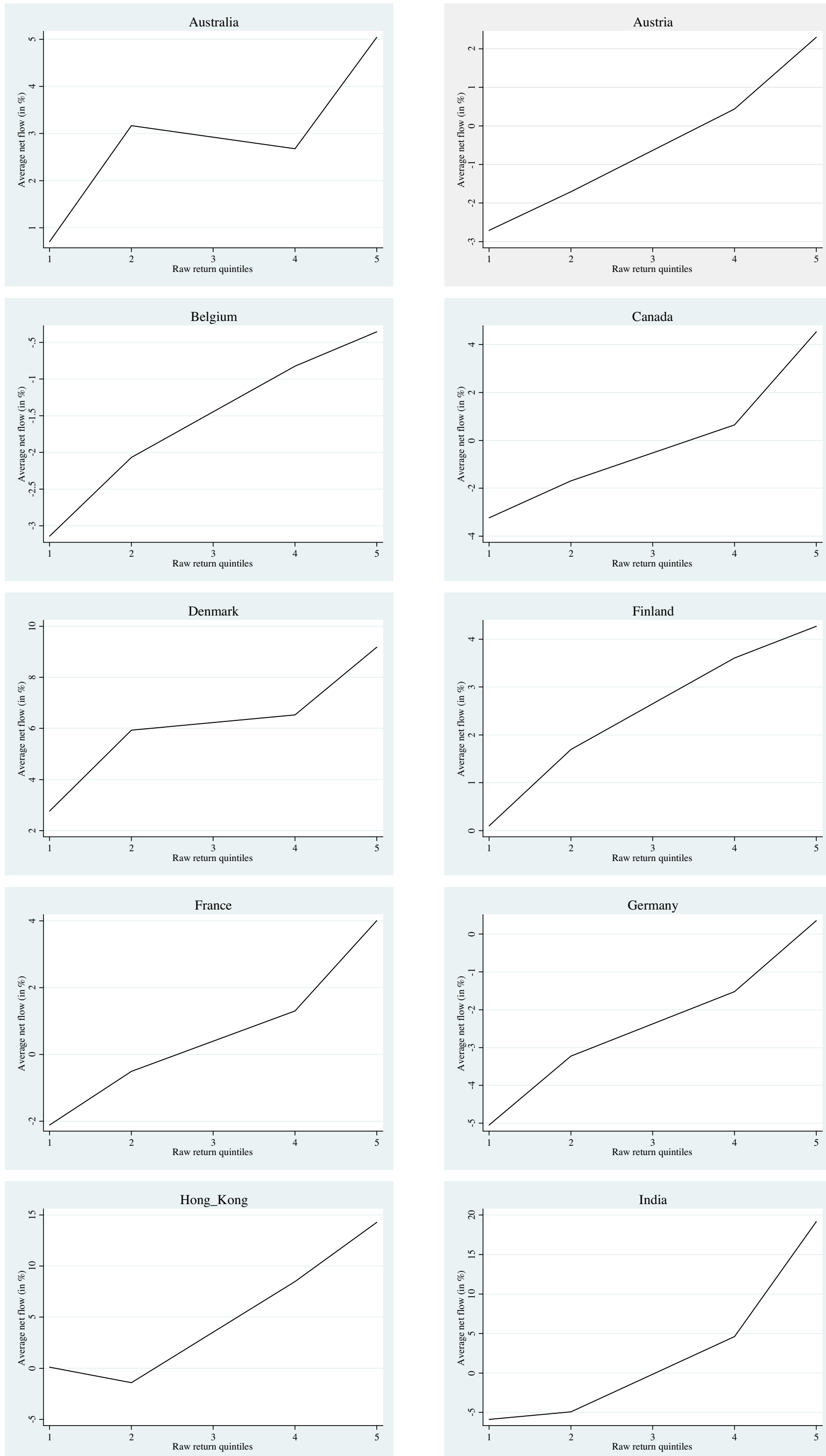

Fig. 1. Flows by raw return quintile by country. This figure presents average quarterly net flows by country by raw return quintile. We first rank funds by average quarterly raw return quintile over the previous four quarters. For each quintile we plot the average net flow.

our sample that have a greater fraction of the number of funds, such as the US, and also to avoid giving greater weight to the latter part of the sample when there are more funds.[13] By comparing the slope of the flow-performance function in the *Low* region with the slope in the *High* region we can examine whether there is convexity in the flow-performance relationship in aggregate for all countries.

The regression results with country and time fixed effects and standard errors adjusted for clustering by fund are presented in Table 5 for the three different performance measures (raw returns, one-factor alpha, and four-factor alpha). To test for convexity, we conduct a Wald test to see whether there is a significant difference in the slope of the flow-performance function between the *Low* and the *High* regions.

[13] We obtain similar findings using ordinary least squares as well. These results are available in the Web Appendix.

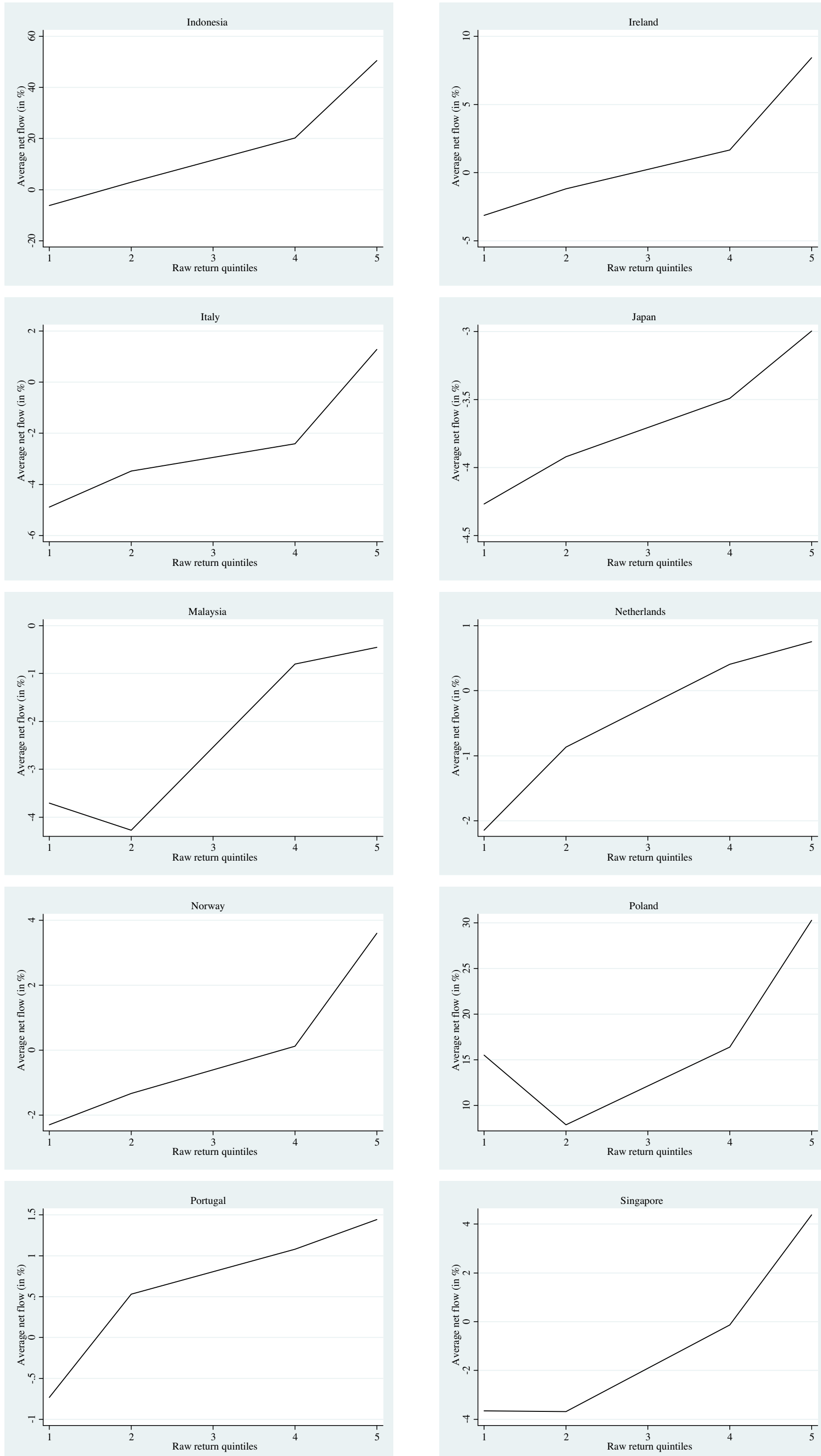

Fig. 1 (*continued*)

Table 5 indicates that whatever performance measure we use and whatever specification we choose, there is statistically significant convexity in the flow-performance relationship for our worldwide sample of funds. The level of convexity is also economically significant. For example, using the *High* coefficient in column (9) of Table 5, an improvement in performance ranking in a given quarter from the 80th percentile to the 90th percentile is associated with an increase in fund flows of 3% (=0.3 $\times$ 0.1).

Regarding the coefficients of the control variables, we find that larger and older funds get less flow consistent with Chevalier and Ellison (1997) and Sirri and Tufano (1998). Interestingly, we find that international funds receive more money and that the number of countries that a fund is distributed in also enhances its flows. To control for autocorrelation in fund flows, we include lagged flows in columns (3), (7), and (11), and, like Cashman et al. (2007), we find that this variable enhances explanatory power. In columns

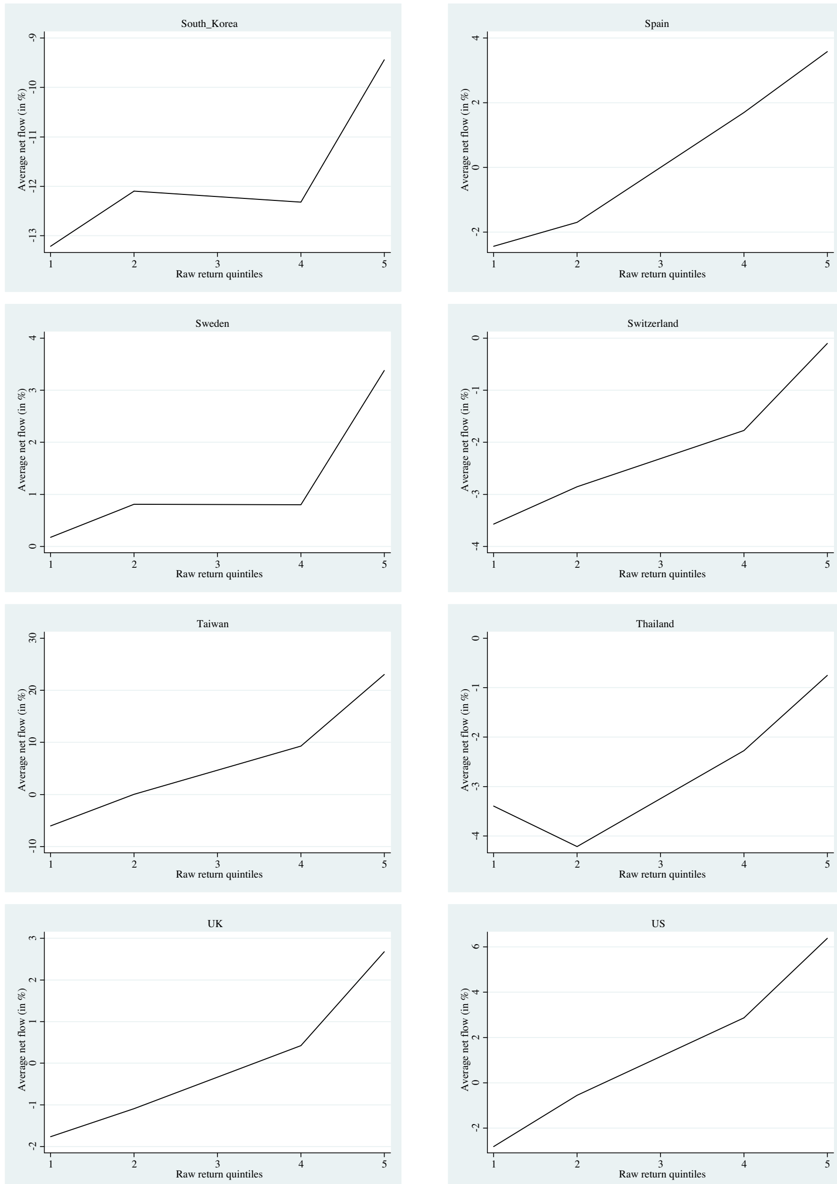

Fig. 1 (*continued*)

(4), (8), and (12), we add fund-level SMB and HML loadings plus average country flows as control variables. In these specifications we do not include country fixed effects because of the overlap with average country flows. The inclusion of these variables does not substantially change our results. Funds that overweight large and value stocks obtain more flows over the sample period. In addition, higher average country flows is associated with higher fund level flow, which can be explained by a spillover effect from the country to the funds located on that country.

3.2. Measuring individual country convexity

We find that the flow-performance relationship is non-linear for our worldwide sample of mutual funds when we do not allow for differential performance sensitivities by country. To examine whether there are differences in the way that investors from different countries respond to funds that do well and those that do poorly we do the following. For each country in the sample, we sort funds into quintiles each quarter on the basis of their raw return performance in the past year and we calculate the average fund flow by quintile.

Fig. 1 plots average fund flow by performance quintile for each country in our dataset. The graphs show how fund performance ranks are related to percentage fund flow. As the range of fund flow is different across countries, we customize the scales for each country. Our graphs join together performance and flow data points relating to quintiles 1–2, 2–4, and 4–5, so that our graphs have three pieces and are therefore comparable with the previous literature which characterizes the flow-performance function by a bottom, middle, and top section (e.g., Gruber, 1996; Sirri and Tufano, 1998; Huang et al., 2007).

The US flow-performance relationship has been shown to be performance-sensitive at the bottom, flat in the middle, and the most sensitive at the top. If we examine the behavior of flows across performance quintiles, it is evident that most countries have three pieces in their relationship. Interestingly, however several countries have two pieces, including Austria, Hong Kong, Indonesia, Portugal, Spain, and the UK. This preliminary evidence suggests that there are clear differences in the flow-performance relationship across countries.

We next estimate the flow-performance relationship for each individual country in the sample using weighted least squares regression. Specifically, we regress fund flows on piecewise past performance, but we now allow coefficients on past performance to vary by country by interacting country dummies with *High* and *Low*. Regressions include the same control variables as in column (4) of Table 5, and we also allow coefficients on control variables to vary by country. We also include time fixed effects and the standard errors are adjusted for clustering by fund. For brevity purposes, we limit our focus to *Low* (the flow-performance slope for the bottom quintile of funds) and *High* (the flow-performance slope for the top quintile of funds) past performance variables only.

Table 6 presents the results. The table is divided into three parts depending on whether past performance is measured using raw returns, Jensen's alpha, or four-factor alpha. As the results are similar for the three measures of performance, we discuss only the four-factor alpha case here. The pairs of columns present the difference between *High* and *Low* coefficients for each country and the results of a Wald test used to determine whether the sensitivity of flow to past performance of a country is significantly different for *Low* and *High* performance levels.

There are nine countries in our sample with statistically significant convexity (plus the US), and all these countries display greater convexity than the US In addition, there is wide variation in convexity levels across countries, as is evident from the *High–Low* column. To confirm the existence of variation in convexity across countries we test the hypothesis that convexity is equal across countries using an *F*-test and we find that this hypothesis is strongly rejected. Our analysis highlights marked differences in the behavior of fund flows across countries and furthermore that fund flows in many countries do not behave like US flows.

Table 6 shows that individual country convexity is in certain cases insignificant particularly for less developed countries. Fewer observations and more noisy flows may explain this lack of significance. Grouping countries together allows us to overcome this problem. When we do so, we find that convexity is statistically significant for all countries together and is also present for more developed and less developed countries when we partition the sample by median GDP per capita. Grouping countries together in this manner also provides an initial indication of how convexity varies with development. The results presented at the bottom of Table 6 show that convexity in less developed countries is three times greater than in more developed countries and that the difference between these two groups is statistically significant.

In unreported results, we also look at fund flow sensitivities to top and bottom performance separately and find considerable variation in the magnitude of these variables across countries. Overall our results indicate that there are substantial variations in the flow-performance relationship across countries and this variation seems to be related with development. We will further explore the relation with development in the next section.

4. Explaining the flow-performance relationship across countries

How much can we explain differences in flow-performance sensitivity across countries? We expect differences in investor sophistication and participation costs across countries to manifest themselves in differences in flow-performance sensitivity. The literature that relates to the US along with our Table 4 suggest that not chasing winners but selling losers is a "sophisticated" thing to do as performance persists for poor performers but not for top performers. Accordingly, we expect investor sophistication to be negatively correlated with convexity. Additionally, the higher the costs of participating in the mutual fund industry are, the higher the rate of return a fund must earn before seeing a large number of investors switching into the fund (Huang et al., 2007).[14] Thus, fund industries with higher participation costs are expected to exhibit a more convex flow-performance relationship at the upper end of the performance scale.

We therefore use two types of variables to explain convexity. The first type is based on proxies for investor sophistication, and the second type is based on proxies for participation costs. Variables in both categories are drawn from three indicators of development in a country, namely, economic development, financial development, and mutual fund industry development. As certain variables proxy for both investor sophistication and participation costs, we group variables according to the development characteristics.

We proxy for economic development using three variables: GDP per capita (GDPC); education measured as average number of years of education (averaged for men and women); and percentage of population that uses the internet. These variables are obtained from the World Development Indicators (WDI) database. We expect investor sophistication to increase with economic development, and therefore to increase not only with a general proxy for development such as GDP per capita but also with specific indicators of development such as education and internet usage. Incidentally, internet usage could also proxy for participation costs as greater internet use is likely to lower the informational participation costs of investing in mutual funds.

We measure financial market development using three proxies for investor sophistication and a proxy for participation costs. To measure investor sophistication, we use a dummy variable that equals one if the country is considered an emerging market country (following the MSCI Barra criteria), stock market trading costs, as we expect these costs to be lower in more financially developed countries, and the percentage of population owning shares. Stock market trading costs are given by the annual average transaction cost in basis points (including commissions, fees, and price impact) from the Global Universe Data-ElkinsMcSherry database. Data on the percentage of population owning shares are from Grout et al. (2009).[15]

We use quality of the judicial system variable to measure the level of investor protection to capture participation costs faced by mutual fund investors. La Porta et al. (1997) show that investor protection is a major determinant of a country's financial development. The quality of judicial system is measured as the sum of five variables from La Porta et al. (1998): (1) efficiency of the judicial system; (2) rule of law; (3) corruption, (4) risk of expropriation; and (5) risk of contract repudiation. We treat this investor protection variable as a measure of participation costs, as we would expect investors in environments with less protection to require quite high levels of performance to induce them to invest in financial instruments such as mutual funds. Khorana et al. (2005) show that mutual fund industries prosper in stronger legal environments, which is consistent with the idea that mutual fund investors are sensitive to the level of investor protection provided them. As this variable displays little variation across most

[14] It is possible to translate these ideas from the fund level to the country level as follows. Suppose funds in country B have double the participation costs of funds in country A (individual funds in each country will naturally have participation costs distributed around this average). Funds in country B will have more convexity in their individual flow-performance relationships on average, and as the aggregate flow-performance relationship in each country is composed of the individual fund level flow-performance relationships, we would expect greater convexity in the aggregate flow-performance relationship for country B than country A.

[15] Data for Indonesia is from Indonesia Central Securities Depository (KSEI) 2011.

Table 6
Convexity by country.

	Raw returns High-Low		One-factor alpha High-Low		Four-factor alpha High-Low	
	Coeff	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value
Australia	0.095	0.577	−0.090	0.581	0.025	0.864
Austria	0.131	0.240	0.001	0.992	0.149	0.154
Belgium	−0.125*	0.074	−0.093	0.228	−0.030	0.705
Canada	0.207***	0.000	0.191***	0.000	0.191***	0.000
Denmark	0.249	0.281	0.263	0.331	0.285	0.236
Finland	0.019	0.910	−0.119	0.337	0.046	0.774
France	0.048	0.183	0.025	0.503	0.028	0.403
Germany	0.009	0.863	0.024	0.646	−0.037	0.466
Hong Kong	0.701	0.283	0.522	0.389	0.255	0.654
India	1.480***	0.000	1.662***	0.000	1.586***	0.000
Indonesia	1.426	0.241	1.430*	0.090	1.188	0.300
Ireland	0.277	0.186	0.095	0.673	0.088	0.714
Italy	0.149**	0.007	0.098*	0.068	0.068	0.171
Japan	0.043	0.139	0.057*	0.055	0.032	0.324
Malaysia	−0.025	0.695	0.011	0.881	−0.010	0.894
Netherlands	−0.140**	0.006	−0.085	0.124	−0.051	0.360
Norway	0.065	0.566	0.225	0.118	0.223**	0.039
Poland	0.826	0.338	0.007	0.994	−0.238	0.647
Portugal	−0.093	0.555	−0.024	0.890	−0.151	0.374
Singapore	0.342***	0.000	0.242**	0.003	0.276**	0.001
South Korea	0.133	0.292	0.091	0.448	0.025	0.827
Spain	0.149*	0.052	0.194**	0.011	0.258**	0.001
Sweden	0.174**	0.002	0.168**	0.005	0.236**	0.001
Switzerland	0.029	0.713	−0.027	0.736	−0.056	0.424
Taiwan	0.742**	0.029	1.113**	0.001	1.102**	0.001
Thailand	0.167*	0.071	0.224**	0.009	0.177**	0.015
UK	0.109**	0.028	0.110**	0.025	0.132**	0.007
US	0.064**	0.004	0.101***	0.000	0.076**	0.001
All countries	0.259	0.000	0.229	0.000	0.208	0.000
More developed	0.133	0.000	0.090	0.001	0.111	0.006
Less developed	0.385	0.000	0.367	0.000	0.306	0.000
Difference (*p*-value)	0.029		0.009		0.045	

This table presents convexity measured as the difference between *High* and *Low* coefficients estimated using panel regressions across 28 countries. Weighted least squares is used where each fund is weighted by the inverse of the number of funds in each country-quarter together with time fixed effects. A piecewise linear regression is used to define three linear segments in the flow-performance relationship. In each quarter, by country, fractional performance ranks ranging from zero to one is assigned to funds according to their average raw returns in the past four quarters, one-factor alpha and four-factor alpha. This procedure designates three performance variables: $Low_{i,c,t-1} = min(0.2, Rank_{i,c,t-1})$, $Mid_{i,c,t-1} = min(0.6, Rank - Low_{i,c,t-1})$, and $High_{i,c,t-1} = Rank - (Low_{i,c,t-1} + Mid_{i,c,t-1})$. Control variables are the same as in column (4) of Table 5. The *p*-value column presents Wald tests of the difference between *High* and *Low* coefficients by country. More developed countries are those with above median GDP per capita and less developed countries are those with below median GDP per capita both at the end of the period. Difference (*p*-value) is the Wald test of the difference in convexity between more developed and less developed countries.
* 10% significance level.
** 5% significance level.
*** 1% significance level.

countries, we use a dummy variable approach instead of using the raw variable itself. We set the dummy variable for judicial system equal to one if a particular country's judicial system offers greater investor protection than the median country.

We proxy for mutual fund industry development using the age of the mutual fund industry, the ratio of the size of the mutual fund industry (from ICI) relative to the size of the economy (as measured by GDP from WDI), and the average transaction costs incurred in buying and selling mutual funds. We expect investor sophistication to increase with the span of time that investors have had to invest in mutual funds and with the mutual fund industry size relative to the size of the economy. We gather data on the start year of the mutual fund industry in each country in our sample from Khorana et al. (2005) and use that to calculate fund industry age. Industry age and the ratio of industry size to GDP might be expected to affect investor sophistication at the early stages of fund industry development but once a critical industry age or size threshold is reached their impact is likely to weaken. To allow for this, we include dummy variables for industry age and the ratio of industry size to GDP that take the value of one if they are above median levels in each quarter.

Transaction costs capture the effect of the costs of participating in the mutual fund industry (at the country level) on the observed flow sensitivity to performance. Huang et al. (2007) investigate whether transaction costs affect the flow-performance relationship by testing whether class C mutual fund shares display less convexity than other classes of mutual fund shares. Across the three main share classes, class C shares are viewed as having lower transaction costs (either buying or selling) because they have no front-end load (in contrast to class A shares) and have a short-lived back-end load (in contrast to class B shares). As share classes are likely to be different across countries, we take a more direct approach to measuring the costs of trading mutual fund shares at the country level by summing front and back-end loads by fund and then averaging these across funds within a country.

Table 7 presents average statistics of the development indicators that we use to explain flow-performance sensitivities by country. As GDP per capita (GDPC) is often viewed as the most fundamental indicator of development, we classify countries as more developed if they have GDPC above the median and as less developed if they have GDPC below the median (at the end of the period). We report the averages of country variables for each

Table 7
Country variables. This table presents country variables averaged across time by country for the period 2001–2007, including economic development variables, financial market development variables, and mutual fund industry development variables. Economic development variables include: the gross domestic product per capita in US dollars (*GDP per capita*); the average number of years in school (*Education*); and the percentage of population that uses the internet (*Internet*). Financial market development variables include: a dummy variable that equals one if the country is an emerging market (*Emerging market dummy*) as defined by MSCI Barra, stock market trading costs (*Trading costs*) given by the annual average stock market transaction cost in basis points; the quality of the judicial system (*Judicial system*), calculated by the sum of five variables: (1) efficiency of judicial system; (2) rule of law; (3) corruption; (4) risk of expropriation; and (5) risk of contract repudiation; and the percentage of population owning shares. Mutual fund industry development variables include: the age of the mutual fund industry (*Mutual fund industry age*); the mutual fund industry size as a percentage of the country's gross domestic product (*Mutual fund industry size/GDP*); and the level of mutual fund transaction costs, calculated as the average of the sum of front-end and back-end loads (*Mutual fund transaction costs*). More developed countries are those with above median GDP per capita and less developed countries are those with below median GDP per capita both at the end of the period.

Country	Economic development			Financial market development				Mutual fund industry		
	GDP per capita ($)	Education (%)	Internet (%)	Emerging market dummy	Trading costs (basis points)	Judicial system	Population owning shares (%)	Mutual fund industry age	Mutual fund industry size/ GDP (%)	Mutual fund transaction costs (%)
Australia	34,671	17.00	69.77	0	32.25	46.50	35.11	42	126.63	2.12
Austria	34,289	15.00	47.23	0	30.38	47.36	7.11	51	38.74	4.53
Belgium	32,050	16.00	41.31	0	29.88	47.43	17.30	60	33.68	2.64
Canada	34,877	14.50	53.99	0	32.33	47.88	37.52	75	46.50	4.91
Denmark	34,373	15.50	50.30	0	34.04	48.98	23.50	45	39.68	2.82
Finland	33,369	16.50	52.01	0	42.34	48.82	14.50	20	28.33	2.07
France	29,871	15.50	38.09	0	27.73	44.87	14.70	43	73.25	3.18
Germany	29,173	15.00	41.43	0	26.84	46.83	12.50	58	12.04	4.38
Hong Kong	41,614	11.00	50.78	0	41.71	43.85	22.98	47	232.50	3.65
India	3499	11.00	4.33	1	65.48	30.61	2.00	43	1.16	2.71
Indonesia	4200	9.50	6.95	1	71.46	21.88	0.15	11	1.10	3.01
Ireland	43,091	14.50	28.21	0	84.60	35.18	7.52	34	351.27	4.91
Italy	28,738	15.00	42.68	0	31.79	39.73	7.98	24	27.00	3.23
Japan	30,214	14.00	56.14	0	20.78	46.86	30.75	42	11.38	2.36
Malaysia	10,941	12.00	39.98	1	56.00	38.54	39.20	48	12.26	6.40
Netherlands	33,580	16.00	65.09	0	27.71	49.33	17.05	78	18.21	1.75
Norway	41,456	17.00	56.14	0	32.35	49.59	7.30	14	19.16	3.01
Poland	14,103	14.50	25.14	1			2.70	15	3.51	4.63
Portugal	21,352	15.50	26.68	0	33.05	39.03	3.07	21	12.81	2.24
Singapore	29,675	16.00	55.27	0	40.26	44.95	11.97	48	238.25	4.69
South Korea	21,786	15.00	65.14	1	56.32	33.55	9.30	38	18.09	0.04
Spain	26,593	15.50	30.32	0	31.58	39.35	5.00	49	26.51	0.92
Sweden	31,818	16.00	69.66	0	30.97	48.98	19.70	49	41.17	0.63
Switzerland	35,579	15.50	46.41	0	29.91	49.96	20.22	69	43.51	4.88
Taiwan	31,723	11.00 .		1	47.86	40.40	34.78	23	8.83	2.73
Thailand	8360	11.00	10.01	1	59.47	29.67	5.30	12	3.62	1.23
UK	32,753	16.50	44.67	0	50.85	47.01	15.09	73	27.53	4.31
US	40,144	16.00	59.51	0	24.41	47.61	21.20	83	72.01	2.56
All countries	33,328	15.45	50.68		31.53	45.79	19.19	43	50.09	3.02
More developed	36,839	15.81	54.70		31.01	47.61	37.52	71	56.00	2.81
Less developed	27,409	14.84	43.78		32.41	42.70	16.19	41	39.77	3.14
Difference (*p*-value)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Emerging	15,780	12.74	38.61		57.40	34.07	15.64	32	10.81	2.97
Non-emerging	34,410	15.62	51.34		29.99	46.49	19.41	60	52.39	3.12
Difference (*p*-value)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

development group at the bottom of Table 7 and *p*-values of a test of whether the country variable concerned is significantly different for more and less developed countries. More developed countries have higher levels of economic, financial markets and mutual fund industry development indicators across all proxies.[16]

Fig. 2 graphs the potential of these variables to explain the relationship between flows and past performance. We sort our countries on the basis of each proxy for investor sophistication and participation costs. We then plot the flow-performance relationship for the top five and bottom five countries sorted by each of these variables. Panel A is based on economic development, Panel B is based on financial market development, and Panel C is based on mutual fund industry development.

When our country variables proxy for investor sophistication, we expect countries with higher sophistication to be less sensitive to top performance and more sensitive to poor performance. For all the economic development variables and all the financial market and mutual fund industry development variables that proxy for investor sophistication, the flow-performance relationship is affected in exactly the way hypothesized.

When our country variables proxy for participation costs (judicial system quality and transaction costs), we expect countries with higher participation costs have higher convexity at the top of the flow-performance relationship. We do find that countries with higher participation costs in the form of higher mutual fund transaction costs have greater convexity at the top of their flow-performance relationship, confirming our predictions. This is due primarily to the effect of higher transaction costs on the slope of the high section of the flow-performance relationship. We also find some evidence that investor protection affects convexity due to its impact on the middle and top sections of the flow-performance relationship.

[16] We also conduct similar tests partitioning countries depending on whether they are emerging market countries or not based on the MSCI BARRA classification. We find in virtually all cases that countries that are classified as emerging markets score lower, on average, in terms of the country development proxies.

Panel A – Economic development variables

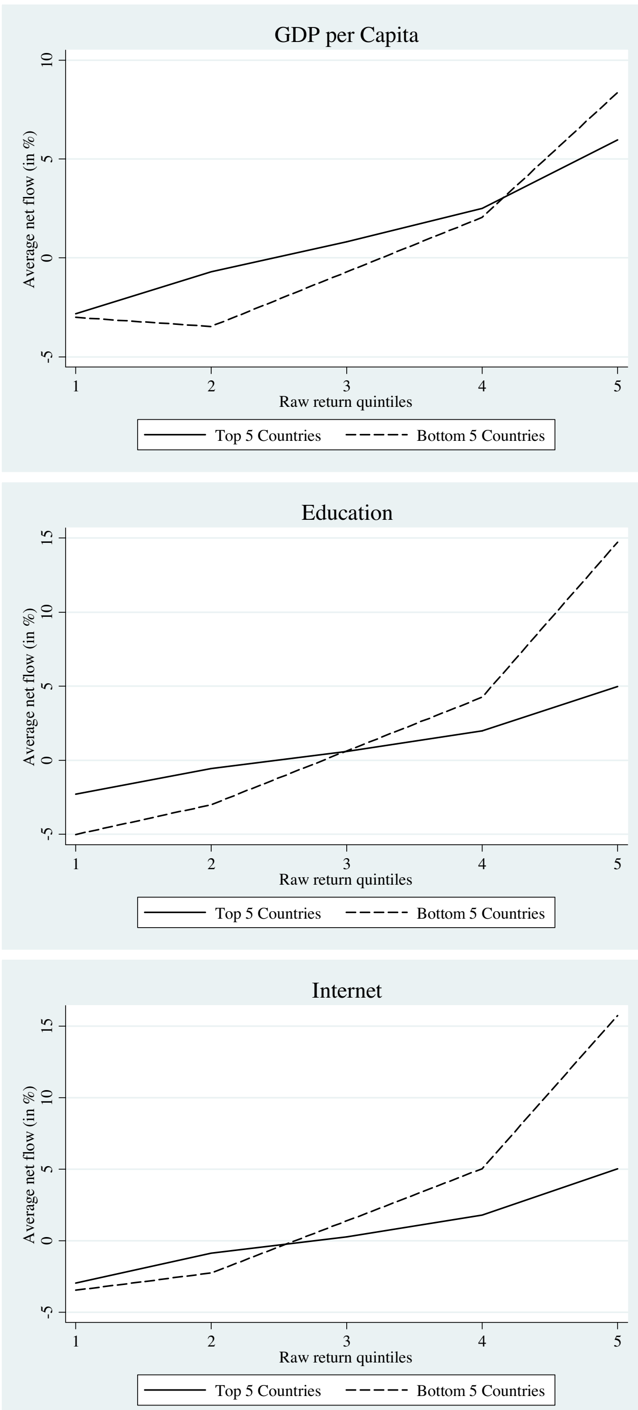

Fig. 2. The flow-performance relationship based on sorts by country-level variables. This figure presents quarterly net flows by past year raw return quintile averaged across top and bottom five countries based on country variables sorts. Panel A uses economic development variables, Panel B uses financial market development variables, and Panel C uses mutual fund industry development variables. In the case of the emerging dummy market variable, we average across all emerging market countries and non-emerging market countries. In the case of the judicial system, mutual fund industry age, and mutual fund industry size as a percentage of GDP dummies our graphs depict the flow-performance relationship for the top half and the bottom half of countries ranked by these variables.

Panel B – Financial market development variables.

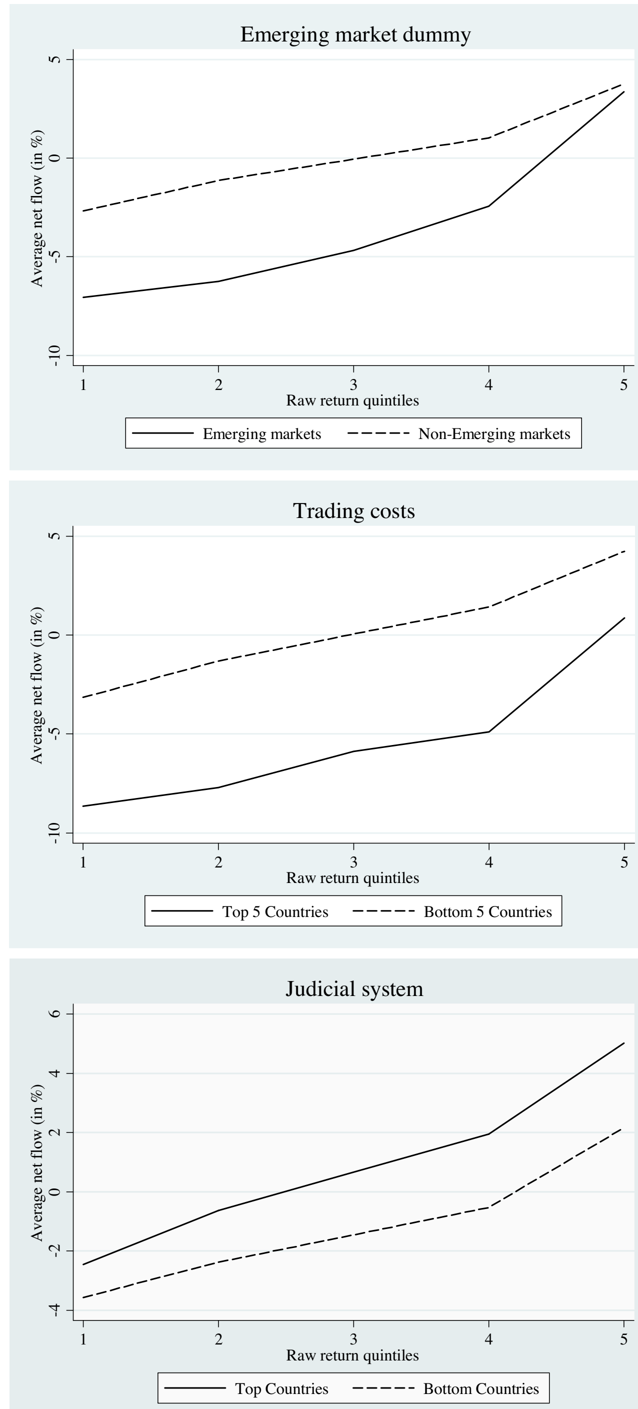

Fig. 2 (*continued*)

To estimate the contribution of these country-level variables to flow-performance sensitivity more precisely while controlling for the determinants of fund flows, we regress flows for all funds on piecewise lagged performance interacted with the proxies for investor sophistication and participation costs. We use weighted least squares, weighting each fund observation by the inverse of the number of funds in each country-quarter as before. Regressions also include the same set of control variables as in column (4) of Table 5 (for brevity coefficients are omitted).

Panel C – Mutual fund industry development variables.

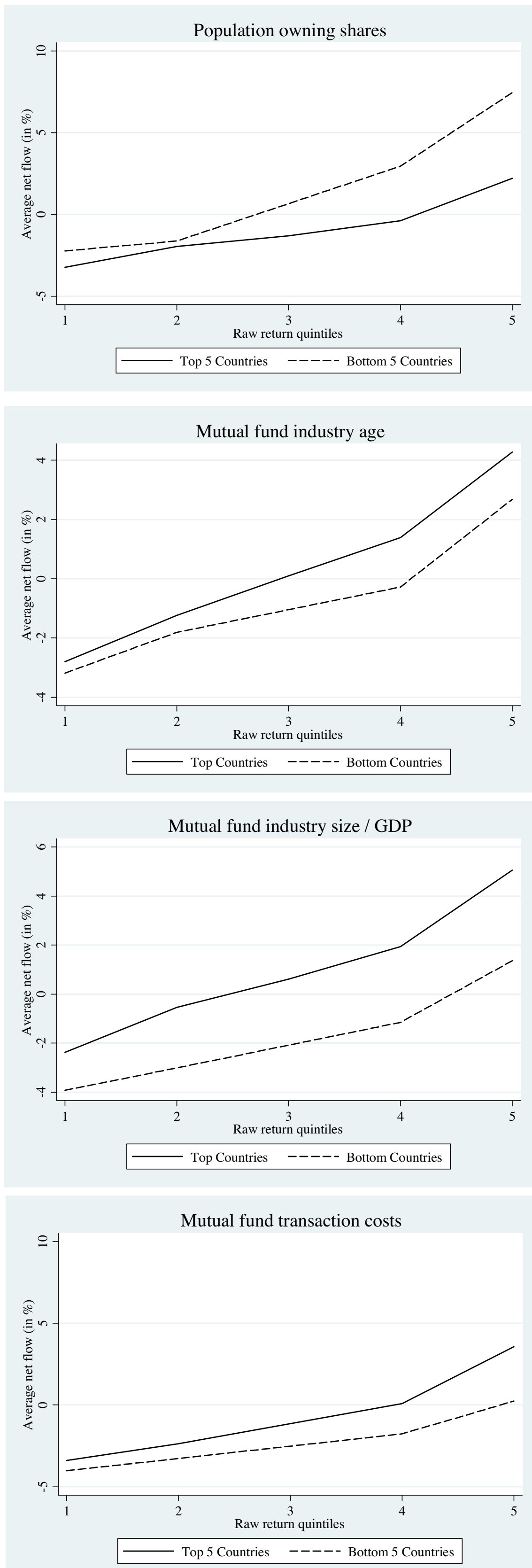

Fig. 2 (*continued*)

In each regression we also include the country-level variables that we are using to explain flow-performance sensitivity. This is to ensure that our estimates of the role of these variables in determining flow sensitivity are not driven by their contribution to the level of flows in the country concerned. Tables 8–10 present the results of the regressions using proxies for economic development, financial market development, and mutual fund industry development to explain flow-performance sensitivity.

We use GDP per capita, level of education and internet usage to capture investor sophistication. Internet usage could also proxy for participation costs. Results in Table 8 show that investors chase winners less intensely in countries with higher GDP per capita and higher education. GDP per capita also increases the sensitivity of fund flows to poor performance. Interestingly, internet usage reduces the sensitivity of flows to high performance and increases the sensitivity to middle-range performance, but does not make a significant contribution to the flow-performance relationship in the low range. The internet usage variable thus behaves more like a proxy for investor participation costs than a proxy for investor sophistication.

Table 9 provides the regression results for financial market development variables. With a stronger judicial system, participation costs fall, which should increase the slope of the middle section and reduce the slope of the high section of the flow-performance relationship of countries. The results for this variable are consistent with our expectations. Emerging market dummy, the percentage of population owning shares, and trading costs proxy for investor sophistication, and thereby they should affect the sensitivity of flow to low and high performance. When we look at whether these variables influence convexity, they do so but only via their impact on the sensitivity of fund flows to high performance. This is consistent with a number of papers that show that it is more difficult to explain the flow-performance relationship for outflows than it is for inflows (Bergstresser and Poterba, 2002; Johnson, 2007; Ivkovic and Weisbenner, 2009). In addition, prior studies across investors with different levels of sophistication (James and Karceski, 2006) find that retail fund investors chase good performance significantly more than institutional fund investors, while there is no difference between these two types of investors at the bottom of the flow-performance relationship suggesting that investor sophistication does not drive selling behavior.

Table 10 presents the results for the mutual fund industry development variables. Our hypothesis is that the more developed the fund industry in a country is, the more financially sophisticated its mutual fund investors are, and the lower is the level of participation costs they face.

We begin by considering the two variables that measure investor sophistication. When we look at mutual fund industry age using a dummy for above-median age, we find robust evidence that investors in countries with older mutual fund industries buy winners less and sell losers more readily. Similarly, we find that investors from countries with larger mutual fund sectors (relative to the size of their economy) sell losers much more vigorously, and chase winners less. When we use actual industry age and the ratio of industry size to GDP, rather than dummy variables, in the flow-performance regressions we obtain similar results although statistical significance is weaker in the lower region of the flow-performance relationship, which may be due to the non-linear relationship between these variables and flows.

As countries develop, the cohort of mutual fund investors may widen and reduce the average level of investor sophistication. This may limit the positive impact of mutual fund industry development on sophistication. To investigate this possibility, we test

Table 8
The determinants of flow-performance sensitivity: economic development.

	Raw returns			One-factor alpha			Four-factor alpha		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low $t-1$	−0.927	−0.523	−0.187	0.102	0.433	0.205	0.674	0.817	0.260
	(−1.32)	(−0.77)	(−0.92)	(0.16)	(0.63)	(1.02)	(0.81)	(0.85)	(1.05)
Low $t-1$ × log GDPC $t-1$	0.012**			0.010*			0.014***		
	(2.50)			(1.67)			(2.73)		
Low $t-1$ × log Education $t-1$		0.211			−0.124			−0.275	
		(0.85)			(−0.49)			(−0.78)	
Low $t-1$ × log Internet $t-1$			0.063			−0.030			−0.051
			(1.21)			(−0.58)			(−0.79)
Mid $t-1$	0.808***	1.004***	0.296***	0.514**	0.698**	0.172**	0.505**	0.707**	0.193**
	(3.01)	(3.10)	(3.52)	(2.22)	(2.57)	(2.33)	(2.09)	(2.47)	(2.57)
Mid $t-1$ × log GDPC $t-1$	−0.074***			−0.047**			−0.046**		
	(−2.84)			(−2.08)			(−1.96)		
Mid $t-1$ × log Education $t-1$		−0.351***			−0.244**			−0.247**	
		(−2.96)			(−2.45)			(−2.36)	
Mid $t-1$ × log Internet $t-1$			0.066***			0.036*			0.043**
			(3.01)			(1.89)			(2.18)
High $t-1$	3.787**	4.297**	1.403***	5.063***	5.558***	1.909***	4.576***	5.238***	1.692***
	(2.44)	(2.31)	(2.85)	(3.52)	(3.58)	(3.61)	(2.66)	(2.61)	(2.86)
High $t-1$ × log GDPC $t-1$	−0.351**			−0.473***			−0.430**		
	(−2.33)			(−3.38)			(−2.57)		
High $t-1$ × log Education $t-1$		−1.504**			−1.955***			−1.856**	
		(−2.21)			(−3.44)			(−2.52)	
High $t-1$ × log Internet $t-1$			−0.325**			−0.453***			−0.407***
			(−2.51)			(−3.25)			(−2.61)
Log GDPC $t-1$	0.007			0.019*			0.029**		
	(0.64)			(1.89)			(2.20)		
Log Education $t-1$		0.092**			0.129***			0.155***	
		(2.41)			(3.33)			(2.80)	
Log Internet $t-1$			0.011			0.022***			0.026***
			(1.35)			(2.68)			(2.60)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.084	0.084	0.085	0.085	0.084	0.086	0.081	0.082	0.083
Number of observations	213,351	213,351	212,090	213,351	213,351	212,090	213,351	213,351	212,090

This table presents the results of panel regressions of individual fund flows on lagged performance and lagged performance interacted with a set of country level variables using a sample of 28 countries. Weighted least squares regression is used where each fund is weighted by the inverse of the number of funds in each country-quarter. The dependent variable is fund *flows* and the independent variables are piecewise lagged performance, control variables, lagged piecewise performance interacted with economic development variables. A piecewise linear regression is used to define three linear segments in the flow-performance relationship. In each quarter, by country, fractional performance ranks ranging from zero to one are assigned to funds according to their average raw returns in the past four quarters, one-factor alpha and four-factor alpha. This procedure uses three performance variables: $Low_{i,c,t-1} = min(0.2, Rank_{i,c,t-1})$, $Mid_{i,c,t-1} = min(0.6, Rank - Low_{i,c,t-1})$, and $High_{i,c,t-1} = Rank - (Low_{i,c,t-1} + Mid_{i,c,t-1})$. Control variables are the same as in column (4) of Table 5 (coefficients not reported). Proxies for economic development include the natural log of gross domestic product per capita in US dollars lagged by one quarter ($Log\ GDPC_{t-1}$); the natural log of the number of years of education (averaged for men and women) lagged by one quarter ($Log\ Education_{t-1}$); and the natural log of the percentage of population that use the internet lagged by one quarter ($Log\ Internet_{t-1}$). Robust t-statistics clustered by fund are reported in parentheses.
* 10% significance level.
** 5% significance level.
*** 1% significance level.

whether mutual fund investors from less developed countries are better able to predict future fund performance than investors from more developed countries; i.e., we compare the magnitude of the "smart" money effect for these two groups of countries.[17] To do so, we run a regression of fund performance on lagged flows separately for more and less developed countries. Of course, the relation between fund performance and lagged flows may be affected by fund size and industry size. Our regressions therefore control for fund size (and all other fund characteristics in column (4) of Table 5) and country fixed effects (and time fixed effects). In unreported tests, we find no evidence that mutual investors are "smarter" in less developed countries than in more developed countries when we classify countries based on the median GDP per capita or the emerging market dummy.

Table 10 also presents the results for mutual fund transaction costs, with the aim of measuring participation costs. As these costs affect the top of the flow-performance relationship alone, our focus is on its impact on the slopes of the middle and top sections of the flow-performance relationship. As conjectured, we do find evidence that the costs of buying and selling funds reduce sensitivity to mid-range performance and increase sensitivity to top performance.

In more developed fund industries we expect that a greater number of funds is available to investors. It might be argued that this could make the informational participation costs of investing in mutual funds actually greater in more developed countries. Carlin and Manso (2011) develop a model demonstrating that the number of funds offerings may reduce the ability of investors to process information and make good fund selection decisions even if they are sophisticated. In order to investigate this further we include the number of funds in each country as a mutual fund industry development variable by interacting it with past fund performance. If these information processing costs behave like a participation cost we would expect the number of funds to decrease the slope of the flow-performance relationship in its middle section and increase its slope in its top section. In unreported tests, we do not find evidence that the number of funds in a country

[17] As data on mutual fund investor characteristics across countries is unavailable to use, we use this indirect approach to measure investor sophistication.

Table 9
The determinants of flow-performance sensitivity: financial market development.

	Raw returns				One-factor alpha				Four-factor alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Low $t-1$	0.063***	0.176	0.043*	−0.020	0.096***	−0.118	0.112***	0.088	0.051***	−0.256	0.082***	0.064
	(3.51)	(0.76)	(1.67)	(−0.38)	(5.16)	(−0.48)	(4.05)	(1.59)	(2.93)	(−0.86)	(2.64)	(1.02)
Low $t-1$ × Emerging market dummy	−0.098				0.012				0.128			
	(−0.87)				(0.15)				(1.27)			
Low $t-1$ × log Trading costs $t-1$		−0.034				0.058				0.088		
		(−0.51)				(0.82)				(1.02)		
Low $t-1$ × Judicial system			0.022				−0.049				−0.053	
			(0.61)				(−1.28)				(−1.31)	
Low $t-1$ × log Population owning shares				0.033*				0.000				−0.005
				(1.82)				(0.01)				(−0.22)
Mid $t-1$	0.041***	−0.184**	0.067***	0.070***	0.027***	−0.164*	0.041***	0.038**	0.027***	−0.165**	0.045***	0.034**
	(8.59)	(−2.05)	(7.14)	(4.48)	(5.49)	(−1.87)	(4.38)	(2.45)	(6.00)	(−2.00)	(5.13)	(2.18)
Mid $t-1$ × Emerging Market dummy	0.091***				0.077***				0.067**			
	(3.08)				(2.70)				(2.21)			
Mid $t-1$ × log Trading costs $t-1$		0.067**				0.057**				0.056**		
		(2.55)				(2.22)				(2.35)		
Mid $t-1$ × Judicial system			0.026**				0.005				0.017	
			(2.26)				(0.39)				(1.58)	
Mid $t-1$ × log Population owning shares				−0.008				0.001				0.001
				(−1.39)				(0.16)				(0.26)
High $t-1$	0.145***	−1.301***	0.309***	0.395***	0.173***	−1.278**	0.380***	0.535***	0.138***	−1.256**	0.333***	0.507***
	(7.14)	(−2.70)	(5.48)	(4.35)	(7.94)	(−2.21)	(5.06)	(5.29)	(6.01)	(−2.02)	(4.27)	(4.79)
High $t-1$ × Emerging market dummy	0.477***				0.567***				0.489***			
	(2.83)				(3.20)				(2.64)			
High $t-1$ × log Trading costs $t-1$		0.424***				0.430**				0.414**		
		(3.01)				(2.53)				(2.26)		
High $t-1$ × Judicial system			0.179***				−0.242***				−0.211**	
			(−2.83)				(−3.02)				(−2.56)	
High $t-1$ × log Population owning shares				−0.077**				−0.118***				−0.121***
				(−2.46)				(−3.39)				(−3.32)
Emerging market dummy	−0.016				−0.035**				−0.051***			
	(−0.82)				(−2.42)				(−3.16)			
Log Trading costs $t-1$		−0.023**				−0.037***				−0.042***		
		(−2.24)				(−3.46)				(−3.01)		
Judicial system			0.015***				0.022***				0.026***	
			(2.70)				(3.71)				(3.90)	
Log Population owning shares				0.001				0.009				0.004
				(0.13)				(1.12)				(0.48)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.082	0.063	0.061	0.084	0.083	0.063	0.061	0.084	0.080	0.061	0.059	0.081
Number of observations	213,351	212,955	212,955	213,351	213,351	212,955	212,955	213,351	213,351	212,955	212,955	213,351

This table presents the results of panel regressions of individual fund flows on lagged performance and lagged performance interacted with a set of country level variables using a sample of 28 countries. Weighted least squares regression is used where each fund is weighted by the inverse of the number of funds in each country-quarter. The dependent variable is fund *flows* and the independent variables are piecewise lagged performance, control variables, lagged piecewise performance interacted with financial market development variables, and financial market development variables. A piecewise linear regression is used to define three linear segments in the flow-performance relationship. In each quarter, by country, fractional performance ranks ranging from zero to one are assigned to funds according to their average raw returns in the past four quarters, one-factor alpha and four-factor alpha. This procedure designates three performance variables: $Low_{i,c,t-1} = min(0.2, Rank_{i,c,t-1})$, $Mid_{i,c,t-1} = min(0.6, Rank - Low_{i,c,t-1})$, and $High_{i,c,t-1} = Rank - (Low_{i,c,t-1} + Mid_{i,c,t-1})$. Control variables are the same as in column (4) of Table 5 (coefficients not reported). Proxies for financial market development measures include an emerging market dummy (*Emerging market dummy*), that equals one if the country is an emerging country and zero if the country is a developed country, the natural log of the average stock market transaction costs lagged by one quarter (*Log Trading costs*$_{t-1}$); a dummy that takes the value of one for countries with above median quality of the judicial system (*Judicial system*); and the natural log of the percentage of population owning shares (*Log Population owning shares*). Robust t-statistics clustered by fund are reported in parentheses.

* 10% significance level.
** 5% significance level.
*** 1% significance level.

behaves like a participation cost as it does not affect the flow-performance relationship in this manner.

Overall, the shape of the flow-performance relationship around the world does appear to be determined by levels of investor sophistication and participation costs. The flow-performance relationship is more convex in countries with less sophisticated investors and where investors face higher costs of participating in the mutual fund industry.

To measure the economic significance of our results we look at the case of India, a less developed country with a large number of funds. We examine the impact on Indian convexity of bringing the level of sophistication and participation costs of Indian investors to US levels, a more develop country with a large number of funds. To do this, we raise the level of Indian measures of development to the US levels of these variables; the results are presented in Table 11.

As an example, let us consider the case of one particular proxy for investor sophistication, namely GDP per capita. Indian average GDP per capita in Table 7 is $3499. We raise this to the US GDP per capita level given in the same table of $40,144. We then calculate the impact of this on the *Low* flow-performance sensitivity of India (using four-factor alpha as the performance measure) by multiplying the change in the log of GDP per capita with the interaction coefficient between GDP per capita and *Low*. We do the same for *High*, and use these two estimates to calculate the effect of raising Indian GDP per capita to US levels on Indian convexity. In this case, Indian's convexity changes from 1.586 (see *High–Low* of Table 6) to

Table 10
The determinants of flow-performance sensitivity: mutual fund industry development.

	Raw returns			One-factor alpha			Four-factor alpha		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low $t-1$	−0.005	−0.025	0.063	0.054	0.034	0.033	0.032	0.016	0.008
	(−0.13)	(−0.79)	(1.54)	(1.48)	(1.16)	(0.87)	(0.86)	(0.51)	(0.19)
Low $t-1$ × MF industry age $t-1$	0.095^{**}			0.087^{**}			0.080^{**}		
	(2.29)			(2.18)			(1.97)		
Low $t-1$ × MF industry size/GDP $t-1$		0.144^{***}			0.138^{***}			0.119^{***}	
		(4.54)			(4.78)			(3.99)	
Low $t-1$ × MF transaction costs $t-1$			0.020			0.025			0.010
			(1.01)			(1.31)			(0.53)
Mid $t-1$	0.074^{***}	0.073^{***}	0.043^{***}	0.056^{***}	0.052^{***}	0.042^{***}	0.057^{***}	0.051^{***}	0.033^{***}
	(5.46)	(6.13)	(4.22)	(4.16)	(4.38)	(3.89)	(4.15)	(4.19)	(3.22)
Mid $t-1$ × MF industry age $t-1$	-0.031^{**}			-0.029^{**}			-0.033^{**}		
	(−2.15)			(−2.03)			(−2.30)		
Mid $t-1$ × MF industry size/GDP $t-1$		-0.030^{**}			−0.022			-0.023^{*}	
		(−2.18)			(−1.59)			(−1.68)	
Mid $t-1$ × MF transaction costs $t-1$			-0.016^{**}			-0.007^{*}			-0.010^{**}
			(−2.45)			(−1.70)			(−2.09)
High $t-1$	0.360^{***}	0.313^{***}	0.193^{***}	0.413^{***}	0.401^{***}	0.225^{***}	0.326^{***}	0.332^{***}	0.221^{***}
	(4.74)	(4.40)	(3.19)	(4.70)	(4.87)	(3.32)	(3.65)	(3.97)	(3.24)
High $t-1$ × MF industry age $t-1$	-0.227^{***}			-0.240^{***}			-0.165^{*}		
	(−2.89)			(−2.69)			(−1.81)		
High $t-1$ × MF industry size/GDP $t-1$		-0.136^{*}			-0.223^{**}			-0.184^{**}	
		(−1.75)			(−2.56)			(−2.08)	
High $t-1$ × MF transaction costs $t-1$			−0.007			0.020^{*}			0.021^{*}
			(−0.50)			(1.75)			(1.66)
MF industry age $t-1$	0.000			0.000			0.000		
	(0.60)			(0.40)			(0.27)		
MF industry size/GDP $t-1$		0.001^{***}			0.001^{***}			0.001^{***}	
		(3.52)			(3.54)			(2.89)	
MF transaction costs $t-1$			0.003			−0.000			−0.001
			(1.22)			(−0.15)			(−0.42)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.078	0.078	0.078	0.078	0.078	0.078	0.075	0.076	0.075
Number of observations	213,351	213,351	213,351	213,351	213,351	213,351	213,351	213,351	213,351

This table presents the results of panel regressions of individual fund flows on lagged performance and lagged performance interacted with a set of country level variables using a sample of 28 countries. Weighted least squares regression is used where each fund is weighted by the inverse of the number of funds in each country-quarter. The dependent variable is fund *flows* and the independent variables are piecewise lagged performance, control variables, lagged piecewise performance interacted with mutual fund industry development variables, and mutual fund industry development variables. A piecewise linear regression is used to define three linear segments in the flow-performance relationship. In each quarter, by country, fractional performance ranks ranging from zero to one are assigned to funds according to their average raw returns in the past four quarters, one-factor alpha and four-factor alpha. This procedure designates three performance variables: $Low_{i,c,t-1} = min(0.2, Rank_{i,c,t-1})$, $Mid_{i,c,t-1} = min(0.6, Rank - Low_{i,c,t-1})$, and $High_{i,c,t-1} = Rank - (Low_{i,c,t-1} + Mid_{i,c,t-1})$. Control variables are the same as in column (4) of Table 5 (coefficients not reported). Proxies for mutual fund industry development include a dummy that takes the value of one for countries with above median mutual fund industry age (*MF industry age*$_{t-1}$); a dummy that takes the value of one for countries with above median mutual fund industry size as a percentage of GDP (*MF industry size/GDP*$_{t-1}$); and the level of mutual fund transaction costs in each country lagged by one quarter, calculated as the average of the sum of front-end and back-end loads (*MF transaction costs*). Robust t-statistics clustered by fund are reported in parentheses.
* 10% significance level.
** 5% significance level.
*** 1% significance level.

0.503, which represents an economically substantial reduction in convexity of 68%.

We also calculate the impact on Indian convexity of changing other Indian development proxies to US levels. Altering education or internet usage to US levels results in a reduction in convexity of a substantial 44% and 67%, respectively. Making India a non-emerging market country reduces its convexity by 31%, and changing its trading costs to US levels reduces its convexity by 26%. Raising the Indian judicial system to US levels also leads to a reduction in Indian convexity of 17%, while increasing the percentage of Indian population investing in shares decreases its convexity by 18%. Raising Indian mutual fund industry age and its mutual fund industry size as a percentage of GDP above median levels like the US reduces the country's convexity by 15% and 19%, respectively. There is, however, a less marked impact in the case of mutual fund transaction costs.

These are economically sizeable changes in convexity. Overall, it is clear that investor sophistication and participation costs can have a considerable impact on observed convexity levels around the world.

5. Implications of the flow-performance relationship across countries

One might ask whether fund managers respond to different levels of convexity in the flow-performance relationship in their countries. Chevalier and Ellison (1997) show that US fund managers toward the end of a performance evaluation period have an incentive to take additional risk if there is a chance that by doing so they will get to the top of the performance scale. According to their hypothesis, intra-year fund-level risk shifting is affected by the past performance and the level of convexity that the fund faces.[18] What we do examine is whether the general level of risk taking is influenced by the level of convexity in a country.

To test this idea we relate tracking error, a proxy for the level of risk taking by managers of mutual funds, to a lagged measure of country-level convexity. We expect higher fund tracking error in

[18] As we have access to only monthly fund return data, it would be noisy to estimate measures of intra-year risk shifting.

Table 11

The impact of raising Indian sophistication and participation costs to US levels on convexity. This table shows levels of economic development variables, financial market development variables and mutual fund industry development variables for India and the US averaged over 2001–2007. Economic development variables include: the gross domestic product per capita in US dollars (*GDP per capita*); the average number of years in school (*Education*) *and* the percentage of population that uses the internet (*Internet*). Financial market development variables include: a dummy variable that equals one if the country is an emerging market (*Emerging market dummy*) as defined by MSCI Barra; stock market trading costs (*Trading costs*) given by the annual average transaction cost in basis points; the quality of the judicial system (*Judicial system*), calculated by the sum of five variables: (1) efficiency of judicial system; (2) rule of law; (3) corruption; (4) risk of expropriation; and (5) risk of contract repudiation; and the percentage of population owning shares (*Population owning shares*). Mutual fund industry development variables include: the age of the mutual fund industry (*Mutual fund industry age*); the mutual fund industry size as a percentage of the country's gross domestic product (*Mutual fund industry size/GDP*); and the level of mutual fund transaction costs, calculated as the average of the sum of front-end and back-end loads (*Mutual fund transaction costs*). If the variable proxies for development, we multiply the difference between the coefficients on *High* interacted with the development variable concerned and the coefficient on *Low* interacted with the development variable concerned with the difference in the level of that development variable between the US and India. We do likewise if the variable proxies for participation costs except that instead of considering the impact on *Low* we measure the impact on *Mid*. We consider the impact of variables on *High*, *Mid* or *Low* only if the development or participation costs proxy concerned is statistically significant at the 10% level or above for the relevant performance range. We also calculate the percentage impact of these changes on convexity by dividing these changes by the initial level of Indian convexity estimated using four-factor alpha as the performance measure from Table 6.

	Economic development			Financial market development				Mutual fund industry		
	GDP per capita ($)	Education (%)	Internet (%)	Emerging market dummy	Trading costs (basis points)	Judicial system	Population owning shares (%)	Mutual fund industry age	Mutual fund industry size/ GDP (%)	Mutual fund transaction costs (basis points)
US	40,144	16	59.51	Non-emerging	24.41	Top	21.20	Top	Top	2.57
India	3499	11	4.33	Emerging	65.48	Bottom	2.00	Bottom	Bottom	2.71
Difference	36,645	5	55.18		−41.07		19.20			−0.15
Change in convexity (High–Low)	−1.083	−0.695	−1.067	−0.489	−0.408		−0.286	−0.245	−0.303	
Change in convexity (High–Mid)			−1.180			−0.211				−0.004
% Change in convexity (High–Low)	−68.3%	−43.8%	−67.3%	−30.8%	−25.8%		−18.0%	−15.4%	−19.1%	
% Change in convexity (High–Mid)			−97.2%			−17.4%				−0.4%

countries with more convex flow-performance relationships, as fund managers in these countries have more incentive to deviate from the behavior of their peer group in an attempt to ascend the performance scale.

Tracking error is measured as the annualized standard deviation of the difference between the return on a given fund and the domestic market index return over a 12-month window. If the fund is an international fund, we use as a benchmark the value-weighted return on all countries in the fund investment region. To maximize the number of observations available, we measure tracking error using a 12 months window and roll this window forward one quarter at a time.

We test whether tracking error is related to country-level convexity, measured as the difference between *High* and *Low* coefficients from our usual piecewise linear regression of country-level flows lagged performance over the previous four quarters. Like Chevalier and Ellison (1997), we include as control variables the lagged value of tracking error to allow for mean reversion in manager risk taking; lagged fund size; and also convexity interacted with lagged fund size. Chevalier and Ellison (1997) use the latter variable to recognize that it may be more difficult for larger funds to change the riskiness of their portfolios. In some specifications, we also include fund age in the same manner as fund size, recognizing that younger funds with less established track records stand to gain more by risk taking. Both Chevalier and Ellison (1997) and Huang et al. (2011) find that younger funds engage in more risk taking behavior. Our risk-taking regressions also include time fixed effects to capture time variation in risk taking unexplained by our control variables. We use Newey–West adjusted *t*-statistics to correct for overlapping observations.

Table 12, Panel A, presents the results of the fund tracking error regressions across all countries using all three measures of fund performance to estimate country-level convexity. The first two specifications for these regressions use alternately fund size and age as explanatory variables. The third specification uses both. As expected, larger and older funds take less risk and respond less to changes in convexity. More importantly, it is clear that there is robust evidence across specifications that convexity increases risk taking in a statistically significant way. This effect holds using as a managerial risk measure the standard deviation of fund returns as well.

Panel A pools across countries that do and do not have statistically significant convexity to examine risk taking. We expect that if we were to run our tests separately on countries that do have significant convexity that fund manager risk taking would be more pronounced. Panel B of Table 12 presents the results with a sample of funds only from countries that have statistically significant convexity based on the estimates in Table 6. We find stronger evidence that country-level convexity enhances risk taking by fund managers in accordance to our expectations.

To illustrate our results, in keeping with Table 11, we measure the impact on average US fund manager tracking error of an increase in convexity from the level in the US to the level in India (using convexity measured using the difference between *High* and *Low* coefficients and four-factor alphas). Moving from the US to India increases convexity from 0.076 to 1.586 (see Table 6), which translates to an increase in average annualized US mutual fund manager tracking error by ten percentage points using the estimates in column (9) in Panel A of Table 12. Hence the impact of convexity on risk taking is not only statistically but is also economically significant.

We conclude that the level of convexity in the flow-performance relationship has implications in terms of the incentives for fund managers to take risk. Fund managers take more risk in countries with higher levels of convexity, which suggests that regulators and investors should monitor the behavior of fund managers in these countries more closely.

6. Robustness

Ivkovic and Weisbenner (2009) highlight the importance of capital gains taxes in influencing the outflow-performance relationship in the US. We examine whether differences in capital gains taxes are responsible for our results. We gather data on capital gains taxes from the Organization for Economic Cooperation and Development (OECD) tax statistics database. We then re-run our main tests in Tables 8–10 including not only our development vari-

Table 12
The relationship between fund manager risk taking and flow-performance convexity.

	Raw returns			One-factor alpha			Four-factor alpha		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A – All countries									
High minus Low $t-1$	0.079***	0.026***	0.079***	0.070***	0.035***	0.070***	0.064***	0.031***	0.066***
	(6.52)	(4.25)	(6.48)	(5.87)	(7.13)	(5.90)	(5.14)	(5.63)	(5.53)
Log Size $t-1$	−0.001***		−0.001***	−0.001***		−0.001***	−0.001***		−0.002***
	(−7.60)		(−4.00)	(−7.07)		(−4.09)	(−7.78)		(−4.45)
High minus Low $t-1$ × log Size $t-1$	−0.004***		−0.004***	−0.003***		−0.003***	−0.003***		−0.003***
	(−5.19)		(−3.96)	(−3.94)		(−2.82)	(−4.09)		(−2.76)
Tracking error $t-1$	0.657***	0.660***	0.656***	0.654***	0.657***	0.653***	0.659***	0.662***	0.658***
	(183.74)	(179.71)	(168.28)	(178.68)	(173.46)	(162.55)	(180.31)	(176.76)	(163.96)
Log Age $t-1$		−0.001	0.001		−0.001	0.001		−0.001	0.001
		(−0.84)	(0.44)		(−0.60)	(0.71)		(−0.63)	(0.81)
High minus Low $t-1$ × log Age $t-1$		−0.006**	−0.001		−0.008***	−0.004		−0.011***	−0.007***
		(−2.11)	(−0.15)		(−3.72)	(−1.42)		(−4.83)	(−2.73)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted *R*-squared	0.052	0.052	0.052	0.052	0.052	0.052	0.052	0.052	0.052
Number of observations	151,216	151,216	151,216	151,216	151,216	151,216	151,216	151,216	151,216
Panel B – Countries with positive and significant convexity									
High minus Low $t-1$	0.1305***	0.0599***	0.1298***	0.1015***	0.0527***	0.1023***	0.1189***	0.0533***	0.1180***
	(9.34)	(4.60)	(8.97)	(6.64)	(6.10)	(6.85)	(6.84)	(4.56)	(6.28)
Log Size $t-1$	0.0003		0.0000	−0.0002		−0.0003	0.0003		0.0001
	(1.54)		(0.07)	(−1.08)		(−0.66)	(1.45)		(0.23)
High minus Low $t-1$ × log Size $t-1$	−0.0057***		−0.0052***	−0.0042***		−0.0037**	−0.0053***		−0.0048**
	(−6.43)		(−3.24)	(−4.06)		(−2.56)	(−4.55)		(−2.50)
Tracking error $t-1$	0.6266***	0.6271***	0.6261***	0.6062***	0.6075***	0.6063***	0.6208***	0.6218***	0.6206***
	(122.42)	(109.81)	(108.52)	(133.88)	(122.26)	(120.59)	(112.77)	(98.47)	(101.42)
Log Age $t-1$		0.0018	0.0015		0.0006	0.0010		0.0013	0.0009
		(0.73)	(0.47)		(0.28)	(0.36)		(0.53)	(0.27)
High minus Low $t-1$ × log Age $t-1$		−0.0128**	−0.0038		−0.0108***	−0.0051		−0.0120***	−0.0037
		(−2.25)	(−0.48)		(−3.07)	(−1.01)		(−2.73)	(−0.51)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted *R*-squared	0.031	0.031	0.031	0.032	0.032	0.032	0.030	0.030	0.030
Number of observations	91,987	91,987	91,987	101,439	101,439	101,439	88,551	88,551	88,551

This table presents the results of panel regressions of annualized tracking error measured over the past 12 months on lagged country-level flow-performance convexity and control variables. Convexity is measured at the country-level as the difference between the *High* and *Low* coefficients from our flow-performance regression using the set of control variables in column (4) of Table 5. Control variables include fund size, measured by the natural log of fund's TNA in US dollars lagged ($Log\ Size_{t-1}$); natural log of fund age lagged ($Log\ Age_{t-1}$); corresponding proxy of fund manager risk taking lagged; lagged convexity interacted with the natural log of fund size lagged ($High\ minus\ Low_{t-1} \times Log\ Size_{t-1}$); and lagged convexity interacted with the natural log of fund age lagged ($High\ minus\ Low_{t-1} \times Log\ age_{t-1}$). Panel A presents estimates for the sample of all countries. Panel B presents estimates only for the sample of countries with positive and significant convexity based on Table 6. Newey–West adjusted *t*-statistics are reported in parentheses.

* 10% significance level.

** 5% significance level.

*** 1% significance level.

ables interacted with fund performance but also mutual fund capital gains tax rates in each country interacted with *Low*, *Mid*, and *High* performance measures. Our results remain largely unchanged.

Recent work by Kim (2010) relates convexity in US mutual funds to market volatility and the dispersion of managerial ability. We examine whether the variables in this study are responsible for our results. To this end, we re-run our analysis in Tables 8–10 including two additional variables namely, the interaction of past performance (*Low*, *Mid* and *High*) with lagged market volatility and the interaction of past performance with a proxy for the dispersion of managerial ability in the country concerned. Market volatility is calculated using monthly local market returns for domestic funds and using the investment region market returns for international funds over the prior 12 months. The dispersion of managerial ability is measured (using a similar approach to Kim, 2010) as the residual from a regression of the cross sectional standard deviation of fund returns (over 12 months across funds in each country) on the mean and standard deviation of the local market index return in the case of domestic funds and the mean and standard deviation of the relevant investment region market for international funds. We find that the impact of using these additional variables has little bearing on our results.

We conduct a number of further tests to examine the robustness of our results. First, we examine the impact of using a different measure of fund flows. Our tests work with raw fund flow scaled by fund size. However, it is clear from Table 2, that countries have very different average money growth rates and very different volatilities in money growth rates across funds, which might inhibit our ability to compare flow-performance sensitivities. To test whether controlling for differences in the mean and volatility of money growth rates makes a difference in our results, we try two normalized measures of our flow variable. The first is simply a mean-adjusted version of our raw measure, where we subtract from our flow variable the average new money growth rate in the same country-quarter. The second is a mean-adjusted version of the raw measure scaled by the standard deviation of money growth rates across funds in the same country-quarter. Whichever normalization procedure we use, our results are little affected.

Second, we address the concern raised by the fact that certain countries' fund flows do not always increase with fund performance (see Fig. 1). This may be because in these countries, at certain times, non-performance variables are dominant in explaining fund flows. To investigate whether these observations are influential, we drop country-years with negative flow-performance sensitivities and rerun the tests. This has little effect on the results.

Third, we investigate whether using alternative performance measures makes a difference in the results. To check this possibility, we measure fund performance using Sharpe ratios and benchmark-adjusted returns. The benchmark returns are obtained from Lipper.[19] We find that using either of these performance measures has little impact on our findings.

Finally, we drop the US from the sample to see whether our findings are driven by the large number of US funds in the dataset. When we repeat the analysis excluding the US, our results remain largely unchanged. Finally, we test whether our results hold separately for domestic and international funds. We find the results are robust in both samples.

7. Conclusion

Our understanding of what drives the buying and selling decisions of mutual fund investors is based primarily on the behavior of US investors. To fill this gap in the literature we use data on a large sample of equity mutual funds in 28 countries. We show that there are substantial differences in flow-performance relationship across countries, meaning that US findings do not map directly onto other countries.

We hypothesize that investor sophistication and participation costs, proxied by economic, financial, and mutual fund industry development variables, explain the cross-country differences in the flow-performance relationship. Investor sophistication and participation costs capture different elements of fund trading decisions and they have different implications for the flow-performance relationship. When we compare how investors react to top performance in more developed countries and less developed countries, we find that reactions are more restrained in more developed countries. When it comes to selling losers, however, investors in more developed countries are generally more pro-active than elsewhere. Our findings support the view that the more sophisticated investors are and the lower participation costs they face, the less convex the flow-performance convexity we observe.

Understanding how fund flow convexity is likely to evolve across time as countries develop is difficult because of the short time span of data typically available and because the variables that explain convexity are slow-moving. It is an advantage to use a sample of countries which are at different stages of development to show how convexity relates to different dimensions of development. We thus shed light on the likely evolution of convexity in a given country, which would be difficult to ascertain if we were working with a single country in time series.

We also demonstrate that there are important implications of the convexity of the flow-performance relationship for the risk-taking behavior of mutual fund managers. One would expect managers faced with greater flow-performance convexity to take more risk, as they have more to gain if they perform well and less to lose if they perform poorly. Our evidence shows that managers in countries with more convex flow-performance relationships take more risk. This suggests that in less developed countries, which usually have less developed mutual fund industries, investors and regulators should pay particular attention to fund manager actions.

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Appendix A. Calculation of factors for risk adjustment of fund performance

We construct the monthly benchmark factors for each individual country except the US using all stocks included in the Datastream/Worldscope database. For the US we use the factors constructed by Fama and French (1992).[20] The local market return is computed using the value-weighted average return in local currency of all stocks in each country in each month. The investment region market factor is computed using the value-weighted average return of all countries' market returns in the region. The regions are Europe, Asia–Pacific, North America, Emerging Markets, and World.

To form the size and book-to-market equity portfolios, we follow the procedure described in Fama and French (1992). For each country, we calculate the small-minus-big (SMB) and high-minus-low (HML) factors from July of year t through June of year $t+1$ using six value-weighted portfolios formed at the end of June of year t on the intersection of two size portfolios (market equity capitalization, ME) and three book-to-market equity (BE/ME) portfolios. The size breakpoint is the median market capitalization of each country as of the end of June of year t. Half of the firms are classified as small market capitalization and the other half as big market capitalization. For the BE/ME classification, the breakpoints are the 30th and 70th percentiles of BE/ME in each country as of the fiscal year in $t-1$. The bottom 30% is designated as the value portfolio, the middle 40% as neutral, and the highest 30% as growth.

The SMB factor is the monthly average return of the three small portfolios minus the average return of the three big portfolios:

$$\begin{aligned}\text{SMB} = (&\text{Small Value} + \text{Small Neutral} + \text{Small Growth} \\ &- \text{Big Value} - \text{Big Neutral} - \text{Big Growth})\end{aligned}$$

The investment region SMB is the monthly value-weighted average of all countries' SMB factors in the region.

The HML factor is the monthly average return of the two value portfolios minus the monthly average return of the two growth portfolios:

$$\begin{aligned}\text{HML} = (&\text{Small Value} + \text{Big Value} - \text{Small Growth} \\ &- \text{Big Growth})/2\end{aligned}$$

The investment region HML factor is the monthly value-weighted average of all countries' HML factors in the region.

The momentum factor (MOM) for month t is calculated using six value-weighted portfolios formed at the end of month $t-1$, as a result of the intersections of two portfolios formed on size (ME) and three portfolios formed on prior (2–12) month returns. The ME breakpoint is the median market equity in each country as of the end of month $t-1$. For the return classification, the 30th and 70th percentiles of the prior returns (2–12) in each country are the breakpoints. The bottom 30% are designated as the down-month prior return portfolio, the middle 40% as medium, and the highest 30% as up. The MOM factor is the monthly average return

[19] Lipper determines the benchmark of a fund from the fund prospectus.

[20] The US factors are drawn from French's website: http://www.mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

in local currency on the two high-prior return portfolios minus the monthly average return on the two low-prior return portfolios:

$$MOM = (\text{Small High} + \text{Big High} - \text{Small Low} - \text{Big Low})/2$$

The investment region MOM factor is the monthly value-weighted average of all countries' MOM factors in the region.

Appendix B. Supplementary material

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2012.01.019.

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