Do fund flows moderate persistence? Evidence from a global study[*]

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Abstract

We investigate whether fund flows eliminate future abnormal performance and persistence as in Berk and Green (2004) using a sample of open-end domestic equity mutual funds from 32 countries. We show that flows have only a small moderating effect on persistence even in the United States, where fund industry conditions most closely resemble the Berk and Green assumptions. In fact, we find that most countries do not have decreasing returns to scale in fund management and, as a result, flows have limited impact on mutual fund performance persistence.

JEL Classification: G15; G23

Keywords: Mutual fund persistence; Fund flows; Returns to scale; Berk and Green model

1. Introduction

The Berk and Green (2004) model shows that fund performance is not persistent, even in the presence of manager skill, if the assumptions of perfect capital markets, rational learning of fund performance, and decreasing returns to scale in fund management hold. The model has been used to justify why the limited persistence detected in the US fund industry (e.g., Carhart,1997, Fama and French, 2010, and Berk and van Binsbergen, 2015) is not inconsistent with managers having skill. At the core of the model lies a two-step mechanism that is responsible for the elimination of fund abnormal performance and its persistence. In step one, money flows to any funds that earn positive abnormal returns. In step two, the growth of these funds causes their subsequent performance to decline because of decreasing returns to scale in fund management. A similar process occurs when funds perform poorly as investors will withdraw money out of the fund, which will cause the fund abnormal return to converge to the benchmark expected return. Flows into and out of funds are therefore expected to eliminate both positive and negative abnormal returns.[1]

In reality, of course, the assumptions of the Berk and Green (2004) model may not be met. For example, there may be frictions in capital markets and biases in learning. Fama and French (2010, p. 1923) claim that the *"model is attractive theory"*, but their tests clearly reject the Berk and Green (2004) prediction that having fund managers with sufficient skill to cover expenses is the general rule. The findings in Ferreira, Keswani, Miguel, and Ramos (2013) that *"diminishing returns to scale is not a universal truth"* may also affect the Berk and Green mechanism,

[1] In Section 2, we provide a detailed discussion of the predictions of the Berk and Green (2004) model.

suggesting that "*fund flows may not eliminate performance persistence in the manner predicted by the Berk and Green (2004) model*." (Ferreira, Keswani, Miguel, and Ramos, 2013, p.486).

Given real world imperfections, we ask the following question: do fund flows materially moderate persistence in the manner predicted by the Berk and Green (2004) model? To study this question, we use a sample of open-end domestic equity mutual funds from 32 countries and find that the economic effect of flows on persistence is small or even has the incorrect sign. One important reason for this is that flows into funds do not always weaken persistence, as our results show that most countries do not have decreasing returns to scale in fund management. Even in the US, where market conditions might be deemed to be closest to the Berk and Green assumptions, we find a relative small effect of flows on performance persistence. This explains why we find significant persistence in most fund industries around the world, including those fund industries with decreasing returns to scale.

A critical assumption of the Berk and Green model is that there are decreasing returns to scale in funds' investment technologies. A decline in returns occurs when a fund gets too large, leading fund managers to spread their information gathering capacities too thinly. In addition, when a fund gets too large relative to the size of the underlying asset pool, its trades have a greater price impact.

It is possible that funds may not experience decreasing returns to scale if they are not large enough or have not grown large enough relative to their underlying asset market which is likely in younger or smaller fund management industries. Another reason for increasing returns to scale at the fund level might be that fund fixed costs are spread across a larger pool of money. Funds may even experience increasing returns to scale if fund families channel their best ideas and more resources to their fastest-growing funds in the hope of making these funds "star" funds (Nanda, Wang, and Zheng, 2004). If many fund industries are young or are not of sufficient size, this might

explain why we observe performance persistence in so many industries. Ferreira, Keswani, Miguel, and Ramos (2013) show that, unlike US domestic funds, funds located outside the US and funds that invest overseas do not present decreasing returns to scale. To examine this further, we analyze the properties of investment technologies individually for each of the 32 fund industries in our sample. We find that only a minority of countries has decreasing returns to scale while most have constant returns, and some even display increasing returns to scale.

When we divide countries into three groups on the basis of their returns to scale properties, we show that fund flows affect persistence differently across the groups. For the increasing returns to scale group, fund flows actually add to persistence, while for the constant returns to scale group, fund flows leave persistence unaffected. For the decreasing returns to scale group, fund flows reduce persistence, as predicted by Berk and Green (2004). Our results show that returns to scale differences across countries explain how flows affect persistence.

In the group of countries with decreasing returns to scale, even though flows change persistence in the direction predicted by the Berk and Green (2004) model, we still find persistence in most countries, which is exactly where we would not expect to find persistence according to the Berk and Green (2004) model. Additionally, we do not find persistence in all countries where we might expect to find it, namely, increasing returns to scale and constant returns to scale countries. To shed light on this issue, we sort funds on prior year performance and identify funds at the bottom and at the top of the performance scale (i.e., funds in the 10^{th} and 90^{th} percentiles of performance ranks, respectively) in each country and calculate the expected flow these funds receive. For top performing funds, we show that fund inflows reduce persistence in decreasing returns to scale countries by no more than 6.65% per year. In increasing returns to scale countries, flows increase the persistence of 90th percentile performing funds by 9.22% per year. In the case

of funds at the bottom of the performance scale, fund outflows increase persistence in decreasing returns to scale countries by only 4.32% per year, and reduce persistence in increasing returns to scale countries by 4.88%. Our results show that the Berk and Green mechanism is slow to operate. As a result, while the Berk and Green mechanism correctly predicts the dynamics of persistence in our sample, it is limited in its ability to explain the cross-section of persistence observed across countries.

How does our work contribute to our understanding of fund management? Our first finding is that decreasing returns to scale in fund management are not present in the majority of countries around the world. While Ferreira, Keswani, Miguel, and Ramos (2013) show that decreasing returns to scale are not present outside the US, our results indicate clear differences on how fund size affects fund performance across non-US countries. We find that most non-US countries in our sample have constant returns to scale (15), nine countries have increasing returns to scale, and we even find a minority of countries with decreasing returns to scale. Our results indicate therefore that the evidence of increasing returns to scale in non-US countries observed in Ferreira, Keswani, Miguel, and Ramos (2013) is also not a universal truth. Second, contrary to the predictions of the Berk and Green (2004) model, we demonstrate that persistence is present across the majority of fund industries around the world, which is consistent with the findings in Ferreira, Keswani, Miguel, and Ramos (2019).[2] Third, while Ferreira, Keswani, Miguel, and Ramos (2013) suggest that fund flows may not eliminate persistence as predicted by the Berk and Green (2004) model,

[2] Ferreira, Keswani, Miguel, and Ramos (2019) also find fund performance persistence in the majority of countries in their study. This is where the overlap between our work and their study ends. Ferreira, Keswani, Miguel, and Ramos (2019) build on the US literature that shows that fund managers that face less competition are able to generate a more persistent alpha (e.g., Wahal and Wang, 2011, and Hoberg, Kumar, and Prabhala, 2018), to show that the level of competitiveness in the mutual fund industry is an important determinant of fund performance persistence. In our study, we run additional specifications of our tests where we control for the level of competition in the mutual fund industry and find that our main results are preserved.

we show exactly under what circumstances the Berk and Green mechanism works in practice.[3] When fund industries observe decreasing returns to scale, we find that the Berk and Green mechanism does work as predicted and flows do eliminate abnormal performance and persistence. However, we find that in countries that do not have decreasing returns to scale that the Berk and Green mechanism does not work and flows into mutual funds do not eliminate abnormal performance and persistence. Fourth, the knowledge that the Berk and Green mechanism only operates slowly, suggests that the predicted impact of flows on performance persistence is significant but over long horizons only.

Finally, our results have practical implications for both investors and fund managers. Showing that performance persistence across fund industries is the norm rather than the exception is of value to investors as they use past performance to predict future performance (e.g., Sirri and Tufano, 1998). Differences in performance predictability across countries are indicative of the relative weights that investors around the world should put on past performance information. Our finding that the effect of fund flows on persistence varies with returns to scale in the fund industry, suggests that persistence tests potentially underestimate or overestimate the degree of predictability and hence the perception of observed skill. In countries with decreasing returns to scale in fund management, persistence tests will underestimate the degree of predictability and hence the observed fund manager skill. In the presence of constant returns to scale, measured persistence will not be affected by flows, and persistence will reflect fund manager's skill. In countries with increasing returns to scale, the fact that persistence statistics are upwardly biased

[3] Ferreira, Keswani, Miguel, and Ramos (2013) examine the relation between fund size and performance internationally, which has also been examined for the US (e.g., Chen, Hong, Huang, Kubik, 2014, Elton, Gruber, Blake, 2012, Reuter and Zitzewitz, 2015, and Pastor, Stambaugh, and Taylor,2015. However, these studies do not analyze the impact of fund flows on mutual fund performance, which in the Berk and Green (2004) model is the key driver of performance persistence.

by flows does not allow to conclude if there is performance persistence, and therefore whether managerial skill is present. However, we show that flows do not have a material effect on persistence, which suggests that the observed performance persistence is a valid indicator of skill even in fund management industries with increasing returns to scale.

2. The empirical predictions of the Berk and Green model

In this section, we discuss the predictions of the Berk and Green (2004) model, which inform us how the model should be tested using our worldwide sample. The Berk and Green (2004) model makes four main assumptions. First, the supply of capital is assumed to be perfectly elastic. This means that investors chase down abnormal returns opportunities. Second, there is a distribution of managers with different levels of skill. Third, there are decreasing returns to scale in the fund investment technology. Fourth, it is assumed that neither managers nor investors are aware of the level of managerial skill, but learn about managerial skill from the past performance of funds.

Berk (2005) discusses how the model converges to its steady-state. Investors have their initial priors about the distribution of managerial ability. First, they will invest in the manager who is perceived to have the highest level of skill. Subsequently, the fund will grow but, because of decreasing returns to scale, the expected returns will eventually equal the expected returns of the second-best manager. At that point, investors will be indifferent between the first and second-best managers and therefore will invest in both. This will continue until the money invested in the first and second managers is such that both managers earn the expected returns of the third-best manager. This process will continue until abnormal performance and persistence are eliminated. At this point, the fund industry will be at its initial steady-state.

Additionally, if there is learning, past performance information is used to update inferences

regarding who the best managers are. When the performance of a fund is better than expected and the fund earns positive alpha, investors will revise upwards their beliefs about the perceived skill of the manager. This manager will now be expected to earn positive abnormal returns with his current level of capital. Investors will therefore react to this by investing more funds with the manager. Due to decreasing returns to scale this will cause the expected performance of this fund to decline until the fund is again expected to make future abnormal returns of zero.

A similar process occurs when a fund earns negative abnormal returns as investors will withdraw money out of the fund, which will cause the fund return to converge to zero due to decreasing returns to scale. This will again cause persistence to be eliminated by money flows. As funds earn inflows after earning positive alpha and outflows after negative alpha, the model endogenously creates a relation between lagged alpha and inflows. With learning, investors' beliefs about managerial skill will converge to the true level of skill. Until they do so, fund performance may display persistence, but this persistence should decline with time. Hence, if we partition funds on the basis of age, we should see limited persistence for mature funds.

The discussion above informs us on how to test the Berk and Green (2004) model. First, it suggests that if we want to test for persistence, we should only study mature funds. The model predicts there should be limited persistence for these funds. Concerning the Berk and Green mechanism, there are two main predictions of the model. First, fund flows should have a positive relation with lagged abnormal fund performance. Ferreira, Keswani, Miguel, and Ramos (2012) show robust evidence that investors chase fund performance using a worldwide sample of funds. A second prediction of the model is that flows into funds should eliminate fund persistence. Abnormal positive fund performance should be followed by inflows, which will cause fund size to grow, leading to a decline in subsequent fund performance. Likewise, negative abnormal

performance should lead to outflows causing fund size to decline, leading to an increase in subsequent fund performance. Fund flows will therefore break the link between past and future performance, and thus eventually eliminate persistence. Whether fund industries are in the process of converging to their initial steady-state or during the period where fund investors and managers are learning about fund performance, the downward impact of flows on persistence should be present. Thus, there is no necessity of using only mature funds for testing the relation between flows and persistence.

3. Data and variables construction

In this section we describe our data and explain how we measure mutual fund performance and how we measure fund flows.

3.1. Data

In this study we use mutual fund data from 32 countries in the 2001-2015 period. The data is from the Lipper database, includes domestic actively managed equity funds and is survivorship-bias free.[4] Although Lipper database lists multiple share classes separately, treating each fund class as if it were a separate fund, we follow Ferreira, Keswani, Miguel, and Ramos (2013 and 2019), Cremers, Ferreira, Matos, and Starks (2016), and Demirci, Ferreira, Matos, and Sialm (2019) and use the primary share class identified by Lipper. This is to prevent double counting of funds as multiple share classes have the same holdings and the same returns before expenses. We compute the total net assets (TNA) of each fund as the sum of TNA across all share classes, and fees are calculated by size-weighted fees across share classes.

We impose a few additional filters. First, we exclude indexing-tracking, exchange trade,

4 This dataset is used in Demirci, Ferreira, Matos, and Sialm (2019).

closed-end, funds-of-funds and funds domiciled in offshore centers such as Liechtenstein, Luxembourg or Dublin. Second, we impose a minimum of 36 continuous monthly observations of fund returns to assure enough time series observations to calculate risk-adjusted performance measures. Our observations of funds are also required to have data on all control variables, including size (TNA), family size, age, total expense ratio and front-end loads). This leads to a final sample of 10,617 domestic open-ended actively managed funds from 32 countries.[5] Table 1 presents the number of unique funds and TNA (sum of all share classes in millions of US dollars) of our sample by country at the end of 2015. The number of funds and TNA managed are considerably different across countries. The US is the country with by far the highest number of mutual funds and the largest TNA, while Hong Kong and Singapore, and Argentina are the countries with the lowest number of funds and the lowest TNA, respectively.

3.2. Measuring fund performance

Risk-adjusted performance is measured using four-factor alpha (i.e., Carhart,1997, four-factor alpha). We follow Bekaert, Hodrick, and Zhang (2009), and Demirci, Ferreira, Matos, and Sialm (2019), and we estimate four-factor alpha using regional factors based on a fund's investment region (Asia-Pacific, Europe, North America, and emerging markets).[6] We run the following regression:

$$R_{i,t} = \alpha_i + \beta_1 MKT_{i,t} + \beta_2 SMB_{i,t} + \beta_3 HML_{i,t} + \beta_4 MOM_{i,t} + \varepsilon_{i,t} \qquad (1)$$

where $R_{i,t}$ is the return net of fees in US dollars of fund *i* in month *t* in excess of the one-month US. Treasury bill rate, $MKT_{i,t}$ (*market)* is the excess return in the fund's investment region in month *t*, $SMB_{i,t}$ (*small minus big*) is the average return on the small-capitalization stock portfolio minus

[5] See Ferreira, Keswani, Miguel, and Ramos (2013), and Cremers, Ferreira, Matos, and Starks (2016) for a detailed description of Lipper's worldwide data coverage.
[6] Factors are from AQR (https://www.aqr.com/Insights/Datasets).

the average return on the large-capitalization stock portfolio in the fund's investment region, $HML_{i,t}$ (*high minus low*) is the average return on high book-to-market stock portfolio minus the average return on low book-to-market stock portfolio in the fund's investment region, and $MOM_{i,t}$ (*momentum*) is the average return on past 12-month winners portfolio minus the average return on past 12-month losers portfolio in the fund's investment region. The previous 36 months of net fund returns are used to estimate the time series regression of monthly excess returns based on the fund's factor portfolios. The next step is to compare the difference between the expected return and the realized return of the fund and use this to estimate the fund's abnormal return (or alpha) in each month. We compound monthly alphas to calculate annual alphas.

In robustness tests, we also use benchmark-adjusted returns calculated as the difference between the raw return and the return of the benchmark given in the Lipper database.

Table 2, Panel A, shows that the average benchmark-adjusted return and the average four-factor alpha across funds in our sample are 0.19% and −1.27%, respectively.

3.3 Fund flow

We follow, e.g., Chevalier and Ellison (1997), Sirri and Tufano (1998), and Ferreira, Keswani, Miguel, and Ramos (2012), and calculate mutual fund flow as the new money growth rate that is due to new external money. Fund flow for fund *i* in country *c* at year *t* is calculated as:

$$Flow_{i,c,t} = \frac{TNA_{i,c,t} - TNA_{i,c,t-1}(1+R_{i,c,t})}{TNA_{i,c,t-1}}, \qquad (2)$$

where $TNA_{i,c,t}$ is the total net asset value in local currency of fund *i* in country *c* at the end of year *t*, and $R_{i,c,t}$ is fund *i*'s raw return from country *c* in year *t*. Table 2, Panel A, shows that the average annual flow aggregated across countries in our sample is 4.52%.

4. Performance persistence across countries

To measure mutual fund persistence, we start by regressing current fund performance on last year fund performance together with a number of control variables (see, e.g., Busse, Goyal, and Wahal, 2010 and Ferreira, Keswani, Miguel, and Ramos, 2019).[7,8] We therefore estimate the following equation:

$$\alpha_t = \mu + \theta\alpha_{t-1} + \delta X_{t-1} + \varepsilon_t \quad (3)$$

where we regress fund performance (α_t) measured using four-factor alpha in a given year on prior year performance (α_{t-1}) together with a set of lagged control variables (X_{t-1}) that have a bearing on how funds perform in the future.[9] If the coefficient θ is positive and significant, this indicates that fund performance persists. If θ is negative and significant, this indicates that performance has a tendency to reverse. The regressions also include year fixed-effects and benchmark fixed-effects. Standard errors are clustered at the fund level or at the country level, when we run the regressions by country or pooled across countries, respectively.[10]

We follow Busse, Goyal, and Wahal (2010), and Ferreira, Keswani, Miguel, and Ramos (2019)

[7] This study analyzes persistence over a one-year frequency. Although performance persistence can be examined at different frequencies, most authors study persistence at a yearly frequency (e.g., Carhart, 1997, Elton, Gruber, and Blake, 2012, and Ferreira, Keswani, Miguel, and Ramos, 2019). This is because investors, fund managers, and investors tend to evaluate performance of mutual funds over annual time periods.

[8] Barras, Scaillet and Wermers (2010) propose a new methodology - the False Discoveries Rate (FDR) - to measure fund performance. In their influential study, they show that FDR allows to separate skill (alpha) from luck, which helps to identify the funds that generate the true alpha. The authors also show that controlling for false discoveries improves the ability of finding persistent performance. Andrikogiannopoulou and Papakonstantinou (2019) raise substantive concerns regarding the results in Barras, Scaillet and Wermers (2010) and the FDR's applicability in fund performance evaluation. In a reply to Andrikogiannopoulou and Papakonstantinou (2019), Barras, Scaillet, and Wermers (2020) incorporate these concerns and propose revised parameter values. They acknowledge that the use of FDR in finance needs to be carefully implemented, particularly when the sample size is small. This discussion highlights the importance of a sufficient large sample to the accuracy of the FDR estimator. Therefore, using the FDR methodology in our study would potentially lead to incorrect estimations as our sample include many countries with a relative small number of observations.

[9] In robustness tests we also use benchmark-adjusted returns as our performance measure.

[10] In unreported results, we obtain similar results when clustering our standard errors by fund-year or country-year, when we run the regressions by country or pooled across countries, respectively.

and control for size, family size, fund flow, age, and fees, measured as total shareholder costs.[11] Following Ferreira, Keswani, Miguel, and Ramos (2019), we control for the impact of fund style by using loadings on SMB and HML factors, as style differences might explain differences in the dynamics of persistence. Finally, we also include in our regressions the size of the mutual fund equity industry as a percentage of the stock market capitalization in each country-year, as Pastor and Stambaugh (2012), and Pastor, Stambaugh, and Taylor (2015) show that the size of the active mutual fund industry determines fund performance.

Table 2, Panel A, presents fund-level variables averaged by country over the sample period. It is clear from Panel A that there are considerable differences in the average size of funds across countries. Average fund size varies from $9 million in Argentina to $1.39 billion in the US. Table 2, Panel B, presents correlations between fund variables within each country averaged across fund industries. These correlation coefficients suggest that using these variables together to explain fund performance should not be a cause for concern.

Table 2, Panel C, reports averages for the country-level variables and shows that there are also clear differences in the scale of operation of the fund industry across the countries in our sample that may have a bearing on the performance of funds within each country.

Table 3 presents the results of regressions estimating the performance persistence country by country. The first column shows that there is statistically significant performance persistence in 18 out of 32 countries in our sample. We also find clear differences in the level of persistence across countries. The country with the lowest level of significant persistence is the US with a coefficient on lagged four-factor alpha of 0.0499, while the country with highest significant performance persistence is Denmark, with a coefficient on lagged four-factor alpha of 0.2711.

[11] We compute Total Shareholder Costs (TSC) by adding one-fifth of the front-end load to annual total expense ratio.

These differences are also economically important as in the US one-twentieth of past performance in a given year carries over to the next year, while in Denmark more than one-fourth of past performance in a given year is carried over to the next year. We also estimate persistence jointly for all countries taken together. The results are presented at the bottom of the first column of Table 3 and show evidence of a statistically significant persistence. Overall, our results are consistent with the findings in Ferreira, Keswani, Miguel, and Ramos (2019) that find performance persistence in the majority of countries in their study.[12]

5. Returns to scale across countries

The results in Table 3 indicate that persistence in fund performance is pervasive across countries. The Berk and Green (2004) model predicts that persistence should not exist in long-run equilibrium. How can we reconcile our findings with the predictions of the Berk and Green (2004) model? A key assumption of the Berk and Green (2004) model is that there are decreasing returns to scale in fund management. Decreasing returns to scale are likely to be observed because of greater price impact from trading larger blocks of securities (Edelen, Evans, and Kadlec, 2007, and Yan, 2008), and because managers broaden their portfolios to include additional less promising securities (Chen, Hong, Huang, and Kubik, 2004).

It is actually not necessary that decreasing returns to scale be present in all the countries in our sample, particularly if greater price impact occurs only when funds reach a certain size relative to the asset pool. Funds in certain countries may even experience increasing returns to scale. Increasing returns to scale may occur if larger funds get a greater share of family resources as they grow. In addition, because of the positive externality enjoyed by a star fund, fund families may

[12] Ferreira, Keswani, Miguel, and Ramos (2019) use data from 27 countries in the 2001-2010 period.

channel their best ideas to the best-performing funds (Nanda, Wang, and Zheng, 2004, and Gaspar, Massa, and Matos, 2006). If there are constant or increasing returns to scale across countries, then when funds grow, their performance will not necessarily decline, and persistence in performance will not be eliminated.

Our sample allows us to investigate returns to scale in fund management around the world. The second column of Table 3 provides the estimates of the effect of fund size on future performance by country. By looking at the coefficient on lagged fund size, we are able to understand the returns to scale present in each country. A country is classified as having increasing returns to scale if the coefficient on lagged fund size is positive and significant (at the 10% level), as larger fund size is associated with better fund performance. A country is classified as having decreasing returns to scale if the coefficient is negative and significant, as larger funds perform more poorly. Otherwise, countries are classified as having constant returns to scale.[13] We find that eight countries have decreasing returns to scale in fund management, which represents only one-fourth of the countries in our sample. These countries include the US and also Australia, Canada, Germany, Japan, South Korea, Taiwan, and the United Kingdom. Interestingly, most countries in our sample do not have decreasing returns to scale; 15 countries have constant returns to scale, and 9 countries have increasing returns to scale, including Argentina, Brazil, Denmark, France, Greece, Malaysia, Portugal, Singapore, and South Africa. When we estimate returns to scale across all countries in our sample, we find evidence of constant returns to scale. This is consistent with most countries outside the US not having decreasing returns to scale.

[13] In unreported regressions we also determine the returns to scale of countries on the basis of the size of the coefficient on lagged size rather than its statistical significance. This is to address the possibility that countries may be classified as having constant returns to scale due to having few fund observations when in fact they have decreasing or increasing returns to scale in practice. When we use this alternative classification approach this does not alter the tenor of our results.

These findings contribute to our understanding of returns to scale in different fund industries, as we are the first to study returns to scale using a large sample of countries. This is important because we would expect that, without decreasing returns to scale, flows into funds will not eliminate persistence as predicted by the Berk and Green (2004) model.

Table 3 also informs us about the relation between family size and industry size and fund performance. Fund families can grow either by growing their assets under management in established funds or by opening new funds. If assets under management grow simply by growth in the size of established funds, it is difficult to explain why fund family size should affect fund performance above and beyond the fund size effect. If, however, the growth occurs through opening new funds, this might lead to greater competition for ideas within the fund family. It also might be more difficult to coordinate the operations of an increased number of funds, which might have a negative effect on fund performance. The results in Table 3 show that family size has a positive and significant effect on performance in eight countries and a negative and significant effect in two countries. The effect is not significant in the remaining countries in our sample.

Table 3 also shows that industry size has a negative and significant effect of on fund performance in 11 countries. With more competition for profit-making opportunities, we would expect growth in industry size to worsen fund performance, so it makes sense that in most of the cases where industry size has an effect on fund performance the effect is negative. In addition, we find that there is a significant negative effect of industry size on performance when we estimate the effect of industry size on performance across all countries. The results in Table 3 also show that in eight countries (Austria, Brazil, China, France, Malaysia, Singapore, South Korea, and Taiwan) fund performance improves with industry size. What might cause a positive effect of industry size on fund performance above and beyond the effect of fund size? If fund industries

grow due to entry by new fund families of the same size as current families, this might lead to a growth in industry size, but cause little change in average fund and family size. On entering the industry, new fund families have to establish a favorable track record if they want to stay in the industry, so they have a greater incentive to perform better than established fund management companies with a large amount of invested money that is not performance-sensitive. In this case, new fund families will outperform older fund families, causing a positive relation between fund performance and fund industry size.[14]

Pastor and Stambaugh (2012) present a model that explains why the size of active management is so large relative to the size of passive management despite its poor average performance. One crucial assumption of their model is that there is decreasing returns to scale at the industry level in fund management. It is interesting to note that this vital assumption for their model is borne out in the data.

6. The effect of flows on persistence

The Berk and Green (2004) model explains the absence of persistence in fund management with fund flows eliminating future abnormal performance. The model is constructed based on certain assumptions such as, perfect capital markets, rational learning of agents and decreasing returns to scale in fund management. In reality these assumptions may fail to hold. We have already seen that decreasing returns to scale are not present in most fund industries in our sample. In this section we examine how flows affect persistence in actual capital markets.

To investigate how persistence changes when funds grow, we run a regression of fund

[14] It is possible to test whether younger fund families in increasing industry returns countries perform better than older fund families from these countries. In unreported tests, we find that younger funds outperform older funds in these seven countries.

performance on lagged fund performance, and interact lagged fund performance with lagged fund flows. In this regression, we include the same control variables as in Table 3. The regressions in Table 3 include the size of the domestic equity fund management sector scaled by the stock market capitalization (*Fund industry eq. size/mcap*), as Pastor and Stambaugh (2012), and Pastor, Stambaugh, and Taylor (2015) show that industry size affects fund performance in the US. The literature as shown other country-level characteristics, including the competition in the mutual fund industry, economic development, and investor protection, to explain mutual fund performance across countries (Ferreira, Keswani, Miguel, and Ramos, 2013, and Cremers, Ferreira, Matos, and Starks, 2016), and fund persistence (Ferreira, Keswani, Miguel, and Ramos, 2019). We therefore run an additional specification where we also control for these country characteristics. We use the Herfindahl index (*Fund industry Herfindahl*) to proxy for the level of competition in the mutual fund industry, the gross domestic product per capita (*GDP per capita*) proxies for the level of economic development in the country, and *Judicial* measures the quality of a country's judicial system.

A positive (negative) coefficient on the interaction between lagged performance and lagged flows, means that flows increase (decrease) mutual fund performance persistence.

We would expect that, in countries with decreasing returns to scale in fund management, persistence will behave as predict by the Berk and Green (2004) model. In these countries, we would therefore expect to see that, as funds grow, persistence declines. However, in countries with increasing returns to scale in fund management, we would expect fund flows into mutual funds to increase persistence. Finally, in countries with constant returns to scale in fund management, fund flows should have no bearing on fund performance persistence.

Table 4 presents the results of our regressions testing the link between persistence and fund

flows estimated separately using the sample of funds in countries with: (1) constant return to scale; (2) increasing returns to scale; (3) decreasing returns to scale; (4) decreasing returns to scale but excluding the US; and (5) the US by itself.

Columns (1) and (2) of Table 4 present the results for the constant returns to scale countries. The coefficients on lagged flows interacted with performance are not statistically significant. This indicates that for this group of countries, flows have no bearing on their future performance, and therefore flows do not affect performance persistence. Columns (3) and (4) of Table 4 present the results for the increasing returns to scale group of countries. The coefficients on the interaction between lagged flows and performance are positive and significant, indicating that, as funds earn flows, performance persistence increases. Columns (5) and (6) present the results for the decreasing returns to scale countries. In this case, the coefficients on the interaction between lagged flows and lagged performance are negative and significant, indicating that, in these countries, performance persistence declines when funds get more flows.

A large fraction of the decreasing returns to scale funds are from the US. To check that the presence of the US is not driving our results for these countries, in Columns (7) and (8) we rerun the analysis for decreasing returns to scale countries excluding the US, and still find the same result: namely, that fund flows reduce persistence. Columns (9) and (10) present the results for only the US.[15] Here we see that fund flows reduce persistence because of the decreasing returns to scale in the US.

Overall, our results are according to our hypotheses and show that flows increase performance persistence in the presence of increasing returns to scale, decreases performance persistence in the presence of decreasing returns to scale, and have no effect in performance persistence in the

[15] We exclude Judicial from US regressions in column (10) as this variable is time-invariant.

presence of constant returns to scale. The results are always robust when controlling for differences across countries in the level of competition in the mutual fund industry, the level of economic development, and the quality of the judicial system. Table 4 shows that countries with strong competition (low industry Herfindahl index) and high economic development (high GDP per capita) have lower performance, while countries with stronger legal institutions, higher law enforcement, and better investor protection display better performance. These results are consistent with findings in Ferreira, Keswani, Miguel, and Ramos (2013).

In order to establish the economic magnitude of the effect of flows on persistence in a given year for funds at the top, middle and bottom (i.e., funds in the 90th, 50th, and 10th percentile respectively) of the performance scale, we start by measuring the size of flows we would expect in a given year for such funds. To calculate this, we estimate the flow-performance relationship for each country, according to the following equation:

$$Flows_t = \mu + \beta Performance\ rank_{t-1} + \eta X_{t-1} + \varepsilon_{i,t}. \quad (4)$$

We regress annual fund flows in year t ($Flows_t$) on the fund performance rank in the prior year based on four-factor alpha ($Performance\ rank_{t-1}$), and all prior year fund-level controls presented in Table 3 (X_{t-1}), including fund size, fund family size, age, flow, total shareholder costs, SMB and HML factors, together with benchmark and year fixed-effects.[16] This flow performance relationship is used to estimate flows at the 10th, 50th, and 90th percentile performance

[16] Previous studies, including Hunter et al. (2014), and Kosowski, Naik, and Teo (2007), evaluate funds using the alpha t-statistic rather than the estimated alpha. Kosowski et al. (2006) suggest that ranking funds by their t-statistics controls for heterogeneity in risk-taking across funds, which eliminates unusual nonnormalities in the cross-section of alphas. To check that our results are not affected by our methodology, in unreported tests we repeat the analysis in Table 5 with funds ranked on the t-statistic for their four-factor alpha. The results are similar to those presented in Table 5.

level in each country in each year. These flows are then used together with the coefficients on the performance-flow interaction in Table 4 to estimate the impact of flows on persistence for each country averaged across years. Table 5 presents the results.

Funds in the 90th percentile are expected to get inflows as they are at the top of the performance scale while funds in the 10th percentile are expected to get outflows as they perform relatively poorly. Funds in the 50th percentile are expected to get small inflows or outflows as they are in the middle of the performance scale. For increasing returns to scale countries, there is a 9.22% change in persistence if funds receive flows commensurate with 90th percentile performance, while for decreasing returns to scale countries the change in persistence is –6.65%. In the US, the change in persistence following 90th percentile performance amounts to a –8.11% change in the level of persistence per year. When funds experience outflows at the 10th percentile performance level, we see that increasing returns to scale countries experience a decrease in persistence of 4.88% and decreasing returns to scale countries experience an increase in persistence of 4.32%. Like in decreasing returns to scale countries, in the US, there is an increase in persistence of 5.57%, when funds experience outflows at the 10th percentile performance level. When excluding the US from the sample of decreasing returns to scale countries there is only a marginal decrease on the economic effect of flows on persistence. At the 50th percentile performance level, there is little effect of flows on persistence in percentage terms, as the flows are relatively small at this level of performance.

In summary, flows affect persistence in the manner that the Berk and Green (2004) model predicts, but to only a relatively modest degree, which explains why the Berk and Green (2004) model has difficulty explaining the cross-section of persistence levels. We have shown that there are decreasing returns to scale in eight countries. However, in the large majority of these countries,

there is statistically significant persistence. How can we explain these findings? Despite flows weakening persistence as we would expect in the presence of decreasing returns to scale, we show that the economic impact of flows on persistence is small, which is why persistence is present in most countries with decreasing returns to scale.

7. Robustness

This section provides several robustness tests of our main findings.

7.1 Endogeneity concerns

Reuter and Zitzewitz (2015) and Pastor, Stambaugh, and Taylor (2015) suggest that returns to scale cannot be estimated by regressing fund performance on fund size due to endogeneity in the performance size relationship. Pastor, Stambaugh, and Taylor (2015) solve this problem using a recursive demeaning procedure.[17] In order to test the robustness of our results, we estimate equation (3) using the recursive demeaning approach. This involves running the regressions with forward demeaned values of all the variables apart from forward demeaned fund size, which is instrumented for using backward demeaned fund size.

We start by running the results in Table 3. The results are presented in Table 6 and show that, when using the recursive demeaning approach, our main results are largely preserved. There is little change in the level of significant performance persistence across countries in our sample, and, most important the classification of countries into decreasing, constant, and increasing returns to scale categories remain unchanged. We next rerun the regressions in Table 4, for the groups of

[17] Pastor, Stambaugh, and Taylor (2015) find evidence of constant returns to scale in the US when they use data from 1993 to 2011, but find evidence of decreasing returns to scale using data from 1979 to 2011. We find, using the Pastor, Stambaugh, and Taylor (2015) methodology that there is decreasing returns to scale in the US, which is also consistent with the findings in Chen, Hong, Huang, and Kubik (2004), Edelen, Evans, and Kadlec (2007), Yan (2008), and Ferreira, Keswani, Miguel, and Ramos (2013). After their corrections, Reuter and Zitzewitz (2015) find that fund performance may improve with fund size. As we use an entirely different methodology and control variables to Reuter and Zitzewitz (2015), it is difficult to compare our returns to scale results for the US with those of their paper.

countries that are constant, increasing or decreasing returns to scale, using the recursive demeaning procedure. The results are presented in Table 7 and confirm our main findings, as flows decrease performance persistence in the case of decreasing returns to scale countries, increase performance persistence for increasing returns to scale countries, and have little impact on performance persistence in countries with constant returns to scale.

7.2 Fund size

It could be argued that the largest and the smallest funds in our sample are driving our results. We therefore exclude funds in the bottom and top size quintiles in each country-year, and rerun the analysis of Table 3. The results, presented in Table IA1, show that excluding these funds changes little the performance persistence across countries in our sample and does not alter the classification of countries into constant, increasing, and decreasing returns to scale. The results in Table IA2 also show that flows continue to increase persistence in increasing returns to scale countries, weakens persistence in decreasing returns to scale countries, and do not affect performance persistence in constant returns to scale countries. We therefore conclude that our main results concerning the dynamics of persistence are preserved with the exclusion of funds in the bottom and top size quintiles in each country-year.

7.3 Fund age

In our main tests, we exclude funds with age less than three years, as we impose a minimum of 36 continues monthly observations for each fund when calculating four-factor alpha performance. Because the literature shows that fund age determines performance (e.g., Ferreira, Keswani, Miguel, and Ramos, 2013, and Pastor, Stambaugh, and Taylor, 2015), and it is correlated with fund size (Chen, Hong, Huang, and Kubik, 2004), it is important to examine whether our main findings are robust to a change in maturity cut-off. To do so, we start by rerunning the results

in Table 3 raising the maturity cut-off by excluding funds with age in the bottom age quintile in each country-year.[18]

The results are presented in Table IA3 and show that our main results are largely preserved. The number of countries with significant persistence changes slightly, but significant persistence remains for the sample of all countries together. As regards the coefficients on fund size, the classifications of countries into decreasing, constant and increasing returns to scale categories remains unchanged when we use the greater maturity cut-off. In Table IA4 we rerun the regressions in Table 4 for constant, increasing and decreasing returns and we show that the results are not affected by the maturity cut-off.

7.4 Further robustness

To enhance the power of our estimates of the relationship between fund performance and lagged fund flow, in our analysis above we use the full sample of data to determine the returns to scale of countries. However, this means we are assuming that returns to scale for each country remain constant during our sample period. In addition, this implies that we are estimating the returns to scale of countries in-sample using the same data window as we use to test the effect of flows on persistence. To address these concerns, we estimate the returns to scale for each country out-of-sample on a rolling basis using the prior year's data to determine the returns to scale of a given country-year. We then rerun the tests of Table 4 grouping together country-years that are constant, increasing or decreasing returns to scale. The results of doing so, presented in Table IA5, show that our main findings are not materially affected by estimating countries' returns to scale out of sample. Using the rolling estimates of the returns to scale of each country-year, we still find

[18] By doing so, the average fund age across countries in our sample increases from 13.4 years (see Table 2) to 22.7 years. In South Korea and China, the countries with lowest average fund age in our sample, the average fund age increases from 7.4 years to 10.4 years and from 7.8 years to 11.3 years, respectively.

that flows decrease performance persistence in the case of decreasing returns to scale country-years, increase persistence in the case of increasing returns to scale country-years and do not affect persistence in the case of constant returns to scale country-years.

Table 1 shows clear differences in the number of funds across countries in our sample. A total of 3,584 of the 10,616 funds in our sample are based in the US, which means that the US is responsible for approximately 34% of the funds, while Hong Kong and Singapore represent only 0.1% of the funds in our sample. To account for the US dominance in our sample, our main results present a specification in which we exclude the US from the group of countries with decreasing returns to scale. Because there are also important differences in the number of funds between the remaining countries in our sample, we redo the analysis in Table 4, except that we now use a weighted least squares method where we weight our observations by the inverse of the number of funds in each country-year. This gives less weight to those countries with a higher number of funds in our sample. The results are presented in Table IA6 and show that flows still affect persistence exactly as before.[19]

To address concerns on cross-sectional dependence in our results, we rerun the results in Table 4 using the Fama-MacBeth estimation procedure. Table IA7 presents the results and show that our main results are confirmed.

Finally, we run our regressions using benchmark-adjusted results as in Busse, Goyal, and Wahal (2010) and Pastor, Stambaugh, and Taylor (2015). Benchmark-adjusted returns, i.e., the difference between the fund's net return and the return on its specific benchmark, are computed

[19] Table 1 also shows substantial differences in TNA across countries, in unreported results we also use weighted least squares weighting by the inverse of the average TNA in each country-year, and the results remain similar. Because it can be argued that small industries with fewer funds are driving our results, as the results based on smaller fund industries could be less reliable, in unreported tests we also run the results in Table 4 excluding fund industries with less than 200 observations. The results show that this has no impact in our main findings.

using the Lipper Technical Indicator Benchmark.[20] Table IA8 presents the results and show that changing the risk-adjusted performance measure does not change our main conclusions. Flows do not affected persistence in constant returns to scale countries, increase persistence in increasing returns to scale countries and weakens persistence in decreasing returns to scale countries.

8. Conclusion

The Berk and Green (2004) model provides us with conditions under which mutual fund performance will not persist. These include perfect capital markets, rational learning by investors of managerial skill and decreasing returns to scale in fund management. The intuitive mechanism responsible for this result is the following: investors chase lagged alpha in the model, which causes any subsequent abnormal performance to be eliminated in the presence of assumed decreasing returns to scale. In reality the Berk and Green (2004) assumptions may not hold. In this paper we ask whether flows materially moderate persistence in mutual fund industries worldwide.

Combining information on the size of flows across 32 countries and the effect of flows on persistence, we find performance persistence in most countries, which is contrary to the predictions of the Berk and Green (2004) model. We also find cross-sectional differences in returns to scale of fund industries across countries and that decreasing returns to scale are only present in a minority number of countries in our sample.

When we test the Berk and Green mechanism, we find that the economic effect of flows on persistence is relatively small and often the wrong sign due to the majority of countries not having

[20] For each fund, Lipper reports a self-declared "Fund Manager Benchmark" and a "Technical Indicator Benchmark", which are independently assigned by Lipper based on its assessment of the fund investment strategy. To avoid concerns that the fund may strategically choose its benchmark to rank higher in performance rankings, we follow Cremers, Ferreira, Matos, and Starks (2016) and use the Lipper "Technical Indicator Benchmark" rather than the self-declared "Fund Manager Benchmark".

decreasing returns to scale. Even in the US, where fund industry conditions most closely mirror the Berk and Green assumptions, we still find a small effect of flows on persistence.

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Table 1 – Number and size of mutual funds by country

This table presents the number of unique funds in our sample and total net assets (TNA) under management (sum of all share classes in millions of US dollars at the end of 2015). The sample is restricted to open-end and actively managed domestic equity funds drawn from the Lipper database. The sample period is 2001–2015.

Country	Number of funds	TNA ($ million)
Argentina	32	471
Australia	763	63,351
Austria	15	1,244
Belgium	26	1,264
Brazil	1,284	27,688
Canada	616	136,496
China	22	5,561
Denmark	32	5,410
Finland	35	4,831
France	313	33,164
Germany	69	36,635
Greece	25	721
Hong Kong	12	8,359
India	336	44,402
Indonesia	77	5,473
Italy	59	4,413
Japan	776	55,410
Malaysia	162	13,851
Netherlands	25	2,977
Norway	59	9,265
Poland	69	4,994
Portugal	21	253
Singapore	12	1,311
South Africa	164	18,755
South Korea	709	21,352
Spain	89	4,803
Sweden	132	46,470
Switzerland	133	27,538
Taiwan	196	6,195
Thailand	166	10,878
UK	604	266,425
US	3,584	3,686,750
All countries	10,617	4,556,709

Table 2 – Summary statistics

This table presents, in Panel A, means and total number of observations of fund-level characteristics by country. Panel B presents pairwise correlations for these variables. Panel C presents means of country-level characteristics by country. The sample is restricted to open-end and actively managed domestic equity funds drawn from the Lipper database. The sample period is 2000–2015. See Appendix 1 for variable definitions.

Panel A: Average of fund variables by country

Country	Number of observations	Raw return (% year)	Benchmark–adjusted return	Four-factor alpha (% year)	Size ($ million)	Family size ($ million)	Flows (% year)	Age (years)	TSC (%)	SMB	HML
Argentina	195	10.63	–3.91	–1.15	9	22	21.09	14.05	3.03	0.66	0.21
Australia	4,139	7.07	–0.23	–3.70	156	4,680	0.39	11.14	1.67	–0.07	–0.05
Austria	107	4.17	1.80	–5.30	104	1,359	7.30	14.72	2.53	0.74	0.01
Belgium	165	10.72	0.49	0.75	115	4,726	–0.97	15.08	1.80	0.34	–0.11
Brazil	5,054	–3.71	–5.37	–6.66	75	4,026	–6.27	8.43	1.79	0.36	–0.08
Canada	3,847	6.10	–0.17	–3.28	423	12,422	6.48	14.05	2.76	0.04	0.09
China	102	15.08	4.00	4.94	565	2,799	–12.26	7.78	2.00	0.25	–0.41
Denmark	244	20.31	1.75	1.11	150	2,259	21.34	14.07	1.76	0.58	0.04
Finland	308	13.72	1.09	0.54	162	3,141	14.90	13.01	1.81	0.40	–0.01
France	2,010	7.03	1.15	–0.72	207	4,913	5.13	15.04	2.48	0.16	–0.05
Germany	538	11.96	–0.62	0.23	699	16,058	5.00	24.08	2.33	–0.04	–0.17
Greece	193	0.60	–4.27	–5.51	80	205	8.10	15.31	3.49	0.29	0.57
Hong Kong	70	9.68	2.16	2.57	583	3,491	12.81	10.27	1.69	–0.21	–0.24
India	1,906	20.93	3.82	2.79	134	2,034	19.27	8.89	2.34	–0.03	–0.71
Indonesia	364	8.97	–3.52	0.36	103	427	25.73	9.02	3.31	0.10	–0.05
Italy	346	4.99	0.28	–1.67	207	2,580	3.24	13.20	2.44	0.09	–0.05
Japan	5,353	9.21	0.88	–1.61	100	15,878	–0.76	10.22	1.88	0.24	0.06
Malaysia	1,247	9.70	1.93	4.62	72	1,626	5.47	12.69	2.85	0.21	0.19
Netherlands	172	12.35	3.08	2.79	369	3,916	1.77	17.22	1.19	0.27	0.08
Norway	611	22.87	3.15	–0.08	179	2,498	18.37	14.83	1.64	0.27	0.12
Poland	432	5.25	–3.13	–3.66	158	458	22.22	9.03	3.91	–0.05	0.49
Portugal	200	8.95	–1.22	1.25	41	284	–3.67	13.20	1.93	0.58	–0.15
Singapore	88	10.65	1.93	1.68	128	890	12.13	14.44	2.48	0.10	–0.10
South Africa	925	2.81	–2.06	–2.43	171	1,620	12.30	11.68	1.94	–0.04	–0.25
South Korea	2,700	15.34	1.34	1.55	67	2,785	–13.20	7.44	1.77	0.27	0.16
Spain	680	6.95	3.07	–1.71	74	1,163	7.61	13.79	2.02	–0.23	0.33
Sweden	1,139	17.22	1.41	5.70	439	13,124	11.82	14.16	1.37	0.05	–0.20
Switzerland	800	10.44	0.03	2.51	262	13,072	4.13	12.33	1.64	0.26	–0.20
Taiwan	1,652	12.22	1.92	3.98	56	1,074	6.77	12.46	3.46	0.63	–0.43
Thailand	1,303	10.70	2.40	–1.40	46	802	10.22	10.78	1.78	0.31	–0.27
UK	3,816	9.08	0.62	1.18	639	11,257	6.30	17.58	2.08	0.40	–0.08
US	28,768	9.28	–1.05	–1.55	1,394	61,714	6.45	15.43	1.53	0.24	–0.01
All countries	69,474	8.13	0.19	–1.27	701	29,654	4.52	13.41	1.88	0.22	–0.04

Panel B: Pairwise correlations among fund variables

		1	2	3	4	5	6	7	8	9	10
Raw return	1	1									
Benchmark–adjusted return	2	0.206	1								
Four-factor alpha	3	0.488	0.315	1							
Size	4	0.019	–0.003	0.014	1						
Family size	5	0.027	0.005	0.017	0.322	1					
Flows	6	0.356	0.177	0.207	0.016	0.031	1				
Age	7	–0.008	–0.029	0.012	0.251	0.154	–0.055	1			
TSC	8	0.004	–0.017	0.003	–0.111	–0.162	–0.009	–0.040	1		
SMB	9	0.059	–0.037	0.014	–0.050	–0.020	0.002	–0.076	0.052	1	
HML	10	–0.154	–0.022	–0.089	0.001	0.002	–0.020	0.008	–0.048	–0.221	1

Panel C: Average of country variables by country

Country	Fund industry eq. size/mcap	Fund industry Herfindhal	Judicial	GDP per Capita ($)
Argentina	0.88	0.11	28	11,682
Australia	16.32	0.04	47	56,384
Austria	14.97	0.12	47	48,923
Belgium	12.52	0.29	47	43,501
Brazil	7.99	0.09	32	11,116
Canada	17.92	0.06	48	46,611
China	1.61	0.08	31	6,355
Denmark	16.27	0.10	49	56,883
Finland	18.69	0.18	49	46,200
France	14.35	0.05	45	40,577
Germany	10.54	0.16	47	42,295
Greece	2.61	0.21	34	24,132
Hong Kong	2.06	0.10	44	36,637
India	2.97	0.10	31	1,342
Indonesia	1.93	0.19	22	3,206
Italy	6.63	0.12	40	35,555
Japan	6.18	0.11	47	40,002
Malaysia	3.81	0.38	39	9,113
Netherlands	6.58	0.15	49	49,903
Norway	16.67	0.17	50	83,925
Poland	6.27	0.13	31	12,406
Portugal	3.80	0.18	39	21,256
Singapore	2.21	0.11	45	49,471
South Africa	3.38	0.09	33	6,688
South Korea	5.16	0.12	34	23,114
Spain	2.20	0.10	39	30,427
Sweden	22.93	0.17	49	50,121
Switzerland	10.04	0.19	50	77,748
Taiwan	3.38	0.09	40	19,531
Thailand	3.26	0.12	30	5,117
UK	20.02	0.03	47	43,302
US	29.37	0.05	48	46,922
All countries	18.29	0.08	44	38,887

Table 3 – Mutual fund performance persistence and returns to scale by country

This table presents the results of panel regressions measuring performance persistence and returns to scale in each of the 32 countries in our sample. Results for all countries are also presented at the bottom. For each country, fund level four-factor alpha in a given year is regressed on prior year four-factor alpha and control variables (see Equation 3). Control variables include: *Size*; *Family size*; *Fund industry equity size as a percentage of stock market capitalization*; and also *Flows*; *Age*; *TSC*; *SMB*; and *HML* (not reported). Regressions also include time and benchmark fixed effects. Robust t-statistics clustered by fund or by country, when running the regressions by country or pooled across countries, respectively, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. See Appendix 1 for variable definitions.

	Performance		Size		Family size		Fund industry eq. size/mcap		Adjusted	Number of
Country	Coefficient	t–stat	Coefficient	t–stat	Coefficient	t–stat	Coefficient	t–stat	R–squared	observations
Argentina	0.1520**	(2.57)	0.0079**	(1.97)	0.0037	(1.23)	0.0033	(0.19)	0.885	195
Australia	0.0455**	(2.30)	–0.0017***	(–2.71)	0.0001	(0.08)	–0.0216***	(–3.94)	0.713	4,139
Austria	0.0305	(0.21)	–0.0048	(–0.69)	0.0021	(0.32)	0.0636***	(3.86)	0.843	107
Belgium	0.0555	(0.41)	0.0065	(1.62)	–0.0006	(–0.21)	–0.1256***	(–7.59)	0.559	165
Brazil	0.1462***	(5.49)	0.0018**	(2.27)	0.0029***	(3.29)	0.0212***	(3.91)	0.748	5,054
Canada	0.1256***	(5.93)	–0.0016***	(–2.61)	0.0027***	(3.28)	–0.0443***	(–3.01)	0.661	3,847
China	0.0120	(0.09)	0.0007	(0.05)	–0.0198	(–1.38)	0.5168***	(4.35)	0.841	102
Denmark	0.2711**	(2.40)	0.0031*	(1.86)	0.0023	(0.87)	–0.0026	(–1.05)	0.582	244
Finland	–0.0613	(–0.81)	–0.0075	(–1.22)	0.0013	(0.25)	–0.0071***	(–3.35)	0.589	308
France	0.1007***	(2.73)	0.0042***	(3.67)	0.0013	(1.62)	0.0110**	(2.47)	0.329	2,010
Germany	0.1079	(1.60)	–0.0041**	(–2.33)	0.0032	(1.43)	0.0344	(1.28)	0.571	538
Greece	–0.0594	(–0.57)	0.0092*	(1.91)	0.0080	(0.79)	0.1579	(0.25)	0.901	193
Hong Kong	–0.0681	(–0.71)	–0.0058	(–0.97)	–0.0048	(–0.48)	–0.1530	(–1.25)	0.772	70
India	0.0611*	(1.92)	0.0011	(0.46)	0.0044*	(1.96)	–0.3190***	(–14.56)	0.800	1,906
Indonesia	0.1403*	(1.82)	0.0005	(0.10)	0.0078**	(1.99)	–0.2173***	(–3.64)	0.855	364
Italy	0.1350***	(3.14)	0.0011	(0.19)	0.0012	(0.39)	–0.0377***	(–3.67)	0.612	346
Japan	0.1441**	(2.24)	–0.0027***	(–2.96)	0.0020**	(2.53)	–0.0011	(–0.40)	0.554	5,353
Malaysia	0.0935**	(2.54)	0.0041*	(1.67)	0.0026	(1.31)	0.1051***	(9.21)	0.815	1,247
Netherlands	0.0261	(0.19)	–0.0016	(–0.30)	–0.0015	(–0.47)	–0.0137	(–1.34)	0.379	172
Norway	0.0518	(1.34)	–0.0005	(–0.19)	–0.0013	(–0.66)	–0.0011	(–0.95)	0.849	611
Poland	0.1394**	(2.38)	–0.0065	(–1.53)	0.0086***	(2.59)	0.0097	(1.14)	0.756	432
Portugal	0.0551	(0.41)	0.0048**	(1.98)	–0.0016	(–0.53)	–0.3449**	(–2.10)	0.914	200
Singapore	0.1053	(1.26)	0.0075***	(2.85)	–0.0056*	(–1.68)	0.4305***	(8.41)	0.954	88
South Africa	0.0705**	(1.99)	0.0061**	(2.19)	0.0003	(0.10)	–0.0158	(–1.10)	0.854	925
South Korea	0.1208***	(4.33)	–0.0024**	(–2.56)	0.0035***	(3.01)	0.0440***	(13.67)	0.887	2,700
Spain	0.1068**	(2.48)	–0.0022	(–1.28)	–0.0002	(–0.22)	–0.0703***	(–2.92)	0.740	680
Sweden	0.0807*	(1.91)	0.0022	(1.41)	0.0004	(0.28)	–0.0021	(–1.60)	0.700	1,139
Switzerland	0.0439	(1.12)	0.0015	(0.76)	0.0021*	(1.68)	–0.0045**	(–2.37)	0.524	800
Taiwan	0.0081	(0.09)	–0.0042*	(–1.93)	0.0075***	(3.19)	–0.0217	(–1.54)	0.691	1,652
Thailand	0.0533	(1.64)	0.0018	(0.84)	–0.0092***	(–3.64)	0.0216**	(2.15)	0.910	1,303
UK	0.0655***	(5.10)	–0.0014***	(–2.67)	0.0009	(0.81)	–0.0056***	(–10.46)	0.532	3,816
US	0.0499***	(5.49)	–0.0017***	(–5.05)	0.0019***	(7.37)	–0.0054***	(–19.74)	0.133	28,768
All Countries	0.0628***	(2.81)	0.0026	(1.12)	0.0011	(0.80)	–0.0014**	(–2.01)	0.098	69,474