Journal of Financial Intermediation 38 (2019) 69–81

Contents lists available at ScienceDirect

Journal of Financial Intermediation

journal homepage: www.elsevier.com/locate/jfi

Misspecifications in the fund flow-performance relationship☆

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ARTICLE INFO

Keywords:
Mis-measured performance
Return discrimination
Flow-performance relationship
Inflows and outflows
Investor-substitution effect

JEL classification:
G10
G11

ABSTRACT

This study shows the importance of return discrimination between funds in the flow-performance relationship. To do so, we employ objective-adjusted returns rather than performance ranks. We demonstrate that the net flow-performance relationship is a direct consequence of the convex inflow- and outflow-performance relationships, and that fund size and age have no significant effect on these relationships. When we measure past performance using 12-month objective-adjusted returns, we find a linear net flow-performance relationship after controlling for the *investor-substitution effect*.

1. Introduction

Many studies have examined the relationship between mutual fund flows and past performance. Sirri and Tufano (1998) assert that search costs are an important determinant of fund flows, emphasizing the convex relationship between flows and relative performance. Further supporting this claim, Huang et al. (2007) and Ferreira et al. (2012) illustrate the effects of participation costs on the flow-performance relationship.[1] However, Ferreira et al. (2012) also show a decline in participation costs over time as the mutual fund industry matures, thereby weakening the convex flow-performance relationship. In contrast, Spiegel and Zhang (2013) argue that flow-performance relationship is linear and that convexity occurs with the misspecification of the empirical model. In other words, heterogeneous linear relationships in hot and cold money funds exist; however, the analysis that does not consider this heterogeneity leads to a false convexity relationship, because hot funds produce more volatile returns than cold funds do.

Most studies apply relative performance (i.e., performance ranks), calculated by ordering risk-adjusted returns, without considering the distribution of fund returns. However, it has not been argued that performance rank is not an appropriate measure of fund performance to test the flow-performance relationship. While most funds produce returns similar to market returns, some highly risky funds offer returns that differ dramatically from market returns. The level of fund portfolio risk varies from fund to fund. (See Spiegel and Zhang, 2013). In this sense, relative performance does not reflect the cross-sectional differences in fund returns. Therefore, we firmly believe that return discrimination may actually play an important role in the flow-performance relationship, because investors' decisions do largely depend on past performance.[2] Therefore, we suggest the use of objective-adjusted returns rather than performance ranks when examining the flow-performance relationship. This critical point is the motivation for our study.

According to Lynch and Musto (2003), we expect investors who want to continue to invest in equity mutual funds to realize current profits by redeeming the best-performing funds and then reinvesting those proceeds in the worst-performing funds, following a *contrarian strategy*. At the same time, some investors of the worse- or worst-

☆ We'd like to be grateful to an anonymous referee and the editor (Charles Calomiris) for invaluable and encouraging comments. We also thank to Dr. Insub Lee for helpful comments.

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[1] Recently, Ha and Ko (2017) find that a change in fund risk has a positive and convex relationship with a fund's net flows.

[2] Berk and Green (2004) offer a model wherein fund investors using rational expectations respond to past performance by learning about skill. Recently, Starks and Sun (2016) and Franzoni and Schmalz (2017) allow Bayesian investors to learn about the fund's loading on aggregate risk.

https://doi.org/10.1016/j.jfi.2018.11.001
Received 14 November 2016; Received in revised form 21 October 2018; Accepted 26 November 2018
Available online 06 February 2019
1042-9573/

performing funds may move to better- or even best-performing funds.[3] We call this phenomenon the *investor-substitution effect* or the *contemporaneous effect of opposite flows*. O'Neal (2004) and Cashman et al. (2012) find that, as a consequence, inflows and outflows have a significant contemporaneous correlation at the individual fund level as well as at the aggregate market level.

We adopt the following two approaches to consider the return discrimination between funds and the investor-substitution effect in this flow-performance relationship. First, we use objective-adjusted returns rather than performance ranks.[4] Objective-adjusted returns fully demonstrate the effect of past performance on subsequent fund flows. Second, we control for contemporaneous opposite flows to obtain adjusted (or residual) inflows and outflows, wherein the adjusted net flows are calculated as adjusted inflows minus the adjusted outflows. To prevent any econometric simultaneity problem, we employ the two-stage least squares (2SLS) regression.

Many prior studies have used net flows, calculated with fund returns and total net assets (TNAs), because mutual fund databases typically provide these figures rather than real cash flows. Net flows information is just the summary of both inflows and outflows, and hence is not able to reveal the actual buying and selling decisions of fund investors. Unlike previous studies, this study examines actual net flows, inflows, and outflows using the Form N-SAR filings from the Securities Exchange Commission's (SEC's) Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database. We first analyze the relationship between net flows and performance during various performance-evaluation periods, and then we explain this relationship using inflows and outflows.

Our main findings are as follows. First, we find a linear net flow-performance relationship in the middle- and high-performance domains when we use 12-month objective-adjusted returns that reflect the effects of return discrimination. Second, 12 months is the most appropriate performance-evaluation period for fund-investment decisions. Third, inflows and outflows have a convex relationship with past performance regardless of performance measure. The net flow-performance relationship is a natural consequence of the inflow- and outflow-performance relationships. Fourth, fund size and age have no significant effect on these flow-performance relationships. Finally, after controlling for the investor-substitution effect, we obtain a linear net flow-performance relationship for all performance domains.

This study contributes to the extant literature in three ways. First, unlike the previous studies, we use objective-adjusted returns to correct any errors in performance measures in the flow-performance relationship. The use of objective-adjusted returns helps us outline the effects of fund size and age on the relationship, as suggested by Spiegel and Zhang (2013). Second, we explain the linear net flow-performance relationship by using actual inflows and outflows from the Form N-SAR filings. Third, we test the flow-performance relationships after controlling for the investor-substitution effect.

This paper proceeds as follows. Section 2 describes the data and summary statistics. Section 3 analyzes the net flow-performance relationship, and Section 4 examines the inflow- and outflow-performance relationships. We investigate these flow-performance relationships after controlling for the investor-substitution effect in Section 5. Section 6 concludes this study.

2. Data

We obtain our data from the Center for Research in Security Prices (CRSP) mutual fund database and the SEC's EDGAR database. The CRSP mutual fund database provides monthly returns and TNAs for individual funds. However, we do not use cash flows as estimated from the CRSP database. Instead, we collect cash inflows and outflows for individual funds from the Form N-SAR filings in the SEC's EDGAR database and calculate net flows by subtracting outflows from inflows.

A regulation under the Investment Company Act of 1940 requires registered investment companies to file semi-annual reports (Form N-SAR A/B) with the SEC's EDGAR database starting in 1994. Consequently, our sample period is from January 1994 to June 2015. In the N-SAR form, Item 28 includes cash-flow information on a monthly basis at the portfolio level. Following Edelen et al. (2011), we define a fund at the portfolio level as including all share classes in the fund. Since the CRSP database contains various fund data at the share-class level, we also aggregate all share-class TNAs to compute the TNAs of a fund and the TNA-weighted monthly average returns for that fund. We manually merge the CRSP fund data with the EDGAR data by matching fund names, since the CRSP fund codes are not directly related to the N-SAR fund codes of the central index key (CIK).

We also focus on actively managed U.S. domestic equity mutual funds for the following three styles: growth, growth and income, and mid- and small-cap fund styles. After excluding exchange-traded funds (ETFs) and index funds, we obtain 19,352 domestic equity share classes or funds from the CRSP database. Among these 19,352 share classes or funds, 18,048 match the EDGAR data by using the fund name. These 18,048 share classes or funds belong to 6138 individual funds, as an individual fund may have several share classes. Following Elton et al. (2001), we eliminate funds with average TNAs that are less than \$15 million. We also eliminate funds with a duration of less than three years. Through this screening process, we obtain 3562 domestic equity funds.

The three kinds of monthly fund flows (inflows, outflows, and net flows) are defined as follows:

$$Inflows_{i,t} = new\ sales_{i,t}/TNA_{i,t-1} \tag{1}$$

$$Outflows_{i,t} = redeemed\ cash_{i,t}/TNA_{i,t-1} \tag{2}$$

$$Net\ flows_{i,t} = inflows_{i,t} - outflows_{i,t} \tag{3}$$

where new $sales_{i,t}$ is the amount of fund *i* shares sold in month *t*, redeemed $cash_{i,t}$ is the amount of fund *i* shares redeemed and repurchased in month *t*, and $TNA_{i,\ t\text{-}1}$ is the TNAs for fund i at the end of month *t*–1. Additionally, we exclude observations with TNAs less than \$15 million in the previous month, net flows less than −90%, inflows greater than 1000%, and outflows greater than 100%.[5] On the other hand, estimated net flows are calculated using a fund's TNAs and returns data from the CRSP database as in previous studies.

Table 1 shows the summary statistics for the sample funds, including the number of funds, TNAs, annual fund returns, cross-sectional standard deviations of annual returns, and monthly aggregate cash flows for each year from January 1994 to June 2015. The number of funds includes those in existence for 12 months during each year. TNAs are the simple average of fund size at the end of a year. Fund returns are the cumulative annual returns, and cross-fund volatility is the standard deviation of annual returns across the funds each year. All figures for 2015 are calculated as of the end of June. The next three columns show the monthly average aggregate cash flows (net flows, inflows, and outflows) from the Form N-SAR filings in the SEC's EDGAR database. Monthly aggregate inflows (outflows) are calculated by dividing the

[3] Ben-Rephael (2017) finds that the sell-off of illiquid stocks occurs only after the initial deterioration of market conditions, consistent with retail investors' response to bad performance.

[4] Owing to the tournament behavior in the mutual fund industry, as suggested by Brown et al. (1996), most studies use performance ranks rather than raw returns to investigate the flow-performance relationship.

[5] There are two cases in which outflows exceed 100%: First, there exist extremely unusual outflows for no apparent reason. In most case, a fund's TNAs in the previous month are less than \$15 million. We exclude such observations. Second, both inflows and outflows are greater than 100%, and inflows are greater than outflows. This case is possible but unusual. We also exclude these observations.

Table 1
Summary statistics of the sample funds.

Year	Number of funds	TNAs ($M)	Fund returns	Cross-fund volatility	Aggregate net flows	Aggregate inflows	Aggregate outflows	Difference between aggregate and estimated net flows
1994	242	942	−0.0113	0.0534	0.0102	0.0350	0.0248	−0.0001 (−0.11)
1995	356	1295	0.3177	0.0806	0.0092	0.0309	0.0216	−0.0005 (−0.72)
1996	524	1260	0.1891	0.0650	0.0089	0.0324	0.0235	0.0000 (0.07)
1997	620	1649	0.2391	0.0981	0.0072	0.0306	0.0235	−0.0005 (−1.10)
1998	739	1846	0.1427	0.1468	0.0041	0.0297	0.0257	−0.0006 (−0.92)
1999	870	2069	0.2747	0.3033	0.0026	0.0305	0.0279	−0.0004 (−0.83)
2000	973	1852	−0.0119	0.1527	0.0039	0.0332	0.0293	−0.0006 (−0.92)
2001	1061	1485	−0.0956	0.1580	0.0025	0.0270	0.0245	−0.0001 (−0.49)
2002	1122	1107	−0.2132	0.0923	0.0000	0.0270	0.0270	−0.0002 (−1.52)
2003	1191	1523	0.3305	0.1110	0.0047	0.0253	0.0206	−0.0003 (−1.10)
2004	1315	1669	0.1239	0.0619	0.0038	0.0218	0.0180	−0.0003 (−1.54)
2005	1405	1703	0.0730	0.0488	0.0016	0.0216	0.0200	0.0000 (−0.21)
2006	1485	1889	0.1279	0.0563	0.0026	0.0217	0.0191	−0.0004 (−1.09)
2007	1569	1923	0.0675	0.0932	0.0006	0.0206	0.0201	−0.0002 (−1.13)
2008	1576	1120	−0.3805	0.0713	−0.0032	0.0227	0.0259	−0.0003 (−0.73)
2009	2015	1290	0.3190	0.1109	−0.0008	0.0226	0.0234	−0.0002 (−0.17)
2010	2222	1371	0.1813	0.0691	−0.0017	0.0216	0.0232	0.0000 (0.11)
2011	2250	1296	−0.0245	0.0493	−0.0023	0.0211	0.0234	−0.0003 (−0.78)
2012	2227	1450	0.1445	0.0423	−0.0038	0.0192	0.0230	−0.0002 (−1.78)
2013	2226	1874	0.3110	0.0959	−0.0007	0.0202	0.0209	0.0000 (0.00)
2014	2188	1985	0.0745	0.0485	−0.0021	0.0171	0.0192	−0.0005 (−1.66)
2015	2022	2010	0.0513	0.0528	−0.0032	0.0158	0.0190	−0.000 (−0.72)

The table shows the summary statistics for the sample funds including the number of funds, TNAs (total net assets), annual fund returns, cross-sectional standard deviations of annual returns, and monthly aggregate cash flows in each year from January 1994 to June 2015. The number of funds is calculated for funds that have been in existence for 12 months in each year. TNAs are the simple average of fund size at the end of the year. Fund returns are the cumulative annual returns, and cross-fund volatility is the standard deviation of annual returns across the funds in each year. All figures for 2015 are calculated as of the end of June. The next three columns show the monthly average aggregate cash flows (net flows, inflows, and outflows) from Form N-SAR filings of the SEC's EDGAR database. Monthly aggregate inflows (outflows) are calculated by dividing the sum of monthly new sales (redeemed cash) of the sample funds by the sum of TNAs at the end of the previous month. Aggregate net flows are the difference between aggregate inflows and outflows. We also show the difference between aggregate net flows and estimated aggregate net flows to confirm the validity of the two databases. Estimated aggregate net flows are calculated by using a fund's TNAs and returns data from the CRSP database. The paired *t*-statistics are in parentheses.

sum of monthly new sales (redeemed cash) of the sample funds by the sum of TNAs at the end of the previous month. Aggregate net flows represent the difference between aggregate inflows and outflows. Aggregate net flows, inflows, and outflows help indicate the overall fund market trend, because aggregation reduces the impact of small funds. We further show the difference between aggregate net flows and estimated aggregate net flows to confirm the validity of the two databases.

The number of funds has steadily increased by 2011, and the average TNAs are greater than $1 billion for all years except for 1994. Fund TNAs have undergone changes in the fund industry from fund TNAs. From 1994 to 1999, fund TNAs have increased significantly; however, because of the crash in the tech bubble in 2000, they declined from $2069 M in 1999 to $1107 M in 2002. Then, by 2007, the TNAs increased again, only to reach a low value again ($1120 million) during the global financial crisis of 2008. Since then, fund TNAs have recovered through high stock market returns rather than an increase in fund flows. Annual returns also experienced low values in 2002 (−21.32%) and 2008 (−38.05%). Cross-fund volatility peaked in 1999 (30.33%) and then dropped to its minimum in 2012 (4.23%). Aggregate net flows peaked in 1994 (1.02%), but more importantly, they have had negative net flows since 2008. These trends illustrate that investor desire to use aggressive mutual funds as an investment vehicle has not fully recovered after the crisis. Instead, investors are considering using Exchange Traded Funds (ETFs) or index funds with lower fees as alternative vehicles. Furthermore, the difference between aggregate net flows and estimated aggregate net flows for each year should be statistically zero if the two databases (i.e., CRSP and EDGAR) are consistent. The last column shows the validity of the two databases because the difference is close to zero. Hence, we can use the cash flows from the EDGAR database with considerable confidence.

3. Net flow-performance relationship

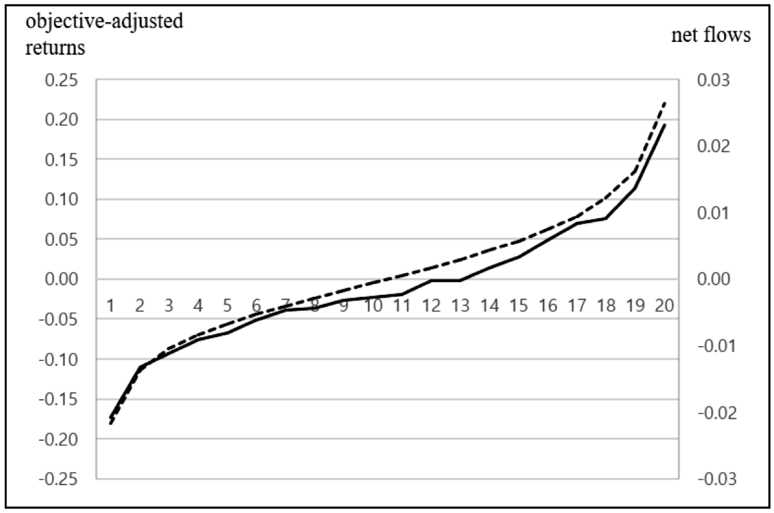
3.1. Graphical analysis

Many studies have examined the net flow-performance relationship (e.g., Sirri and Tufano, 1998; Lynch and Musto, 2003; Berk and Green, 2004; Huang et al., 2007; Ferreira et al., 2012). Following these studies, we investigate this relationship in terms of the performance measure. We use objective-adjusted returns to measure abnormal performance, namely the difference between fund returns and their investment objective returns.[6] For each month, we sort funds by past objective-adjusted returns into 20 groups and then calculate their average monthly objective-adjusted returns and net flows. The first (20th) group is the lowest-performing (highest-performing) group.

Fig. 1 shows the relationship between past objective-adjusted returns and net flows. Panel A plots the objective-adjusted returns together with net flows for each of these 20 performance groups. The dashed line represents objective-adjusted returns, and the solid line indicates net flows. Whereas the extant research shows only the net flows of each performance group, we plot the returns of performance groups as well as net flows to closely review their relationship or similarity. The results are sufficiently striking to offer new insight into the flow-performance relationship: Net flows have almost the same pattern as that of objective-adjusted returns. That is, both returns and net flows rapidly increase in the high-performance groups (above the 80% quantile) and rapidly decrease in the low-performance groups (below the 20% quantile).

[6] Sirri and Tufano (1998) emphasize the use of objective-adjusted returns. However, their results do not change qualitatively when we employ market-adjusted returns for abnormal performance.

Panel A: Objective-adjusted returns and net flows across the performance groups



Panel B: Scatter plot of net flows against objective-adjusted returns

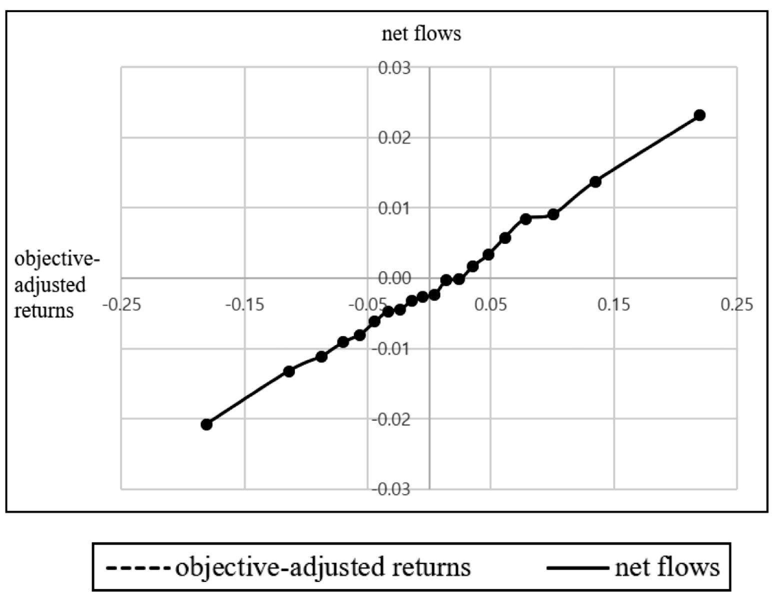


Fig. 1. Relationship between objective-adjusted returns and net flows. This figure shows the relationship between past objective-adjusted returns and net flows. Objective-adjusted returns are the difference between fund returns and their investment objective returns using the past 12-month returns. For each month, we sort funds by past objective-adjusted returns into 20 groups and then calculate their average monthly objective-adjusted returns and net flows. The first (20th) group is the lowest-performing (highest-performing) group. Panel A plots objective-adjusted returns together with net flows across the 20 performance groups. The dashed line represents objective-adjusted returns and solid line, net flows. Panel B shows a scatter plot of net flows with objective-adjusted returns on the horizontal axis.

The sharp growth in net flows in the high-performance groups has been explored by many studies that show the convexity of net flow-performance relationship. Furthermore, Huang et al. (2007) and Ferreira et al. (2012) explain the sharp decline in net flows in the low-performance groups. Huang et al. (2007) show that net flows become significantly more sensitive in the low-performance groups in later years. Ferreira et al. (2012) also mention that the convex relationship has weakened in the U.S. However, when we consider net flows along with objective-adjusted returns in Panel A of Fig. 1, we expect their relationship to be almost linear. Without consideration for the real scale of objective-adjusted returns, however, the flow-performance relationship could appear to be non-linear.

Panel B of Fig. 1 shows a scatter plot of net flows with objective-adjusted returns on the horizontal axis in order to consider the difference in past performance and net flows between performance groups. The higher or lower the performance, the larger the absolute net flows are across the 20 groups. In the middle-performance groups, both net flows and return differences are likely to be densely concentrated. In this case, the net flow-performance relationship appears to be linear. We also assert that mis-measured performance might lead to a non-linear flow-performance relationship, suggesting the use of objective-adjusted returns instead of performance ranks as an appropriate measure of past performance.

To understand how mis-measured performance affects the net flow-performance relationship, we review the distributions of objective-adjusted returns and net flows. Fig. 2 shows their histograms and include all observations. The horizontal axis represents objective-adjusted returns and net flows, and the vertical axis represents probability. For the purpose of comparison, we also draw the corresponding normal distributions with a solid line using the same means and standard

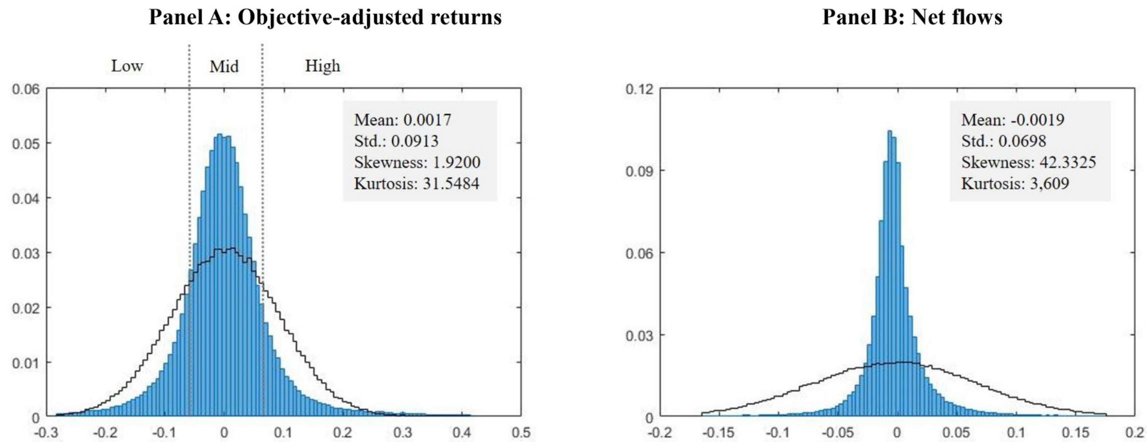


Fig. 2. Histograms of net flows and objective-adjusted returns. This figure is the histograms of fund objective-adjusted returns and net flows that include all observations. Objective-adjusted returns are the difference between fund returns and their investment objective returns using the past 12-month returns. The horizontal axis represents objective-adjusted returns and net flows, and the vertical axis, probability. For comparison purposes, we also draw the corresponding normal distributions by using a solid line with the same means and standard deviations as those of objective-adjusted returns and net flows. The range of the horizontal axis runs from the 0.5% to 99.5% quantile values of objective-adjusted returns and net flows, and 100 bins are displayed. The vertical dotted lines indicate the average objective-adjusted returns that correspond to the 20% and 80% quantile values, respectively. Hence, they divide all observations into Low (below the 20% quantile), Mid (from the 20% to 80 quantile), and High (above the 80% quantile).

deviations as those for the objective-adjusted returns and net flows. The range of the horizontal axis runs from the 0.5% to 99.5% quantile values of objective-adjusted returns and net flows, and 100 bins are displayed. The vertical dotted lines indicate the average objective-adjusted returns that correspond to the 20% and 80% quantile values, respectively. Hence, they divide all the observations into Low (below the 20% quantile), Mid (from the 20% to 80% quantiles), and High (above the 80% quantile).

As expected, the objective-adjusted returns are far from the normal distribution. They have a right-skewed distribution with a very high positive kurtosis. That is, objective-adjusted returns are concentrated around zero and are more scattered in the right extreme domain. Net flows also deviate from normal distribution and have even larger skewness and kurtosis than the objective-adjusted returns. They are also concentrated around zero and are more scattered in the right extreme domain than the normal distribution; this aspect is not well represented in the figure because of the relatively small number of observations. In sum, we see that objective-adjusted returns and net flows have leptokurtic distributions with fat tails on the right-hand side.

Fama and French (2010) find that the portfolio of active funds that invest primarily in U.S. equities is close to that of the market portfolio, meaning that their risk-adjusted abnormal returns are close to zero. Our findings support their results on the returns of equity funds. Therefore, when we divide past fund returns into performance groups with the same observations each, the cross-sectional return volatility of a performance group may indeed differ. In particular, high-performance (or low-performance) groups have a much larger return volatility than middle-performance groups have. These differences in cross-sectional return volatilities between performance groups indicate that return discrimination complicates investment decision whenever we use relative ranks to measure fund performance. In other words, if we measure fund performance using relative ranks, it becomes difficult to obtain an appropriate flow-performance relationship.

Then, will the use of past absolute returns instead of relative ranks provide a linear flow-performance relationship for all performance-evaluation periods? To roughly examine these relationships, we plot the net flows for various evaluation periods against the objective-adjusted returns of the 20 performance groups. We use normalized objective-adjusted returns to have zero mean and unit standard deviation for every month to compare various results with different return frequencies; however, normalization maintains the property of the original returns. Fig. 3 shows the net flow-performance relationships for the 1-, 12-, and 36-month evaluation periods, using the above-mentioned normalized returns.[7] In addition, we divide the sample funds into two subgroups of hot and cold money funds. Hot money funds represent a union of small and young funds, and cold money funds are an intersection of large and old funds. Small (large) funds are in the bottom (top) 50% in fund size, whereas young (old) funds are in the bottom (top) 50% in terms of fund age.[8] Hot and cold money funds are mutually exclusive. The number of hot money funds is three times the number of cold money funds.

The scatter-plots in Fig. 3 show the flow-performance relationships with normalized objective-adjusted returns on the horizontal axis. A linear net flow-performance relationship appears to be present, although further statistical tests are needed to draw a concrete conclusion. This finding indicates that the traditional convex relationship may originate from mis-measured past performance (i.e., relative ranks). Next, we summarize the effects of the following two aspects on the relationship: the evaluation period of past performance and fund size/age.

First, we examine the effects of the evaluation period on the net flow-performance relationship. When we use 1-month returns in the left-hand side of Fig. 3, we see the fluctuation in net flows in the middle-performance groups, which disappears as the evaluation period rises to 12 months and then 36 months. This result implies that objective-adjusted returns in the middle-performance groups have a stable effect on net flows, but only with sufficient measurement periods for historical returns (i.e., at least 12 months). This evidence suggests that return discrimination is difficult in the middle-performance groups when the evaluation period is shorter. Net flows are likely to have an almost linear relationship in an eyeball test.

The right-hand side of Fig. 3 shows the effect of fund size and age on the net flow-performance relationship. We compare hot and cold money funds by separately drawing their net flows in response to past returns.

[7] The plotting shape of the plotting is similar for all the evaluation periods except for some fluctuations in net flows for the shorter evaluation periods.

[8] Spiegel and Zhang (2013) define young funds as those with less than five years since the first offer. We define a fund at the portfolio level to include all share classes in that fund. Hence, fund age is higher in our study because it is calculated based on the fund class that was offered the earliest.

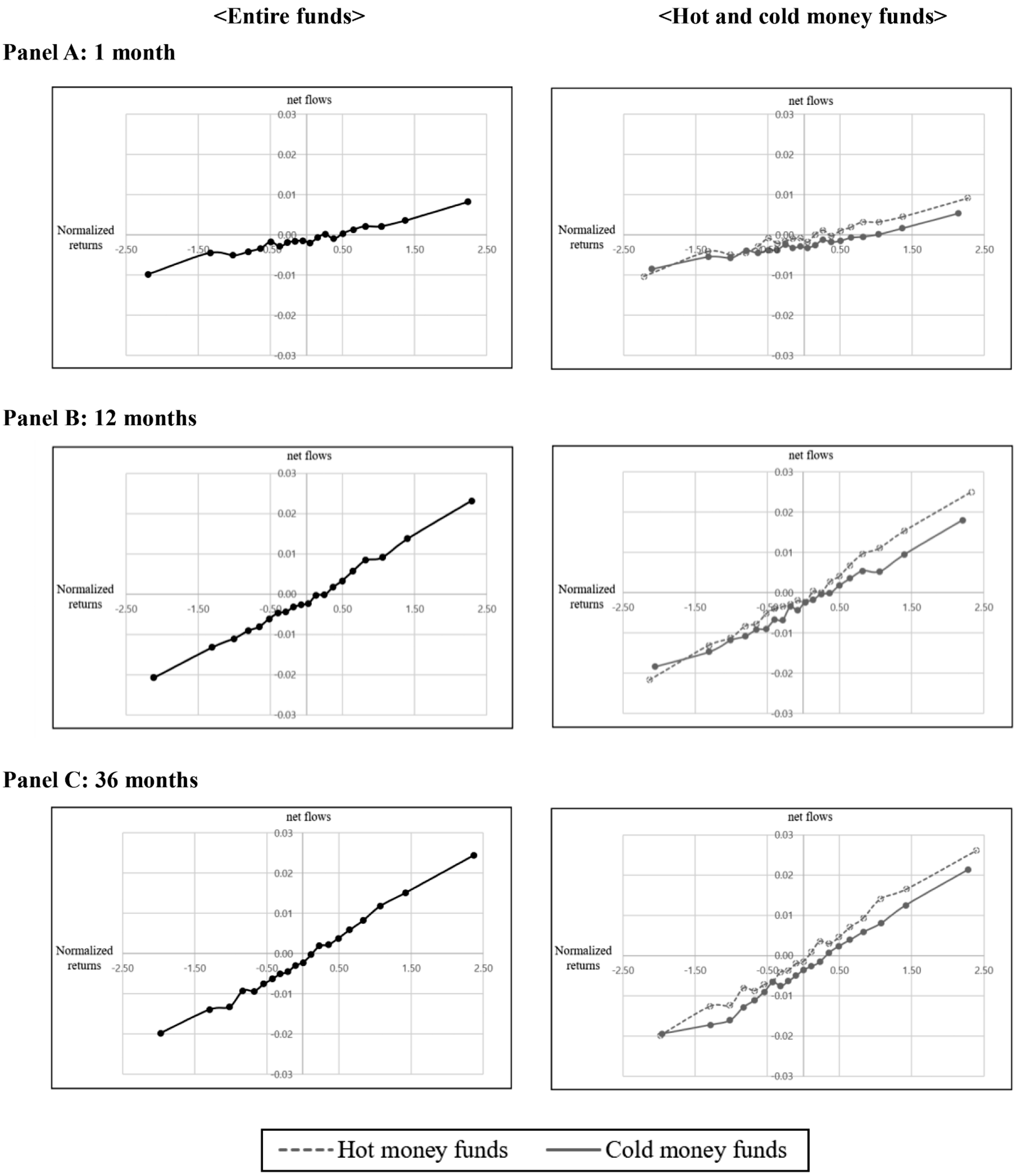


Fig. 3. Effects of the performance period and fund size/age against normalized returns. This figure shows the net flow-performance relationships for the 1-, 12-, and 36-month evaluation periods using normalized objective-adjusted returns to have zero mean and unit standard deviation in every month. In addition, we divide the sample funds into two subgroups of hot and cold money funds. Hot money funds are a union of small and young funds, and cold money funds are an intersection of large and old funds. Small (large) funds are in the bottom (top) 50% in fund size, whereas young (old) funds are in the bottom (top) 50% in fund age. Hot and cold money funds are mutually exclusive. For each month, we sort hot and cold money funds by normalized objective-adjusted returns into 20 groups and then calculate their average monthly net flows. The scatter plots show the flow-performance relationships with normalized objective-adjusted returns on the horizontal axis.

While the returns and net flows of hot money funds seem to be more volatile than those of cold money funds, they have a similarly shaped relationship. This finding implies that we may obtain a linear net flow-performance relationship for both hot and cold money funds when we use absolute returns to measure their past performance. Our approach using objective-adjusted returns may resolve the issue that Spiegel and Zhang (2013) present, because these objective-adjusted returns reflect the return discrimination between groups that then affects net flows.

Despite these graphical representations, we proceed to test the net flow-performance relationship by using objective-adjusted returns in the statistical sense.

3.2. Piecewise linear regressions

To examine whether objective-adjusted returns affect the flow-performance relationship, we run the following piecewise linear regression model every month.

Table 2
Net flow-performance relationship for the various evaluation periods.

Evaluation period	1 month	3 months	6 months	12 months	24 months	36 months
Panel A: Using performance ranks (relative performance)						
Constant	0.0053 (1.95)*	0.0010 (0.37)	−0.0010 (−0.37)	−0.0006 (−0.22)	0.0041 (1.45)	0.0057 (1.91)*
Low	0.0262 (5.84)***	0.0426 (11.21)***	0.0505 (11.02)***	0.0519 (13.21)***	0.0375 (7.85)***	0.0324 (7.58)***
Mid	0.0059 (5.10)***	0.0104 (8.28)***	0.0135 (10.31)***	0.0155 (13.08)***	0.0157 (11.32)***	0.0163 (12.47)***
High	0.0439 (10.70)***	0.0645 (12.79)***	0.0778 (12.93)***	0.0772 (12.87)***	0.0667 (11.78)***	0.0578 (10.78)***
High-Mid	0.0380 (9.30)***	0.0541 (10.68)***	0.0643 (10.35)***	0.0617 (10.56)***	0.0510 (8.51)***	0.0414 (7.38)***
Mid-Low	−0.0203 (−4.29)***	−0.0322 (−8.19)***	−0.0370 (−7.46)***	−0.0364 (−9.35)***	−0.0218 (−4.20)***	−0.0161 (−3.62)***
Number of obs.	237,275	237,275	237,275	237,275	237,275	237,275
Adjusted R^2	0.1248	0.1316	0.1397	0.1432	0.1370	0.1342
Panel B: Using objective-adjusted returns (absolute performance)						
Constant	0.0135 (5.37)***	0.0143 (5.35)***	0.0139 (5.13)***	0.0143 (5.47)***	0.0154 (5.50)***	0.0153 (5.36)***
Low	0.0037 (6.35)***	0.0062 (10.83)***	0.0067 (9.20)***	0.0069 (10.38)***	0.0053 (6.20)***	0.0047 (6.05)***
Mid	0.0033 (6.80)***	0.0057 (10.16)***	0.0074 (12.84)***	0.0086 (14.46)***	0.0084 (14.07)***	0.0083 (14.49)***
High	0.0065 (9.72)***	0.0091 (11.64)***	0.0103 (11.96)***	0.0095 (10.98)***	0.0072 (8.80)***	0.0061 (8.60)***
High-Mid	0.0032 (4.64)***	0.0034 (4.13)***	0.0029 (2.90)***	0.0009 (.92)	−0.0012 (−1.11)	−0.0022 (−2.25)**
Mid-Low	−0.0004 (−0.57)	−0.0005 (−0.78)	0.0007 (0.88)	0.0017 (2.44)**	0.0030 (2.80)***	0.0036 (3.90)***
Number of obs.	237,275	237,275	237,275	237,275	237,275	237,275
Adjusted R^2	0.1268	0.1341	0.1418	0.1451	0.1384	0.1353

This table shows the average coefficients as in Fama and Macbeth's (1973) monthly cross-sectional regressions to estimate the responses of fund net flows to the performance variables. We use performance ranks and objective-adjusted returns to measure past performance. We use normalized objective-adjusted returns to have zero mean and unit standard deviation in every month. Fund performance is divided into three past performance variables: Low, Mid, and High. Low (Mid, High) is a past performance variable that corresponds to below the 20% quantile (from the 20% to 80% quantiles, above the 80% quantile) of the cross-sectional fund performance. Each regression includes fund size, age, volatility, the expense ratio, past net flows, and objective net flows to control for the effects of the fund characteristics. We only report the coefficients of the constant and performance variables. We use Newey and West (1987) standard errors with three lags to take into account any autocorrelation in the coefficients. The associated *t*-statistics are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

$$\begin{aligned} Flows_{i,t} = {} & \alpha + \beta_1 Low_{i,t-m:t-1} + \beta_2 Mid_{i,t-m:t-1} + \beta_3 High_{i,t-m:t-1} \\ & + \gamma_1 Size_{i,t-1} + \gamma_2 Age_{i,t-1} \\ & + \gamma_3 Volatility_{i,t-12:t-1} + \gamma_4 Expense\ ratios_{i,t-1} \\ & + \gamma_5 Past\ net\ flows_{i,t-12:t-1} \\ & + \gamma_6 Objective\ net\ flows_t + \varepsilon_{i,t} \end{aligned} \tag{4}$$

We then calculate the average coefficients as in Fama and Macbeth's (1973) monthly cross-sectional regression to estimate the responses of fund flows (net flows, inflows, and outflows) to the performance variables. Past fund performance is defined in two ways. The first is performance rank (i.e., relative performance), which represents its percentile performance relative to other funds with the same investment objective in the same month. This rank ranges from 0 (worst performance) to 1 (best performance) as seen in Sirri and Tufano (1998). The second is the objective-adjusted return, which is the difference between fund returns and their investment objective returns. We use normalized objective-adjusted returns to have a zero mean and unit standard deviation each month.[9] Fund performance is then divided into three past performance variables: Low, Mid, and High. Each variable is defined as follows. In the case of performance ranks, Low = Min(Rank, 0.2), Mid = Min(Rank-Low, 0.6), and High = Rank−Low−Mid. Meanwhile, in the case of objective-adjusted returns, Low = Min(Return, 20% quantile of returns), Mid = Min(Return-Low, 80% quantile−20% quantile of returns), and High = Return-Low-Mid.

Each regression includes fund size, age, volatility, the expense ratio, past net flows, and objective net flows so as to control for the effects of the fund characteristics. Fund size (age) is log TNAs (age) at the end of the previous month. Age is the number of months since the date of the first offer. Volatility is the standard deviation for previous 12-month returns, and the expense ratio represents the fund's operating expenses at the end of the previous month.[10] Past 12-month net flows are included to control for the persistence of cash flows, and objective net flows in month t, for the fund investor's interest in the fund market. We use Newey-West (1987) standard errors with three lags to take into account any autocorrelation in the coefficients.

Table 2 presents the results of the piecewise linear regressions. We only report the coefficients of the constant and performance variables.[11] Panel A shows the estimated coefficients using performance ranks (i.e., relative performance). The coefficients of Low and High are larger than those of Mid for all the evaluation periods. These results are similar to those in Huang et al. (2007)'s Table VIII. As expected from Panel A of Fig. 1, this finding indicates a significant penalty for the worst-performing funds and a significant bonus for best-performing

[9] When we re-examine Fama and Macbeth's (1973) monthly cross-sectional regressions using raw (or non-normalized) objective-adjusted returns, the results do not change qualitatively.

[10] Although we divide the performance-evaluation period into 1, 3, 6, 12, 24, and 36 months, volatility is calculated by using only the 12-month returns. However, the empirical results do not change, even when we use the corresponding time period.

[11] The coefficients of the control variables are similar when we use performance ranks and objective-adjusted returns. Fund size, age, and volatility have a negative effect on net flows, while past net flows and objective aggregate net flows have a positive effect on net flows. However, the expense ratio does not have any effect on net flows.

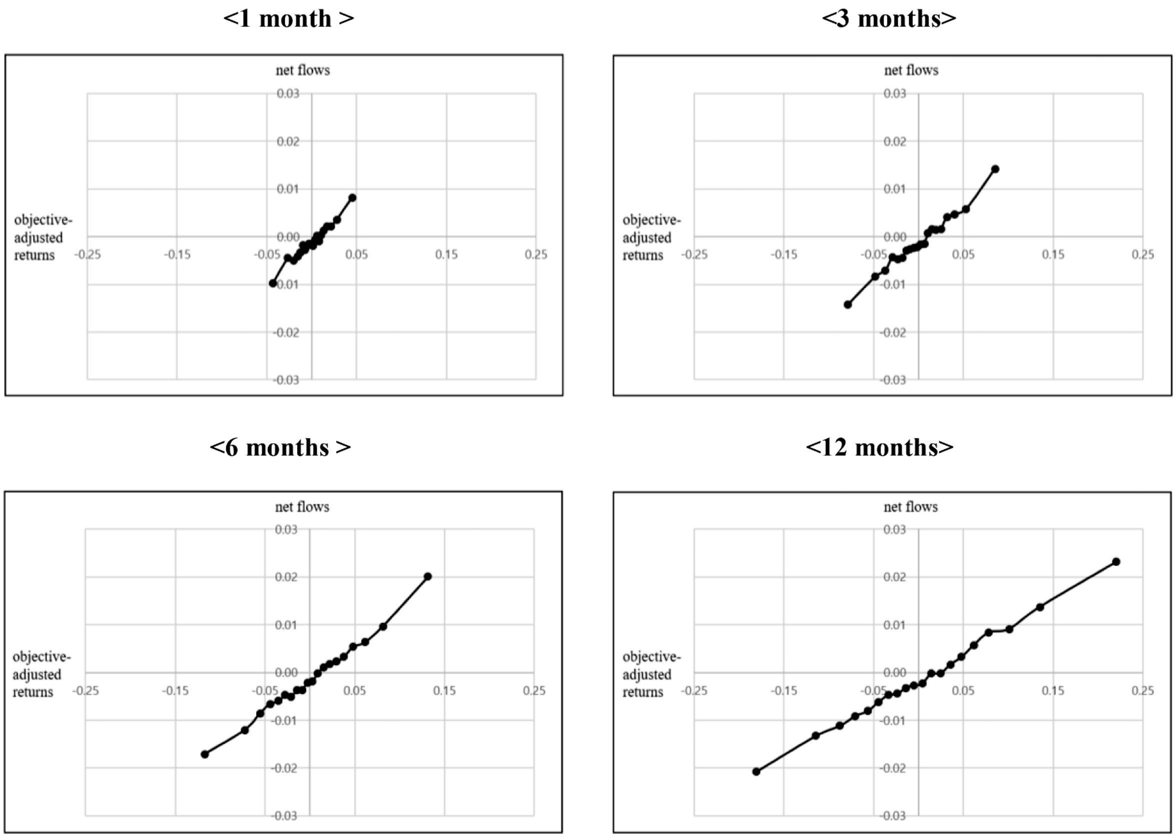


Fig. 4. Effects of the performance period against objective-adjusted returns. This figure shows the effects of the performance period against objective-adjusted returns. We diversify the performance period to 1, 3, 6, and 12 months. For each month, we sort funds by objective-adjusted returns into 20 groups and then calculate their average monthly net flows. The scatter plots show the flow-performance relationships with objective-adjusted returns on the horizontal axis.

funds in terms of net flows. This evidence indicates a convex net flow-performance relationship in the middle- and high-performance domains and a concave relationship in the low- and middle-performance domains. While these relationships are found in all performance-evaluation periods, they are most evident for the 6-month and 12-month periods.

However, return discrimination is not fully reflected in this analysis because performance ranks are arranged using the same interval. That is, we could not incorporate the real scale of cross-sectional performance differences into our analysis. This study thus attempts to explain the steep slopes in the high- and low-performance domains by mis-measured performance. To correct the mis-measured performance, we use objective-adjusted returns instead of performance ranks. Panel B shows the estimated coefficients using normalized objective-adjusted returns. The estimated coefficients are smaller than those of Panel A, because non-ranked performance reflects the magnitude of the cross-sectional differences in the returns between funds. This effect of return discrimination must be strikingly significant in the low- and high-performance domains. The coefficients of Low and High increase up to the 12- and 6-month periods, respectively, and then they decrease sharply as the performance-evaluation period extends beyond 12 months; in contrast, that of Mid increases up to the 12-month period, and then it maintains its level at around 0.0086 afterwards. When we judge the convexity of the flow-performance relationship by the coefficient of the difference (i.e., High-Mid and Mid-Low), we fail to find any significant convexity in the entire domain for all of the evaluation periods.[12]

[12] Spiegel and Zhang (2013) show the estimation results of continuous models using linear and quadratic terms of performance variables to guarantee the power of their tests. This current study also produces the results of continuous models in Section 5.

Overall, it thus becomes difficult to assert the existence of a convex net flow-performance relationship. Rather, we can say that a linear net flow-performance relationship does exist in the middle- and high-performance domains when we use 12-month objective-adjusted returns.

3.3. An issue in the past performance period

When making equity fund investments, how long should the performance-evaluation period be reviewed? Although we do not know the general solution, we can suggest a long term return reversal and a return discrimination for fund selection as two aspects of return behavior.

De Bondt and Thaler (1985) and Moskowitz et al. (2012) insist that there is a return reversal of stock returns for longer periods over 24 or 36 months. As the performance-evaluation period becomes longer, an effect of return reversal can arise. Most investors and practitioners understand this long-term reversal effect. As fund investors understand that this effect may also apply to equity funds, they will not seriously consider long-term past performance that is more than 24 months. As indirect evidence of such a tendency among investors, we observe that the coefficients of High are much less than those of Mid for the 24- and 36- month periods (see Panel B of Table 2).

Meanwhile, past returns should be sufficiently large in absolute value to discriminate between the different performance of funds when buying or redeeming equity mutual funds, if investors learn about a manager's ability from past returns (see Berk and Green, 2004; Starks and Sun, 2016; Franzoni and Schmalz, 2017). To demonstrate return discrimination over performance-evaluation periods, Fig. 4 plots net flows against objective-adjusted returns, showing that the range of objective-adjusted returns is (−4%, 5%) for 1 month and (−8%, 9%) for 3 months relative to (−18%, 22%) for 12 months. It is particularly difficult to discriminate performance difference in the middle-performance groups. As a consequence of poor

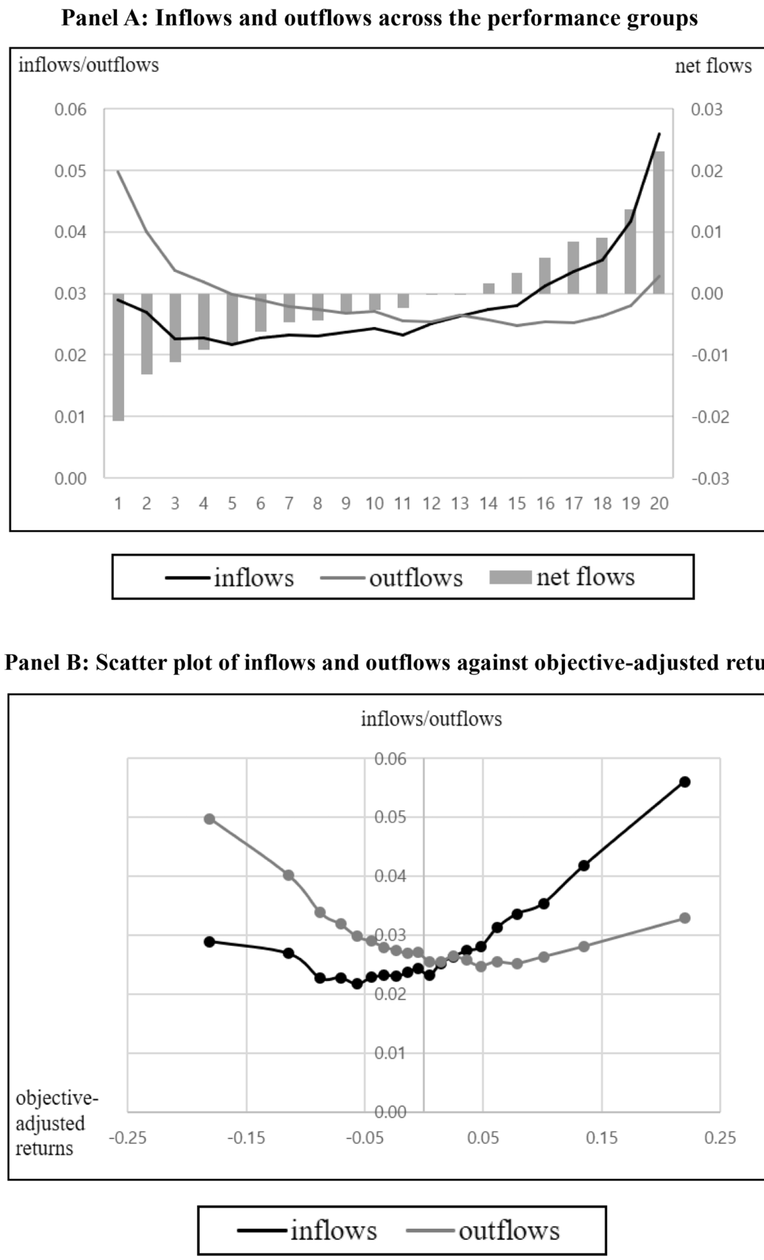


Fig. 5. Relationships between objective-adjusted returns and inflows/outflows. This figure shows the relationship between past objective-adjusted returns and inflows/outflows. Objective-adjusted returns are the difference between fund returns and their investment objective returns using the past 12-month returns. For each month, we sort funds by past objective-adjusted returns into 20 groups and then calculate their average monthly objective-adjusted returns and inflows/outflows. The first (20th) group is the lowest-performing (highest-performing) group. Panel A draws the responses of inflows and outflows as well as net flows to the past 12-month performance ranks. Panel B shows a scatter plot of inflows/outflows with objective-adjusted returns on the horizontal axis. The black (gray) line is for inflows (outflows) and the gray bars are for net flows.

return discrimination, the responses of net flows to past objective-adjusted returns are less monotonic for the 1- and 3-month periods than they are for the 12-month period.

Owing to long-term return reversal and return discrimination, performance evaluation periods that are too short or too long are unsuitable for investors to buy or redeem equity funds. Moskowitz et al. (2012) show the strongest time-series momentum effect in the 12-month interval. Many other studies, including Chevalier and Ellison (1997), Sirri and Tufano (1998), and Ferreira et al. (2012), show that the prior 12-month returns have the greatest effect on net flows. In practice, investors are likely to buy or redeem largely based on these past 12-month returns.

4. Inflow and outflow analysis

As outlined previously, we have investigated the net flow-performance relationship for various past performance-evaluation periods. Our findings suggest that the past 12 months is an appropriate time period for evaluating past returns, finding a linear net flow-performance relationship in the middle- and high-performance domains when we use 12-month objective-adjusted returns. Hereafter, we adopt the past 12-month objective-adjusted returns to explain the net flow-performance relationship by using inflows and outflows.

4.1. Graphical analysis

Panel A of Fig. 5 outlines the responses of inflows and outflows as

Table 3
Inflow- and outflow-performance relationships.

	Inflows	Outflows	Net flows
Panel A: Using performance ranks (relative performance)			
Constant	0.0370 (8.27)***	0.0375 (11.16)***	−0.0006 (−0.22)
Low	−0.0283 (−3.28)***	−0.0803 (−10.17)***	0.0519 (13.21)***
Mid	0.0099 (6.85)***	−0.0056 (−4.78)***	0.0155 (13.08)***
High	0.0893 (12.66)***	0.0121 (2.99)***	0.0772 (12.87)***
High-Mid	0.0794 (11.12)***	0.0176 (3.88)***	0.0617 (10.56)***
Mid-Low	0.0383 (4.07)***	0.0747 (8.87)***	−0.0364 (−9.35)***
Number of obs.	237,275	237,275	237,275
Adjusted R^2	0.0999	0.0625	0.1432
Panel B: Using objective-adjusted returns (absolute performance)			
Constant	0.0277 (5.51)***	0.0135 (3.62)***	0.0143 (5.47)***
Low	−0.0061 (−4.49)***	−0.0130 (−10.07)***	0.0069 (10.38)***
Mid	0.0056 (9.38)***	−0.0030 (−5.85)***	0.0086 (14.46)***
High	0.0120 (11.91)***	0.0024 (4.15)***	0.0095 (10.98)***
High-Mid	0.0064 (5.58)***	0.0055 (5.74)***	0.0009 (0.92)
Mid-Low	0.0117 (6.94)***	0.0100 (6.72)***	0.0017 (2.44)**
Number of obs.	237,275	237,275	237,275
Adjusted R^2	0.1052	0.0682	0.1451

This table shows the average coefficients as in Fama and Macbeth's (1973) monthly cross-sectional regressions to estimate the responses of fund inflows/outflows to 12-month performance. We use performance ranks and objective-adjusted returns to measure past performance. We use normalized objective-adjusted returns to have zero mean and unit standard deviation in every month. Fund performance is divided into three past performance variables: Low, Mid, and High. Low (Mid, High) is a past performance variable that corresponds to below the 20% quantile (from the 20% to 80% quantiles, above the 80% quantile) of the cross-sectional fund performance. Each regression includes fund size, age, volatility, the expense ratio, past net flows, and objective net flows to control for the effects of the fund characteristics. We only report the coefficients of the constant and performance variables. We use Newey and West (1987) standard errors with three lags to take into account any autocorrelation in the coefficients. The associated *t*-statistics are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

well as net flows to the past 12-month performance ranks. The black (gray) line refers to inflows (outflows), and the gray bars represent net flows. First, inflows (outflows) increase sharply in the high-performance (low-performance) groups, which means that investors are likely to buy better-performing funds and redeem worse-performing funds. This phenomenon is consistent with the work of O'Neal (2004), Ivkovic and Weisbenner (2009), Cashman et al. (2012), and Chang et al. (2016). As a natural consequence, net flows increase (decrease) in the high-performance (low-performance) groups, as seen in the gray bars. Panel A shows that both inflows and outflows have a convex relationship with past performance ranks.

Second, inflows and outflows increase slightly in the worst- and best-performance groups (left and right tails), respectively. These interesting patterns imply that fund investors are somewhat likely to buy (redeem) worst-performing (best-performing) funds. In this sub-section, we attempt to explain this exceptional phenomenon. O'Neal (2004) and Cashman et al. (2012) find that inflows and outflows have significant contemporaneous correlations at the individual fund level as well as at the aggregate market level. This evidence indicates that fund investors may move quickly between funds at a low cost in order to seek higher profits. Thus, we expect investors who want to continue to invest in equity mutual funds to realize current profits by redeeming their best-performing funds and then reinvest those proceeds in other funds by using a *contrarian strategy* (i.e., investment in the worst-performing funds).

In addition, Lynch and Musto (2003) argue that worse performance is unlikely to be informative about future performance, because investment companies or fund managers can change their strategies to prevent that continuation. According to their theory, worse performance can be reversed in the future. If fund investors expect to improve the performance of the worst-performing funds, however, inflows will increase in the worst-performance groups. Owing to this contrarian strategy and Lynch and Musto's (2003) theory, outflows from the best-performing funds are partly replaced by the inflows into these funds from the worst-performing funds. At the same time, the outflows from the worst-performing funds are partly replaced by the inflows into these funds from the best-performing funds. This *investor-substitution effect* may cause a small increase in both inflows and outflows in the worst- and best-performance groups, respectively.

Panel B is a scatter plot of inflows and outflows against the objective-adjusted returns. It differs from Panel A, which presents the performance ranks on the horizontal axis. Inflows and outflows still have a convex relationship with the objective-adjusted returns. We observe that the difference in objective-adjusted returns between two adjacent groups becomes larger as the group goes to the left or right extreme ends, while it becomes smaller as the group moves toward the center. Also, the difference between inflows and outflows (i.e., net flows) rapidly increase to the right extreme end and decrease to the left extreme end as shown in Fig. 1, leading to a seemingly linear net flow-performance relationship. If we use the traditional measure of performance ranks, we cannot discriminate performance between two adjacent groups. Therefore, if return discrimination is an important factor for the flow-performance relationship, we must employ objective-adjusted returns instead of performance ranks. In this sense, we conclude that performance rank is a mis-measured performance measure for the flow-performance relationship.

4.2. Piecewise linear regressions

Table 3 presents the estimation results for the piecewise linear

Table 4
Effects of fund size and age on the flow-performance relationships.

	Inflows	Outflows	Net flows
Low (hot)	−0.0051 (−3.67)***	−0.0123 (−9.19)***	0.0071 (10.44)***
Mid (hot)	0.0065 (10.42)***	−0.0024 (−4.71)***	0.0089 (13.87)***
High (hot)	0.0118 (9.84)***	0.0016 (2.54)**	0.0102 (10.06)***
Low (cold)	−0.0114 (−8.09)***	−0.0174 (−12.84)***	0.0060 (8.30)***
Mid (cold)	0.0039 (5.01)***	−0.0041 (−5.71)***	0.0080 (13.45)***
High (cold)	0.0123 (11.07)***	0.0049 (4.69)***	0.0074 (11.03)***
High-Mid (hot)	0.0053 (3.84)***	0.0039 (4.14)***	0.0013 (1.12)
Mid-Low (hot)	0.0116 (6.98)***	0.0099 (6.67)***	0.0017 (2.40)**
High-Mid (cold)	0.0084 (5.90)***	0.0090 (5.98)***	−0.0006 (−0.74)
Mid-Low (cold)	0.0153 (8.23)***	0.0133 (8.20)***	0.0020 (2.83)***
Number of obs.	237,275	237,275	237,275
Adjusted R^2	0.1068	0.0706	0.1445

This table shows the effects of fund size and age on the sensitivity of fund flows to 12-month performance. We use normalized objective-adjusted returns to have zero mean and unit standard deviation in every month. We divide the sample funds into two subgroups of hot and cold money funds. Hot money funds are a union of small and young funds, and cold money funds are an intersection of large and old funds. Small (large) funds are in the bottom (top) 50% in fund size, whereas young (old) funds are in the bottom (top) 50% in fund age. Hot and cold money funds are mutually exclusive. Fund performance is divided into three past performance variables: Low, Mid, and High. Low (Mid, High) is a past performance variable that corresponds to below the 20% quantile (from the 20% to 80% quantiles, above the 80% quantile) of the cross-sectional fund performance. Each regression includes fund size, age, volatility, the expense ratio, past net flows, and objective net flows to control for the effects of the fund characteristics. We only report the coefficients of the performance variables. We use Newey and West (1987) standard errors with three lags to take into account any autocorrelation in the coefficients. The associated t-statistics are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

regressions for the inflows and outflows of equity mutual funds. The results for net flows in the last column are the same as those for 12 months in Table 2. Panel A shows the coefficients of the performance variables using performance ranks. For both inflows and outflows, the estimated coefficients have a similar pattern to those in Fig. 5. The coefficient of High (Mid) is larger than that of Mid (Low), which implies that inflows and outflows have a convex relationship with past performance. The negative and positive coefficients of Low for inflows and High for outflows (Low for outflows and High for inflows), respectively, indicate that the redemption of better-performing (worse-performing) funds is redirected to buying worse-performing (better-performing) funds. This evidence might serve as indirect evidence of the investor-substitution effect.

Now, we try to explain the behavior of net flows by using inflows and outflows. As can be seen in the last column, net flows have the largest coefficient in the high-performance domain and the smallest in the middle-performance domain. Inflows have a large coefficient of High (0.0893), while outflows have a relatively low coefficient of High (0.0121). In the case of high inflows relative to outflows, net flows have the largest coefficient for High. However, regarding absolute value, the responses of inflows and outflows in the middle-performance domain are not large enough to be compared to those in the low- and high-performance domains. Hence, net flows have the smallest coefficient of Mid. Finally, within the low-performance domain, outflows have a negatively large coefficient relative to the coefficient for inflows. While the negative coefficient for inflows can be addressed by the investor-substitution effect noted above, the negatively large coefficient for outflows indicates a high redemption of the worst-performing funds. This finding implies that, because of the high redemption of the worst-performing funds, net flows have the second largest coefficient of Low. In sum, the high (low) net flows in the high-performance (low-performance) domain are largely due to the high inflows (outflows).

Panel B shows the coefficients using objective-adjusted returns. For both inflows and outflows, the convex relationships remain, and the signs and statistical significance levels are the same as shown in Panel A. Moreover, the adjusted R^2s have slightly improved. However, we observe two important differences from Panel A due to the real scale of the performance variables (i.e., objective-adjusted returns). First, inflows and outflows have a similar coefficient of High-Mid, because the real scale of the performance variables slightly decreases the slope of High relative to the slope of Mid for inflows. Naturally, net flows have an insignificant coefficient of High-Mid. Second, we see that the coefficient of Mid-Low for inflows becomes larger than the coefficient for outflows, again because we employ the real scale of the performance variables. This change in the coefficient of Mid-Low produces a positively significant coefficient of Mid-Low for net flows.

4.3. Effects of fund size and age on the flow-performance relationship

Table 4 examines the effects of fund size and age on the sensitivity of inflows and outflows to past fund performance. Here, fund performance is normalized for objective-adjusted returns with a zero mean and unit standard deviation every month. We then ask an important question: Is there a different relationship between hot and cold money funds? Inflows (outflows) are more negatively (positively) sensitive to Low (High) for cold money funds than they are for hot money funds. As a result, the coefficients of Low and High in net flows for cold money funds become less than those for hot money funds. This finding indicates that the investor-substitution effect is stronger for cold money funds than it is for hot money funds. However, when we consider the coefficients of High-Mid and Mid-Low, we still fail to find any significant differences between hot and cold money funds. That is, the convex relationships of inflows and outflows with past performance exist for both hot and cold money funds. In sum, despite the slight differences in the estimated coefficients, it is difficult to identify any significant difference in investors' behavior between hot and cold money funds.

5. Empirical evidence after controlling for the investor-substitution effect

Here, we examine the *investor-substitution effect*. According to the contrarian strategy and Lynch and Musto (2003), some increases could occur in the outflows of the best-performing funds and the inflows of the worst-performing funds, respectively. At the same time, there must also be significant increases in both the inflows of the best-performing funds and the outflows of the worst-performing funds as shown in Fig. 5. Such a phenomenon may then affect the flow-performance relationship. To control for this contemporaneous effect of opposite flows on this relationship, we employ 2SLS regression. First, inflows and

Table 5
The investor-substitution effect on the flow-performance relationships.

	Adjusted inflows	Adjusted outflows	Adjusted net flows
Constant	0.0137 (4.74)***	−0.0065 (−3.87)***	0.0202 (6.17)***
Low	0.0005 (0.87)	−0.0091 (−14.35)***	0.0096 (11.32)***
Mid	0.0061 (11.60)***	−0.0044 (−9.76)***	0.0105 (12.37)***
High	0.0101 (11.73)***	−0.0016 (−2.96)***	0.0117 (9.99)***
High-Mid	0.0040 (3.99)***	0.0028 (4.78)***	0.0012 (0.93)
Mid-Low	0.0056 (7.76)***	0.0047 (7.35)***	0.0010 (1.20)
Number of obs.	237,275	237,275	237,275
Adjusted R^2	0.1379	0.1158	0.2117

This table shows the investor-substitution effect on the flow-performance relationships. To control for this contemporaneous effect of opposite flows in this relationship, we employ two-stage least squares (2SLS) regression. First, inflows and outflows are regressed on their first through 12th lagged variables and the corresponding control variables. The control variables are fund size, age, volatility, the expense ratio, past net flows, and objective net flows. From the first regression, we obtain fitted inflows and outflows. Second, to overcome the simultaneity problem from correctly estimating piecewise linear regression, we regress inflows and outflows on the fitted values of outflows and inflows. From second regression, we obtain adjusted inflows and outflows from each regression's residuals. Adjusted net flows are obtained by subtracting adjusted outflows from adjusted inflows. By using adjusted cash flows as the dependent variables, we retest the flow-performance relationships. We report the average coefficients as in Fama and Macbeth's (1973) monthly cross-sectional regressions to estimate the responses of fund adjusted flows to 12-month performance. We use normalized objective-adjusted returns to have zero mean and unit standard deviation in every month. Fund performance is divided into three past performance variables: Low, Mid, and High. Low (Mid, High) is a past performance variable that corresponds to below the 20% quantile (from the 20% to 80% quantiles, above the 80% quantile) of the cross-sectional fund performance. Each regression includes fund size, age, volatility, the expense ratio, past net flows, and objective net flows to control for the effects of the fund characteristics. We only report the coefficients of the constant and performance variables. We use Newey and West (1987) standard errors with three lags to take into account any autocorrelation in the coefficients. The associated t-statistics are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

outflows are regressed on their first through 12th lagged variables and the corresponding control variables.

$$Inflows_{i,t} = \alpha + \beta_k \sum_{k=1}^{12} Inflows_{i,t-k} + controls + \varepsilon_{i,t} \quad (5)$$

$$Outflows_{i,t} = \alpha + \beta_k \sum_{k=1}^{12} Outflows_{i,t-k} + controls + \varepsilon_{i,t} \quad (6)$$

where controls represent the control variables explained in Eq. (4). From Eqs. (5) and (6), we obtain the fitted values of inflows and outflows.

Second, to overcome the simultaneity problem from correctly estimating the piecewise linear regression, we regress inflows and outflows on the fitted values of outflows and inflows.

$$Inflows_{i,t} = \alpha + \beta Fitted\_outflows_{i,t} + \varepsilon_{i,t}^{Inflows} \quad (7)$$

$$Outflows_{i,t} = \alpha + \beta Fitted\_inflows_{i,t} + \varepsilon_{i,t}^{Outflows} \quad (8)$$

From Eqs. (7) and (8), we obtain adjusted inflows and outflows from the residuals of each regression. Adjusted net flows are obtained by subtracting adjusted outflows from adjusted inflows. By using adjusted cash flows as the dependent variable in Eq. (4), we then retest the flow-performance relationship.

Table 5 shows the estimation results using adjusted cash flows and objective-adjusted returns. We use normalized objective-adjusted returns to have a zero mean and unit standard deviation every month. When we consider the coefficients of High-Mid and Mid-Low, we see that the adjusted inflows and outflows also have a convex relationship with past performance. However, unlike the results in Panel B of Table 3, adjusted inflows (outflows) have positive (negative) and monotonic coefficients from Low to High. Interestingly, there is neither an increase in adjusted outflows in the high-performance domain nor an increase in adjusted inflows in the low-performance domain. Furthermore, the adjusted R^2s greatly improve from 10.52% to 13.79% for the inflows and from 6.82% to 11.58% for the outflows.

As a natural consequence of the above results, the coefficients of High-Mid and Mid-Low in adjusted net flows have no statistical significance. That is, adjusted net flows have a linear relationship with

Table 6
Net flow-performance relationship using continuous model.

Independent variable / dependent variable	Performance ranks / net flows	Objective-adjusted returns / net flows	Objective-adjusted returns / adjusted net flows
Constant	0.0041 (1.68)*	0.0155 (6.20)***	0.0208 (6.60)***
Performance	0.0151 (5.25)***	0.0083 (18.05)***	0.0104 (15.38)***
$Performance^2$	0.0102 (3.58)***	0.0003 (2.12)**	0.0002 (1.52)
Number of obs.	237,275	237,275	237,275
Adjusted R^2	0.1406	0.1446	0.2112

This table shows the average coefficients as in Fama and Macbeth's (1973) monthly cross-sectional regressions to estimate the responses of fund net flows and adjusted net flows controlled for investor-substitution effect to past performance variables. We use performance ranks and objective-adjusted returns to measure past performance. The continuous model includes the linear and quadratic terms of performance variables. We also use normalized objective-adjusted returns to have zero mean and unit standard deviation in every month. Each regression includes fund size, age, volatility, the expense ratio, past net flows, and objective net flows to control for the effects of the fund characteristics. We only report the coefficients of the constant and the linear and quadratic terms of performance variables. We use Newey and West (1987) standard errors with three lags to take into account any autocorrelation in the coefficients. The associated *t*-statistics are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

past performance in all performance domains due to an increase in the coefficient of Low. There must be an investor-substitution effect on the net flow-performance relationship. Therefore, we obtain a linear net flow-performance relationship after controlling for the investor-substitution effect or the contemporaneous effect of opposite flows when we employ 12-month objective-adjusted returns as the measure of past performance. This finding suggests that mis-measured performance and the investor-substitution effect produce a convex or non-linear net flow-performance relationship.

On the other hand, Spiegel and Zhang (2013) estimate continuous models using linear and quadratic terms of performance variables to guarantee the power of their test. We also re-test the net flow-performance relationship using a continuous model. Table 6 shows the estimation results for the continuous model that replaces the categorized performance variables (i.e., Low, Mid, and High) with linear and quadratic terms of performance. If net flows are convex in performance, then this relationship results in a significantly positive coefficient of linear and quadratic terms. If net flows are linear in performance, then this relationship should result in a significantly positive coefficient of the linear term and an insignificant coefficient of the quadratic term. When we use performance ranks (or objective-adjusted returns) and net flows, the coefficients for the linear and quadratic terms are significantly positive. This finding implies that the net flows are not linear in performance. However, when we use objective-adjusted returns and adjusted net flows, the coefficient of the quadratic term is insignificant, while that for the linear term is significantly positive. This evidence confirms that there is a linear relationship of net flows with past performance.

6. Concluding remarks

Many studies have examined the flow-performance relationship of equity mutual funds and debated whether this net flow-performance relationship is linear. Based on the distribution of fund returns, we find evidence that mis-measured past performance affects the flow-performance relationship when performance ranks are used as the performance variable. We further stress that the difference in performance or return discrimination between funds should be considered. Meanwhile, outflows from the best-performing funds are partly replaced by the inflows into these funds from the worst-performing funds, while the outflows from the worst-performing funds are partly replaced by the inflows into these funds from the best-performing funds. This investor-substitution effect may cause a small increase in the inflows and outflows in the worst- and best-performance groups, respectively. To test the flow-performance relationship, we should clearly consider mis-measured performance and the investor-substitution effect.

This study offers the following evidence. First, when we use 12-month objective-adjusted returns, we obtain a linear net flow-performance relationship in the high- and middle-performance domains. Second, 12 months is the most appropriate performance-evaluation period for fund-investment decisions. Third, inflows and outflows have a convex relationship with past performance, regardless of the performance measure. The net flow-performance relationship is a natural consequence of inflow- and outflow-performance relationships. Fourth, fund size and age have no significant effect on the flow-performance relationships. Finally, when we measure past performance using 12-month objective-adjusted returns, we obtain a linear net flow-performance relationship after controlling for the investor-substitution effect.

Acknowledgments

This study was completed when the first author was a NRF research professor at Pusan National University.

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