Time-Varying Incentives in the Mutual Fund Industry

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Abstract

This paper re-examines the incentives of mutual fund managers arising from investor flows. We provide evidence that the convexity of the flow-performance relationship varies with economic activity. We show that the effect is economically large and is not driven by abnormal years. We test two possible channels through which this pattern may arise. We investigate implications of the time-varying convexity for the incentives of managers to alter strategically the risk of their portfolios. We provide evidence that poor mid-year performers increase the risk of the portfolio only when economic activity is strong. Finally, we briefly discuss some methodological implications.

JEL Classification codes: G11, G23

Key words: Mutual funds, Incentives, Flow-Performance Relationship, Convexity, Business Cycles

INTRODUCTION

The mutual fund industry has grown remarkably over the past two decades. According to the Investment Company Institute[1], net cash flows into equity mutual funds have increased by a factor of twenty to one between 1985 and 2005, while gross inflows and outflows have both increased by factors larger than thirty to one. Academic research into mutual fund issues has likewise grown considerably over the same period. One topic that has attracted a lot of attention is the sensitivity of cash flows from investors to fund performance. Since the seminal work by Ippolito (1992), a large and active literature[2] has confirmed the existence of a convex relationship between flows and past performance: investors seem to react strongly to differences in performance among the top performing funds in the industry, but do not react to differences in performance among underperforming funds. This behavior is consistent with rational behavior and competitive equilibrium, as demonstrated by Berk and Green (2004), and the empirical evidence has been found to be robust across different definitions of flows and performance, and across many different sets of control variables.

The convexity of the flow-performance relationship is important because it shapes the incentives of mutual fund managers. Fees raised by mutual funds, and therefore the compensation of mutual fund managers, are proportional to the average net assets held during the year. As first pointed out by Brown, Harlow and Starks (1996) and by Chevalier and Ellison (1997), the nature of the fee structure, the convexity of the flow-performance relationship, and the assessment of performance on a calendar year basis, together imply that mutual fund managers with poor mid-year performances have incentives to increase the risk of their portfolio during the second half of the year. By raising risk, managers of underperforming funds would catch up with stronger performers if successful, but have little to lose if not. This has been called the tournament hypothesis.

The central result of this paper is that the convexity of the flow-performance relationship, and therefore the incentives it provides to fund managers, vary sharply over time. As found by previous researchers, the flow-performance relationship is convex on average. However, we find that convexity is most pronounced when economic activity is strong, while flows can even become a concave function of past performance during recessions. We show that the effect is economically large as even small

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[1] As cited by Cashman et al. (2007).
[2] See e.g. Gruber (1996), Chevalier and Ellison (1997), Goetzmann and Peles (1997), Sirri and Tufano (1998), Del Guercio and Tkac (2002), Lynch and Musto (2003), Barber, Odean and Zheng (2005), Gallaher, Kaniel and Starks (2006) and Huang, Wei and Yan (2007)

fluctuations of economic activity alter the shape of the flow-performance relationship in a significant fashion. We show that the effect is not driven by exceptional years, whether strong booms or deep recessions. We also show that fund managers react to these fluctuations in a way that is consistent with the tournament hypothesis. Finally, we contend that our result carries some methodological implications.

The fact that economic activity changes the shape of the flow-performance relationship should not come as a surprise. First, we know that aggregate flows into mutual funds are strongly correlated with economic activity[3]: because of consumption smoothing, agents invest money into mutual funds when the economy is booming and divest when economic activity is slowing down. We also know that gross outflows are less sensitive to past performance than are gross inflows[4]. This likely is because investors hold concentrated portfolios of risky assets and are forced to liquidate their holdings, regardless of performance, whenever they need to finance consumption[5]. As outflows constitute a larger fraction of total flows when economic activity is weak than when it is strong, the flow-performance relationship becomes flatter throughout when economic growth slows down. If in addition some investors suffer from a disposition effect, whereby they hold on past losers while liquidating past winners[6] then investor flows may even become a weakly decreasing and concave function of past performance during recessions, as we observe in our data.

An alternative channel through which economic activity can affect the flow-performance relationship is volatility[7]. It is well-known that stock market volatility is countercyclical[8]. It is therefore reasonable to expect that any fixed level of performance by a mutual fund manager contains more "noise" during a recession than during a boom. If the flow-performance relationship is at least partially driven by investors trying to infer the skill of the mutual fund manager as a function of the manager's past performance, we should again expect flows to be less responsive to strong past performance when economic activity is weak than when it is strong.

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[3] See e.g. Kosowski (2006)

[4] See evidence in Tables IV and V of Cashman et al. (2007)

[5] The fact that investors typically invest in very few assets has been known at least since Blume and Friend (1975). More recently, Calvet, Campbell and Sodini (2007) present new evidence from a detailed database at the individual investor level which includes mutual fund holdings. They note that most investors do indeed hold very few assets in their risky portfolio but show that this does not necessarily result in significant under-diversification of the portfolio thanks to mutual fund holdings.

[6] For the seminal paper on prospect theory which provides theoretical grounding for the disposition effect, see Kahneman and Tversky (1979). For application and evidence to the stock market, see Shefrin and Statman (1985) or Odean (1998)

[7] We are grateful to Laurent Calvet for pointing out this alternative hypothesis to us.

[8] See e.g. Schwert (1989a and b), Hamilton and Lin (1996) or Mele (2007)

Our analysis is based on actively managed US domestic equity funds appearing in the CRSP database between 1980 and 2006. We obtain three closely related sets of results. First, we investigate the impact of economic activity, as measured by US GDP growth, on the shape of the flow-performance relationship. We consider six specifications corresponding to six different measures of performance. In all specifications, GDP growth is found to have a statistically significant impact on the flow-performance relationship. The impact of economic activity on the convexity of the flow-performance relationship is strongest when performance is measured by a year-by-year ordinal ranking of fund managers, as in Sirri and Tufano (1998) or in Huang, Wei and Yan (2007). Our point estimates suggest that the flow-performance relationship no longer exhibits any convexity as soon as GDP growth falls by 1% below its sample mean. Conversely, a GDP growth rate 1% above its sample mean implies a flow-performance relationship twice as convex as that found at the sample mean of GDP. In other words, we find that even moderate fluctuations in economic activity have a significant impact on the nature of incentives faced by mutual fund managers. In line with this point estimate, we provide direct evidence showing that none of our results are driven by "abnormal years" corresponding to either deep recessions or strong booms.

Next, we evaluate the two possible channels through which economic activity may affect the flow-performance relationship: composition of aggregate flows and stock market volatility. In all specifications, we find strong evidence that years where aggregate flows into the mutual fund industry are large (and therefore gross outflows are small relative to gross inflows) are years with the strongest convexity in the flow-performance relationship. Although we find some evidence that higher stock market volatility leads to a lower sensitivity of flows to performance, we also find that stock market volatility does not explain the pattern of convexity of the flow-performance relationship across the business cycle.

Our final set of results verify whether time variation in the shape of the flow-performance relationship directly translates into time variation in risk-shifting by underperforming managers, as predicted by the tournament hypothesis. We call conditional tournament hypothesis the prediction that poor mid-year performers increase the risk of their portfolio only when economic activity is strong. As in Koski and Pontiff (1999), we consider three different measures of risk: total risk, idiosyncratic risk and systematic risk. We regress the change in risk exposure of the fund between the second and first halves of the year on mid-year performance and on an interaction variable equal to the product of GDP

growth and mid-year performance. We find the strongest evidence in favor of the conditional tournament hypothesis when looking at the impact of mid-year performance on idiosyncratic risk. Regardless of the specification adopted, the coefficient of the interaction variable is statistically significant. In addition, point estimates of the regression suggest effects that are economically significant. For instance, in the case of a mild boom (GDP growth 1% above its sample mean), the change in risk exposure when going from bottom to top performer corresponds to around 30% to 40% of the risk of the average performer in our sample. Results of regressions where risk is measured by total risk are also consistent with the conditional tournament hypothesis. However, the effects are of smaller economic magnitude. The weakest results of all are obtained when looking at the impact of performance on systematic risk. This should however not come as a surprise as the reason why managers of underperforming funds may wish to change their risk exposure is so as to generate "spurious" alphas by the end of the year, which can only be achieved by changing idiosyncratic risk and not by changing the betas of their portfolios. Overall, our results suggest that choices of risk by fund managers are indeed consistent with the incentives provided to them by the (time-varying) convexity of the flow-performance relationship.

This paper is quite closely related to work by Kosowski (2006) who studies the evolution of mutual fund performance and fund flows across the business cycle. Kosowski shows that the performance of mutual funds is negative on average but becomes positive during recessions. He also shows that aggregate flows are significantly larger during booms than during recessions[9]. Our focus here is different as we show that the flow-performance relationship is convex on average but may become concave during a recession, which is not implied by any of Kosowski's findings. We also show that the effect of economic activity on the shape of the flow-performance relationship arises under normal economic conditions, and is driven neither by deep recessions not by strong booms. Nonetheless, our results in the second half of the paper may cast a new light on Kosowski's results. Our results indicate that the divergence of the objectives of fund managers (who care about net flows) from the objectives of investors (who care about performance) is an increasing function of economic activity. A natural conjecture to make is that the distortion of incentives faced by fund managers may be partly

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[9] Given the result in Cashman et al. (2007) that inflows are more sensitive to performance than outflows, Kosowski's findings also imply that investors display more of a performance-chasing behaviour during booms than during recessions. This has been recently pointed out by Cederburg (2008) who investigates implications on the smart money effect.

responsible for the underperformance of mutual funds during expansion phases documented by Kosowski[10].

Our paper is also closely related to the empirical literature on the tournament hypothesis, which has so far obtained only mixed evidence. Chevalier and Ellison (1997) and Koski and Pontiff (1999) initially provided evidence generally supportive of the tournament hypothesis. Khorana (1996) does not find any conclusive evidence that underperforming managers take additional risk in the hope of offsetting accrued losses. Using contingency tables, Brown, Harlow and Starks (1996) find evidence supporting the tournament hypothesis but report conflicting results across sub-samples. Busse (2001) discusses methodological issues concerning the interpretation of contingency tables, and finds that results regarding the tournament hypothesis are very sensitive to the sample period chosen, the frequency of returns used to compute measures of risk, and the method used to compute standard errors. Goriaev, Nijman and Werker (2005) complement methodological issues raised by Busse. They also report that, depending in the sample period, the evidence in their sample as often supports the tournament hypothesis as it does the opposite result, namely, that poor half-year performers *decrease* the level of risk of their portfolio relative to that of strong half-year performers. Qiu (2003) reports similar evidence and suggest that it may be due to agency problems within mutual funds.

The joint evidence we report of time-varying convexity in the flow-performance relationship and of matching time-variation in the risk-shifting behavior of fund managers provides a unified explanation to the seemingly contradictory findings of the existing literature, which does not rely on unobserved agency problems within mutual funds. Our solution to the "tournament puzzle" is related to that provided in a recent working paper by Kempf, Ruenzi and Thiele (2007) who find that risk-shifting by mutual fund managers is correlated with market returns. There are however significant differences between their work and ours. Kempf, Ruenzi and Thiele argue that the correlation they find is due to the differential cost for a mutual fund manager to be fired under bad rather than good market conditions.[11] However, they do not estimate this differential cost nor do they compare it with the high-powered incentives typically provided in the compensation package of mutual fund managers. In contrast, we provide direct and new evidence of time variation in the incentives of fund managers arising from the convexity of investor flows rather than from career concerns of managers. We provide

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[10] This conjecture is reinforced by recent findings by Huang, Sialm and Zhang (2008) who show that risk shifting by mutual fund managers is detrimental to performance.

[11] See Hu et al (2007) for another resolution of the tournament puzzle based on employment risk of fund managers.

quantitative estimates of this effect and show that it is large enough to alter incentives of mutual fund managers in a significant fashion. We then relate the risk-shifting of fund managers in the second half of our paper to the incentives we identified in the first half.

Finally, the central result of our paper carries some methodological implications. The methodology most frequently used in the existing literature on the flow-performance relationship, Fama-MacBeth (1973) regressions, assumes that slope coefficients of all single-year regressions are drawn from the same distribution. In this paper, we provide direct evidence that the slope parameter, i.e. the sensitivity of flows to past performance, actually varies at business cycle frequencies. Using the Fama-MacBeth methodology when the slope coefficient is time-varying can lead to severely misleading conclusions, as first pointed out in the asset pricing literature on the conditional CAPM[12].

The remainder of the paper is structured as follows: in Section I, we describe the data, the variables, and the methodology we use in our analysis. In Section II, we report evidence on the time-varying nature of the flow-performance relationship and investigate the different channels through which economic activity may affect this relationship. Section III is devoted to the analysis of the conditional tournament hypothesis. Section IV concludes.

I) Data and Empirical Methodology

A) Data source

We use mutual funds that appear in the CRSP Survivor-Bias-Free US Mutual Fund Database between 1980 and 2006. As with most papers in the literature, we focus on US domestic equity mutual funds, and exclude fixed income funds, international equity funds and balanced funds, as well as any fund for which the proportion of stocks in the portfolio never exceeds 80%. As in Pastor and Stambaugh (2002), we exclude funds with front loads. We do this not only for the reason given by Pastor and Stambaugh (namely that it is not clear how to treat load fees in a single period setting) but mostly because of results obtained by Barber, Odean and Zheng (2005) which show that front loads have a stronger impact on the flow-performance relationship than any other fees. They also show that

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[12] See e.g. Harvey (1989) and Jagannathan and Wang (1996)

there have been substantial changes both in the proportion of funds with front loads (from over 90% in the 1940's to less than 40% in the 90's) and in the way investors react to front loads with investors learning to avoid funds with higher front-end loads. As our objective is to identify time-variation in the flow-performance relationship due to the business cycle, we want to eliminate as much as possible any other source of time variation in our sample, thus our choice to focus on no-load funds. Further restrictions of the sample follow commonly adopted procedures in the literature since Chevalier and Ellison (1997): we exclude funds closed to investors, index funds, funds of funds, very small funds (conservatively defined as funds that never reached $10M of total net assets during their existence), and multiple share classes. We exclude funds with rear loads strictly larger than 1%. Finally, for regressions that require estimating factor loadings, we require the fund to have more than 2 full years of return history. We are left with a sample of 942 funds for regressions based on excess returns, and 865 funds for regressions requiring the estimation of factor loadings. For each fund, we select the largest contiguous sample period for which we have no missing observations for TNA or returns, and during which the fund did not acquire the assets of a delisted fund, as indicated by the merge_icdi series in CRSP. This leaves us with a total of 6146 observations for the regressions based on excess returns, and 4342 observations for regressions requiring the estimation of factor loadings.

Apart from mutual fund data, we require the risk-free rate, returns on the equally weighted market portfolio, Fama and French (1993) SMB and HML factors, and Carhart's (1997) momentum factor, which we obtained from the CRSP Mutual Fund Monthly Returns and Fama-French Factors file. We construct monthly volatility using daily equal weighted returns, including distributions, obtained from the CRSP indices file. Finally, data on Real GDP is from the US Department of Commerce, Bureau of Economic Analysis and was downloaded via the FRED (Federal Reserve Economic Data) website.

B) The Variables

Our empirical analysis consists in two types of regressions. In Section II, we run regressions of flows on past performances, and control variables. In Section III, we regress changes in risk exposure on past performances. We construct data on flows using data on Total Net Assets ($TNA_{i,t}$) and returns $r_{i,t}$. As in Goetzmann and Peles (1997) and Lynch and Musto (2003), we focus on annual dollar flows ($FLOW_{i,t}$) defined as:

$$FLOW_{i,t} = TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1}$$

Although several authors in the literature focus on percentage flows, obtained by dividing dollar flows by the previous year's TNA, we choose not to do so for two reasons. First, from a statistical standpoint, it is well-known that percentage flows contain many extreme outliers generally associated with small or new funds. Small changes to the procedure used to trim the sample or to winsorize the data seem to have large effects on the outcome of the regressions. Second, from an economic standpoint, we care about flows only to the extent that flows contribute to fees collected by the mutual fund and to the compensation package of the fund manager. Given the fee structure of mutual funds, where fees are a constant fraction of total net assets, we believe that dollar flows provide a better proxy for the true determinants of a fund manager's compensation package than do percentage flows. Put differently, it is unlikely that all other things being equal, a fund manager's compensation is a sharply decreasing function of the fund's initial size, as would be the case if compensation was indexed on percentage flows.

Numerous different measures of performance have been used in the literature on the flow-performance relationship. In this paper, we use the three most commonly used measures, namely:

(i) Excess returns, defined as the return of the fund minus the return of the market portfolio

(ii) One factor alpha (CAPM), where the fund's beta has been estimated using the past 24 months of return data.

(iii) Four factor alpha, where the four factors are as proposed by Carhart (1997), namely the return on the market portfolio, the SMB and HML factors of Fama and French (1993), and a momentum factor, and where factor loadings of the fund have again been estimated using the past 24 months of return data.

These measures can be used directly, as in Gruber (1996), Chevalier and Ellison (1997), Lynch and Musto (2003), Barber, Odean and Zheng (2005), among others. Alternatively, these measures can be used to rank funds within each year, and the ranks[13] used as a measure of performance, as in Sirri and Tufano (1998), and Huang, Wei and Yan (2007), among others. We use both types of measures of performance in the paper, using the terminology "absolute performance" to refer to the first type and "relative performance" or "rank" to refer to the second type. We therefore have six different measures

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[13] The ranks within each year are normalized to lie between 0 and 1.

of performance, three of which are measures of absolute performance and three of which are measures of relative performance.

We use two types of control variables: we use cross-sectional variables of funds' characteristics that have been found by the existing literature to have an impact on flows from investors. We also use time-series variables, which we interact with performance variables so as to capture and interpret time-variation in the sensitivity of investor flows to past performance. Cross-sectional variables include expenses expressed in percentage, the age of the fund in years, and the fund's initial relative size, which is defined as $TNA_{i,t-1} / \Sigma_i TNA_{i,t-1}$, where the sum in year $t-1$ is computed over all the funds that are in our sample in that year. Time series variables include real GDP growth, average flow, and annual market volatility. Real GDP growth is computed as 100 times the difference of the log of annual GDP measured in billions of chained 2000 dollars. Average flow $AFLOW_t$ is the year by year average dollar flow, that is

$$AFLOW_t = (1 / n_t)\Sigma_i FLOW_{i,t}$$

where n_t is the number of funds in our sample in year t. For annual market volatility $\sigma_{M,t}$, we use realized volatility calculated as

$$\sigma_{M,t} = \sqrt{\sum_\tau r^2_{M,t,\tau}}$$

where $r_{M,t,\tau}$ is daily returns in year t, with distributions, of an equal weighted portfolio of stocks listed on NYSE/AMEX. Table I includes summary statistics about the flow, performance, control, and interaction variables.

[INSERT TABLE I AROUND HERE]

Our final set of variables are risk exposure variables. We follow Koski and Pontiff (1999) and focus on three measures:

(i) Total risk, defined as the standard deviation of the fund's monthly returns minus the monthly risk-free rate

(ii) Idiosyncratic risk, measured by the standard deviation of the residuals of a market model regression ran on monthly returns.

(iii) Systematic risk, measured by the estimated beta coefficient of a market model regression ran on monthly returns.

These risk exposure variables are used in the regressions in Section III. In particular, the dependent variable in these regressions will be the difference between the standard deviation of the fund's risk variable (total, idiosyncratic, or systematic) during the July to December period and the standard deviation of the risk variable during the January to June period. This implies that each standard deviation in that difference is estimated from only six data points and thus contains a fair amount of noise. A natural solution to this problem is to use daily instead of monthly returns to estimate risk. Busse (2001) and Goriaev, Nijman and Werker (2005) discuss this issue thoroughly and show that the presence of autocorrelation in daily returns makes the choice between daily and monthly returns non-trivial. However, Goriaev, Nijman and Werker conclude that "tests of the tournament hypothesis based on monthly data are more robust to autocorrelation effects than tests based on daily data". This motivates our choice.

C) Estimation Technique

As far as the flow-performance relationship is concerned, the most common procedure followed by the existing literature is to use Fama-MacBeth regressions. This would however be inappropriate for our purposes, for two reasons. First, Fama-MacBeth regressions consist in running separate regressions for each year and to treat differences in estimated slopes across different years in the sample as noise, based on which standard errors are computed. Our objective is to show that the true value of the slopes is time-varying and is driven by business cycle variables, which makes Fama-MacBeth impossible to use. In addition, it is unlikely that our set of control variables is sufficient to capture all of the effects of fixed funds' characteristics on investor flows, which require us to adjust the computation of standard errors beyond that suggested by Fama and MacBeth.

We run an unbalanced panel, allowing for time fixed effects via a full set of year dummy variables (whose coefficients are unreported in the tables). Including time dummies captures any deterministic

time trend in the flow variable. However, time dummies cannot capture stochastic trends, i.e., trends driven by unit roots. If there are stochastic trends in the flow variable, results we obtain given our current specification may be spurious. To address this issue, we run panel unit root tests on $FLOW_{i,t}$, using both the common unit root tests of Levin, Lin, and Chu (2002) and the individual unit root tests of Im, Pesaran, and Shin (2003). In both tests, we reject the presence of unit roots, thus validating our specification.

In addition to the year dummy variables, we control for fund-specific effects by using standard errors clustered by funds. As a robustness check, we ran the same regressions using White standard errors and obtained t-statistics quite substantially larger than the ones obtained with fund clustering. As pointed out by Petersen (2008), the difference in t-statistics between the two methods is strongly suggestive of fund specific effects left unexplained by the control variables. As a consequence, all p-values reported in the paper are based on the more conservative cluster standard errors. We use the same methodology of unbalanced panel data analysis with time fixed effects and clustering of standard errors by funds for the tournament regressions in Section III, for which we know from the analysis of Busse (2001) and Goriaev, Nijman and Werker (2005) that correlation of standard errors is a serious problem.

II) The Time-Varying Convexity of the Flow-Performance Relationship

A) Identifying the business cycle effect

Our primary objective in this section is to show that the sensitivity of investor flows to past performance changes in a systematic way along the business cycle. We first establish the facts and explore their robustness to various definitions of performance. We then investigate possible explanations of this phenomenon.

Our main results regarding the flow-performance relationship are in Tables II and III. Table II uses measures of relative performance while Table III uses measures of absolute performance. In each table, regressions (1), (3) and (5) show the standard flow-performance relationship as identified by the existing literature, with performance (either relative or absolute) measured by excess returns, 1-factor alpha and 4-factor alphas respectively. Regressions (2), (4) and (6) measure the time-varying flow-

performance relationship, with the sensitivity of flows to past performance allowed to vary with the business cycle. Regressions (2), (4) and (6) are similar to regressions (1), (3) and (5) except that regressions (2), (4) and (6) contain an additional interaction variable, constructed as the product of performance with deviations of GDP growth from its sample mean. The advantage of testing for the impact of economic activity using an interaction variable rather than simply splitting the sample between, say NBER recession years and other years is that it allows us to detect both effects occurring during normal years and effects driven by exceptional years of severe economic slowdown. This specification also provides a direct estimate of the magnitude of the impact of economic activity on the sensitivity of flows to past performance.

Using the chain rule, we can decompose the total effect of a change in performance on investor flows in the following way:

$$\frac{dFlow_{i,t}}{dPerformance_{i,t-1}} \;=\; \frac{\partial Flow_{i,t}}{\partial Performance_{i,t-1}} \;+\; (g_{GDP,t} - \overline{g}_{GDP})\frac{\partial Flow_{i,t}}{\partial((g_{GDP,t} - \overline{g}_{GDP})*Performance_{i,t-1})} \qquad (1)$$

The interpretation of (1) is straightforward. The coefficients in multivariate regressions are interpretable as partial derivatives. The first term in the RHS of (1) is equal to the coefficient of performance in a regression of flows on past performance and other control variables. Similarly, the partial derivative in the second term of the RHS is given by the coefficient on the interaction variable previously defined. Under average economic activity, that is, when the growth rate of GDP is equal to its sample mean, the second term in the RHS of (1) is equal to 0. In that case, the total effect of past performance on flows is just given by the partial derivative of flows on performance. This implies that one can interpret the coefficient of flows on past performance as the sensitivity of flows to performance *under average economic activity*. On the other hand, when economic activity is strong (resp. weak), that is when the growth rate of GDP is larger (resp. lower) than its sample mean, the total effect of past performance on flows is equal to the partial derivative of flows on past performance plus a term of the same sign (resp. of the opposite sign) as the coefficient of flows on the interaction variable. This allows us to make the following statement which underlies the interpretation of all regressions in this section:

The sensitivity of flows to past performance is an increasing function of economic activity if and only if the coefficient on the interaction variable is positive

A standard feature of flow-performance regressions is that they separate out observations with "good" performance and observations with "bad" performance and allow the sensitivity of flows to past performance to differ depending on whether the past performance falls in the "good" or in the "bad" category. Defining the thresholds of regions of "good" vs. "bad" performance is in many ways an ad-hoc decision left to the econometrician. In the existing literature, papers that use relative performance use either three or five different quintiles while papers using absolute performance often divide performance into only two regions corresponding to positive vs. negative returns[14]. We follow the procedure used in the existing literature and use different partitions for relative and absolute performances even though it implies that results in our Tables II and III are not immediately comparable to one another.

More specifically, we follow the same procedure as Sirri and Tufano (1998) for Table II and partition relative performance into three unbalanced quintiles. We allow the sensitivity of flows to past performance (rank) to depend on whether the fund's performance in the past year ranked in the bottom quintile, the top quintile, or in between. In other words, the relationship between flow and past rank takes the form of a piecewise linear function. As in Sirri and Tufano (1998), we restrict this piecewise linear relationship to be continuous. Technically, this is achieved by defining:

$$Rank_{i,t-1}^{BOTTOM} \equiv \min(Rank_{i,t-1}, 0.2)$$

$$Rank_{i,t-1}^{MIDDLE} \equiv \min(Rank_{i,t-1} - Rank_{i,t-1}^{BOTTOM}, 0.6)$$

$$Rank_{i,t-1}^{TOP} \equiv \min(Rank_{i,t-1} - Rank_{i,t-1}^{BOTTOM} - Rank_{i,t-1}^{MIDDLE}, 0.2)$$

where $Rank_{i,t-1}$ refers to the rank of fund i in year $t-1$, and running the regression:

$$FLOW_{i,t} = a_1 Rank_{i,t-1}^{TOP} + a_2 Rank_{i,t-1}^{MIDDLE} + a_3 Rank_{i,t-1}^{BOTTOM} + (\text{time dummies}) + (\text{controls})$$

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[14] Other specifications include using a semi-parametric approach as in Chevalier and Ellison (1997) or adding the square of performance as an additional independent variable as in Barber, Odean and Zheng (2005).

The coefficient a_1 measures the sensitivity of flows to past good performance, and a_3 measures the sensitivity of flows to past bad performance. This is the specification of regressions (1), (3), and (5) in Table II.

To allow a_1, a_2, and a_3 to change with the level of economic activity, we adopt the following specification, used in regressions (2), (4) and (6) in Table II:

$$FLOW_{i,t} = a_1 Rank_{i,t-1}^{TOP} + a_2 Rank_{i,t-1}^{MIDDLE} + a_3 Rank_{i,t-1}^{BOTTOM}$$
$$+ a_4 Rank_{i,t-1}^{TOP}(g_{GDP,t} - \overline{g}_{GDP}) + a_5 Rank_{i,t-1}^{MIDDLE}(g_{GDP,t} - \overline{g}_{GDP}) + a_6 Rank_{i,t-1}^{BOTTOM}(g_{GDP,t} - \overline{g}_{GDP})$$
$$+ (time\ dummies) + (controls)$$

For the absolute return regressions in Table III, we follow the same procedure as Lynch and Musto (2003) and others, and simply partition (absolute) performance into two regions. A fund i is allocated to the positive (resp. negative) region during year t if its absolute performance in year $t-1$ is positive (resp. negative), in which case the dummy variable $\delta_{i,t}^+$ (resp. $\delta_{i,t}^-$) takes value 1 for that fund and that year. This yields the following specifications:

For regressions (1), (3) and (5) in Table III:
$$FLOW_{i,t} = a_1 Performance_{i,t-1} * \delta_{i,t-1}^+ + a_2 Performance_{i,t-1} * \delta_{i,t-1}^- + (time\ dummies) + (controls)$$

For regressions (2), (4) and (6) in Table III:
$$FLOW_{i,t} = a_1 Performance_{i,t-1} * \delta_{i,t-1}^+ + a_2 Performance_{i,t-1} * \delta_{i,t-1}^-$$
$$+ a_3 Performance_{i,t-1} * \delta_{i,t-1}^+(g_{GDP,t} - \overline{g}_{GDP}) + a_4 Performance_{i,t-1} * \delta_{i,t-1}^-(g_{GDP,t} - \overline{g}_{GDP})$$
$$+ (time\ dummies) + (controls)$$

As in the existing literature, we say that the flow-performance relationship exhibits convexity if and only if flows are more sensitive to good than to bad performances. Given the partitions of performance defined above, we obtain convexity for regressions (1), (3) and (5) in Table II if and only if the coefficient on the variable $Rank_{i,t-1}^{TOP}$ is strictly larger than the coefficient on the variable $Rank_{i,t-1}^{BOTTOM}$. Similarly, we obtain convexity for regressions (1), (3) and (5) in Table III if and only if the coefficient on the variable $Performance_{i,t-1} * \delta_{i,t-1}^+$ is strictly larger than the coefficient on the variable

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$Performance_{i,t-1} * \delta_{i,t-1}^{-}$. For all the specifications, we perform a one-sided t-test of the sign of the difference of the two coefficients and report the result in the tables immediately below coefficients of performance variables.

We can perform with convexity the same decomposition analysis as we did with the sensitivity to performance. Convexity of the flow-performance relationship can be decomposed into convexity under average economic activity, which obtains when the coefficient of performance in the good region is strictly larger than the coefficient of performance in the bad region, and the impact of economic activity on convexity. Using equation (1) and the same reasoning as previously, we get that:

With relative performance, convexity of the flow-performance relationship is an increasing function of economic activity if and only if the coefficient of $(g_{GDP,t} - \overline{g}_{GDP}) * Rank_{i,t-1}^{TOP}$ is strictly larger than the coefficient of $(g_{GDP,t} - \overline{g}_{GDP}) * Rank_{i,t-1}^{BOTTOM}$.

With absolute performance, convexity of the flow-performance relationship is an increasing function of economic activity if and only if the coefficient of $Performance_{i,t-1} * (g_{GDP,t} - \overline{g}_{GDP}) * \delta_{i,t-1}^{+}$ is strictly larger than the coefficient of $Performance_{i,t-1} * (g_{GDP,t} - \overline{g}_{GDP}) * \delta_{i,t-1}^{-}$.

In either case, the result of the corresponding one-sided t-test is included in the tables immediately below the coefficients of the interaction variables.

[INSERT TABLE II AROUND HERE]

Looking at the results of Table II, we first observe that fund characteristics explain investor flows in the usual way: larger and younger funds attract more dollar flows. As found by Barber, Odean and Zheng (2005), expenses do not seem to play a huge role once we exclude front loads. We also see that the sensitivity of flows to past performance fits the pattern that has been observed by the existing literature: regardless of whether the ranking of funds is done on the basis of excess returns, 1-factor

alpha or 4-factor alphas, we find that investor flows react positively and significantly to relative performance if the fund belongs to the top or to the middle quintile but do not react to relative performance if the fund belongs to the bottom quintile. As a consequence, tests of convexity under average economic activity yield p-values around 0.01 to 0.02 if funds are ranked according to excess returns or 1-factor alpha, and p-values around 0.05 to 0.06 if funds are ranked according to 4-factor alphas.

However, the most important result in Table II concerns the impact of economic activity, measured by GDP growth, on the sensitivity of flows to performance and on the convexity of the flow-performance relationship. Observing the coefficient a_4, we observe that investor flows react more to performance of funds in the top quintile during years with strong economic activity. The effect is statistically significant at the 5% level of confidence when the ranking of funds is done according to excess returns and 1-factor alphas. It is also economically significant. If one compares the respective size of the coefficients a_1 and a_4, one observes that the sizes are almost identical. Using equation (1) and recalling that $(g_{GDP,t} - \overline{g}_{GDP})$ is expressed in percentage, we can conclude that a +1% change in GDP growth induces a sensitivity of flows to performance in the top quintile which is twice as large as the average sensitivity of flows to performance. Similarly, a -1% change in GDP growth implies that investor flows become completely insensitive to performance. As the standard deviation of GDP growth in our sample is equal to 1.7%, our point estimates imply that even small fluctuations of economic activity can have a large impact on the sensitivity of flows to performance.

The same conclusion can be reached when looking at the impact of economic activity on the convexity of the flow-performance relationship. We find a strong statistical impact, with p-values ranging from 1.4% to 5.2%. We also find strong economic significance with again a +1% or -1% change in GDP growth implying, respectively, either twice as much convexity as the average convexity in the sample, or no convexity at all.

Results in Table III, using absolute returns instead of relative returns, are somewhat weaker. When performance is based on 1-factor alphas (regressions 3 and 4), results are qualitatively similar to results in Table II: the flow-performance relationship exhibits convexity on average and the impact of GDP on convexity is both statistically and economically significant. When performance is computed with excess returns or with 4-factor alphas, we still get a significant positive effect of GDP growth on the

sensitivity of flows to performance at the 5% level of confidence. We also get point estimates suggesting that faster GDP growth leads to more convexity. However, the effect on convexity is no longer statistically significant.

[INSERT TABLE III AROUND HERE]

One possible explanation for the relatively weaker results for absolute returns is the coarser partition of performance regions used in Table III and the fact that flows into funds in the 3rd-5th decile are more sensitive to performance than flows into funds in the bottom two deciles. Other explanations are provided in the next two subsections, where we investigate the nature of the business cycle effect in more detail.

B) Sources of the business cycle effect

Before understanding why economic activity may have an impact on the convexity of the flow-performance relationship, we need to understand why convexity arises in the first place. The key premise is that investors look for funds delivering positive alphas. We know from the recent literature that, once one properly accounts for the luck factor, at best only a small fraction of mutual funds deliver positive alphas[15]. Thus, it is optimal for investors to invest primarily only in the very best performers in the industry. Berk and Green (2004) have demonstrated that performance chasing behaviour of investors and a convex flow-performance relationship may arise as the outcome of a competitive equilibrium model even if mutual fund performance is not persistent, as suggested by the empirical literature.

While this argument applies to both new investment flows and portfolio rebalancing flows, it is unlikely to apply for outflows. Indeed, we observe empirically that investors invest only in very few assets[16]. As a consequence, investors are forced to liquidate whichever asset they invested into, regardless of its performance, whenever they need to finance consumption. In fact, evidence to that

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[15] See Barras, Scaillet and Wermers (2007), and Kosowski et al. (2006)
[16] See e.g. Blume and Friend (1975), or Calvet, Campbell and Soldini (2007) for more recent evidence.

effect is provided in Tables IV and V of Cashman et al. (2007) where it appears that outflows are much less sensitive to performance than inflows. The relationship between outflows and performance could even go in a counter-intuitive way if at least some investors suffer from a disposition effect whereby they hold on past losers and liquidate past winners, as has been demonstrated for the stock market by Shefrin and Statman (1985) and by Odean (1998). If the disposition effect is strong enough, investor flows become a weakly decreasing and concave function of past performance.

In our dataset, we observe neither inflows nor outflows but net flows which is the sum of the two. If inflows are a convex function of performance but outflows are not, net flows will themselves be a convex function of performance if the relative weight of inflows relative to outflows is large enough. Because of consumption smoothing, it is natural to expect that the relative proportion of inflows vs. outflows to be correlated with economic activity. Evidence in that direction has already been provided by Kosowski (2006) and the result holds in our dataset as well. This provides a first possible channel through which economic activity may affect the convexity of the flow-performance relationship: stronger economic activity implies relatively more inflows than outflows.[17]

An alternative explanation starts from the well-known observation that stock market volatility is countercyclical[18]. High volatility increases the "luck factor" in the realized performance of fund managers and thereby complicates the inference process of investors. As the inference process becomes more noisy, we should again expect flows to be less responsive to past performance when economic activity is weak than when it is strong.

In order to disentangle these two effects, we run a "horse race" between the flow composition effect and the countercyclical volatility effect. Instead of interacting past performance with GDP growth, we interact it instead with average flows for year t, $AFLOW_t$, and with lagged annual stock market volatility[19] $\sigma_{M,t-1}$. That is, we run a regression of investor flows into individual funds on to: (i) fund characteristics, (ii) past performance, (iii) interaction variable between past performance and average flows, (iv) interaction variable between past performance and average flows of the year into all mutual

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[17] A possible reinforcing factor, but which we cannot test independently, is the evidence provided by Kumar (2008) which suggests that investors are more likely to suffer from disposition effects during recessions than during times with strong economic activity.

[18] See e.g. Schwert (1989a and b), Hamilton and Lin (1996) or Mele (2007)

[19] Volatility is lagged as it is volatility at period $t-1$ that affects investor's ability to interpret a fund's performance over period $t-1$.

funds. In order to make the coefficient on the interaction variables easier to interpret, we normalize our measures of average flows and of stock market volatility to variables with mean 0 and standard deviation 1. Results of the regressions are presented in Tables IV and V.

[INSERT TABLES IV AND V AROUND HERE]

The most striking feature of the regressions in Tables IV and V is the strong support they provide to the average flow channel. For all six specifications, we find that the sensitivity of investor flows to past performance is a sharply increasing function of $AFLOW_t$ for funds in the top performance region. Looking for instance at the first regression in Table IV and comparing the relative size of coefficients a_1 and a_4, we find that a one standard deviation increase of $AFLOW_t$ leads to a slope which is three times as steep as under average market conditions. This effect is statistically significant in all six specifications. In contrast, $AFLOW_t$ has no discernable impact on the sensitivity of flows to performance for funds in the middle or bottom performance regions. Thus, an increase of $AFLOW_t$ always implies a stronger convexity of the flow-performance relationship. Looking at the results in Table IV, we find that the effect is always statistically significant at the 5% level and that it is economically significant as well: a one standard deviation increase in $AFLOW_t$ leads to a flow-performance relationship which is three times more convex than under average normal conditions.

Looking now at Table V, we see that the same results supporting the conditional tournament hypothesis and the flow composition channel carry through with absolute returns. This is in contrast with results we obtained in the previous sub-section where the evidence in favour of a business cycle effect on the flow-performance relationship was weaker with absolute than with relative returns. An explanation for this finding is provided by the coefficients of the interaction variable between performance and stock market volatility. We find that, when significant, higher stock market volatility implies a lower sensitivity of flows to performance. However, we also find that this effect never affects the top performance region. That is, higher stock market volatility never leads to less convexity. On the contrary, when stock market volatility is high, that is during recessions, investors tend to "forgive" fund managers who obtained disastrous absolute performance, while the same performance in an environment with low stock market volatility would cause investor outflows. This effect goes in the

opposite direction from the flow composition channel, thus leading to the more ambiguous overall effect of GDP growth on convexity for the absolute return case.

To confirm this insight, and since the effect of high stock market volatility is likely to be concentrated in a few abnormal years, we now investigate whether the business cycle effect arises as an outcome of normal economic conditions or whether it is driven by a few outliers corresponding to either deep recessions or strong booms.

C) Normal fluctuations of economic activity vs. extreme fluctuations

Our last robustness checks consist in verifying whether our results carry through in a sample where we remove all years which experienced large economic fluctuations, either downward (recessions) or upwards (strong booms). The objective is to investigate the extent to which our findings are driven by outliers corresponding to exceptional years or whether they arise under normal economic conditions. Mean GDP growth in our sample is equal to 2.9%. Standard deviation is equal to 1.7%. We use somewhat arbitrarily chosen cut-offs for our reduced sample of deviations of GDP growth around the sample mean equal to plus or minus 2%. In other words, we retain in our reduced sample all years during which GDP growth lies in the interval [+0.9%, +4.9%]. This requirement excludes 5 of the 27 years initially in our sample, namely 1980, 1982, 1984, 1991 and 2001. We then test the effect of GDP growth on convexity in our reduced sample and report the results in Tables VI and VII

[INSERT TABLES VI AND VII AROUND HERE]

Comparing results obtained for the reduced sample in Tables VI and VII with results obtained for the full sample in Tables II and III yields unambiguous results. The impact of GDP growth on the sensitivity of flows to performance in the top performance region is much larger in the reduced sample, even by a factor of 3 to 5 in the case of absolute returns. As a consequence, the impact of GDP growth on convexity is stronger in the reduced sample than in the full sample. We find strong statistical support for the hypothesis that convexity of the flow-performance relationship is positively correlated with economic activity in all specifications, including the case of absolute returns, for which p-values are all below 0.03.

These findings show that economic activity has an impact on the shape of the flow-performance relationship above and beyond any effect driven by "abnormal" years with strong negative or positive growth. As such, they complement and reinforce conclusions reached by Kosowski (2006) on the impact of real activity on performance and flows using NBER recessions. Comparing these results with the full sample results suggests that the relationship which associates investor flows to relative performance is more stable than the relationship which associates investor flows to absolute performance. This is because investors seem to interpret absolute performance differently in years with strong economic fluctuations and/or high stock market volatility than they do under normal conditions. Finally, our finding that small variations of economic activity cause significant variation in the sensitivity of flows to past performance contradicts the assumptions of the methodology most frequently used in the existing literature on the flow-performance relationship, namely Fama-MacBeth (1973) regressions, which requires slope coefficients of all single-year regressions to be drawn from the same distribution. Using the Fama-MacBeth methodology when the slope coefficient is time-varying can lead to misleading conclusions, as first pointed out in the asset pricing literature on the conditional CAPM.

Summarizing the results in Section II, we find that:

(i) Convexity of the flow-performance relationship varies with economic activity.

(ii) The effect of economic activity on convexity is economically significant: a +1% change in GDP growth implies a flow-performance relationship which twice as convex as on average

(iii) The effect of economic activity on convexity is driven by a flow composition effect: the stronger the economic activity, the more inflows relative to outflows, and the more sensitive net flows are to (good) performance.

(iv) The effect of economic activity on convexity arises under normal economic conditions and is not driven by years with extreme fluctuations.

III) Application: Solving the Tournament Puzzle

A) Conditional vs. Unconditional Tournament Hypothesis

Having established that the shape of the flow-performance relationship varies with economic activity, we now turn to its implications for the incentives of fund managers. The fact that a convex flow-performance relationship may induce fund managers who underperform during the first part of the year to increase the risk of their portfolio has been well-known since the seminal papers of Brown, Harlow and Starks (1996) and Chevalier and Ellison (1997). The model underlying this conjecture is both simple and appealing given institutional characteristics of the mutual fund industry. We know that the fee structure in the mutual fund industry is such that fees received by funds are maximized when net flows and total net assets are maximized. We also know that the evidence strongly suggests that investor flows are a weakly increasing function of performance with a flat section in the region of worse performance, which makes them like payoffs of a tournament. A simple computation implies that increasing risk for funds currently in the region where flows are insensitive to performance is a "free gamble": either performance falls even deeper in the region of worse performance, but this affects neither flows nor fees, or performance jumps up sufficiently to enter the region with positive slope, in which case both flows and fees go up.

As discussed in the introduction, however, recent empirical evidence has been less supportive of this conjecture than earlier results. Busse (2001) challenges the methodology used by Brown, Harlow and Starks (1996) and argues that their results are very sensitive to the sample period, the frequency of returns used to compute measures of risk, and the method used to compute standard errors. Goriaev, Nijman and Werker (2005) complement the methodological issues raised by Busse. In addition, they report results suggesting that, if anything, the evidence over the 1976-2001 period points half as often in the direction of the tournament hypothesis as it does in the direction of the opposite result, namely that poor half-year performers *decrease* the level of risk of their portfolio relative to that of strong half-year performers. Similar results in the latter direction are provided by Qiu (2003), Hu et al (2007), and Kempf, Ruenzi and Thiele (2007).

How to explain the apparent lack of robustness of tests of the tournament hypothesis? Two answers are provided in the existing literature. The answer provided by Busse (2001) and Goriaev, Nijman and Werker (2005) is that tests based on observed returns are simply not powerful enough given the noise

in estimating the risk exposure of mutual fund managers within a year. They suggest to turn instead toward tests based on the actual composition of the fund portfolios, which is however not readily available. The other answer is provided by Qiu (2003) and Hu et al (2007) who argue that the argument underlined above ignores the possibility that a fund manager is fired as a consequence of poor performance. As Chevalier and Ellison (1999) suggests that the probability of being fired for a fund manager is itself a convex function of past performance, the overall payoff function of the fund manager need not be convex even if the manager's compensation package is based on flows that are a convex function of past performance. This implies that the theoretical prediction of the tournament hypothesis is ambiguous.

Our view in this paper is more optimistic. We use the results we obtained in the previous section showing that incentives provided by the tournament structure of flows changes with the level of economic activity in a significant fashion. When economic activity is strong, there is strong convexity of the flow-performance relationship, thus the difference between the "prize" available to "winners" of the tournament and the payoff of the "losers" is large, and the incentives for "underdogs" to increase the risk of their portfolio in the middle of the tournament are strong. In contrast, when economic activity is weak, the prize for winning the tournament is small and incentives for poor mid-year performers to undertake risk-shifting are much less. In fact, point estimates of the flow-performance regressions in the previous section suggest that the flow-performance relationship becomes concave when economic activity slows down enough, which would actually reverse the incentives provided to managers of funds with poor mid-year performance. In other words, the time-varying nature of the flow-performance relationship implies that the appropriate tournament hypothesis to test is that poor mid-year performers should increase the risk of their portfolio if and only if economic activity is strong. We call this hypothesis the conditional tournament hypothesis, in contrast with the (unconditional) tournament hypothesis tested by the existing literature which implies that poor mid-year performers should always increase the risk of their portfolio.

Three remarks need to be made about the conditional tournament hypothesis:

(i) It does not solely constitute a way to justify why tests of the unconditional tournament hypothesis may fail or may give different results across sub-samples. It also provides strong testable implications about when the tournament hypothesis will hold and when it will not: the change in risk by poor mid-year performers should be positively and significantly correlated with economic activity.

(ii) The conditional hypothesis does not suffer from the same problem of theoretical ambiguity as the unconditional hypothesis, as it is unlikely that the cost for a manager to be fired is lower in a recession than in an expansion phase. A similar point is made by Kempf, Ruenzi and Thiele (2007) who assume that the cost of a manager being fired is a decreasing function of market returns and use that assumption to derive a conjecture similar to our conditional tournament hypothesis.

(iii) A recent paper by Cvitannic, Lazrak and Wang (2007) provides a different motive for poor mid-year performers to increase the risk of their portfolio. Cvitannic, Lazrak and Wang show that this feature naturally arises in an intertemporal optimization setting where managers try to maximize the Sharpe ratio of their portfolios. As a consequence, even if tests of the unconditional tournament hypothesis were positive, they would not be able to distinguish the incentives-based motive of Brown, Harley and Stark (1996) and Chevalier and Ellison (1997) from the intertemporal optimization motive of Cvitannic, Lazrak and Wang (2007). In contrast, a positive result to a test of the conditional tournament hypothesis provides strong support to the incentives motive.

B) Empirical Evidence

Empirical evidence regarding the conditional tournament hypothesis is provided in Tables VIII to XIII. Each table corresponds to one of the six different specifications of measurement of performance we used in Section II. Within each table, results of six regressions are provided. Regressions (1), (3) and (5) are similar to regressions in Koski and Pontiff (1999) for respectively, total risk, idiosyncratic risk and systematic risk as defined in Section I. In each case, the dependent variable, $\Delta Risk_{i,t}$ is defined as the difference between the risk of fund i during the period July-December of year t and the risk of fund i during the period January-June of year t. We then regress $\Delta Risk_{i,t}$ on the performance of fund i during the January-June period of year t (mid-year performance) using unbalanced panel data techniques allowing for fixed year effects through a full set of year dummy variables and using standard errors clustered by funds to allow for fund-specific effects.

Regressions (2), (4) and (6) augment the set of independent variables to allow for economic activity to interact with past performance, and thus test the conditional tournament hypothesis. Regressions (2),

(4) and (6) can be interpreted the same way as we interpreted the time-varying flow-performance relationship regressions. Using the chain rule, we have:

$$\frac{d(\Delta Risk_{i,t})}{dPerformance_{i,t-1}} = \frac{\partial(\Delta Risk_{i,t})}{\partial Performance_{i,t-1}} + (g_{GDP,t} - \overline{g}_{GDP})\frac{\partial(\Delta Risk_{i,t})}{\partial((g_{GDP,t} - \overline{g}_{GDP})*Performance_{i,t-1})} \qquad (2)$$

As in Section II, the first term in the RHS of (1) is equal to the coefficient of mid-year performance. Similarly, the partial derivative in the second term of the RHS is provided by the coefficient on the interaction variable between GDP growth and mid-year performance. We can again interpret the coefficient of mid-year performance as the sensitivity of $\Delta Risk_{i,t}$ to mid-year performance under average economic activity. The prediction of the *unconditional* tournament hypothesis is that this coefficient should be negative: the lowest the mid-year performance, the more the fund manager should increase the risk of his portfolio.

However, when the economic activity is strong (resp. weak), that is when the growth rate of GDP is larger (resp. lower) than its sample mean, the total effect of mid-year performance on $\Delta Risk_{i,t}$ is not just equal to the partial derivative of $\Delta Risk_{i,t}$ on mid-year performance, but it is equal to that partial derivative plus a term of the same sign (resp. of the opposite sign) as the coefficient of $\Delta Risk_{i,t}$ on the interaction variable. The *conditional* tournament hypothesis says that the total effect of mid-year performance on $\Delta Risk_{i,t}$ should be negative if and only if economic activity is strong enough. This property holds if and only if the coefficient on the interaction variable is negative. We thus get:

*The **unconditional** tournament hypothesis is satisfied if and only if the coefficient on mid-year*
performance is negative

*The **conditional** tournament hypothesis is satisfied if and only if the coefficient on the **interaction***
variable is negative

[INSERT TABLES VIII TO XIII AROUND HERE]

Turning to the results, we first find that, as in the existing literature, support for the unconditional tournament hypothesis is pretty weak. Depending on the way we measure performance and the type of risk we consider, all four possible results for the coefficient of mid-year performance (positive significant, positive insignificant, negative insignificant, negative significant) can be obtained.

In contrast, results regarding the conditional tournament hypothesis are strong and unambiguous across all six measures of performance. The strongest results are obtained for the case of idiosyncratic risk, that is, for regressions (4) in the tables. From a statistical standpoint, we observe that the coefficient of the interaction variable between GDP growth and mid-year performance is always of the right sign (negative) and significant at the 0.01 level of confidence. From an economic standpoint, an easy assessment of the magnitude of the effects we observe is available in the case of relative performance, that is for Tables VIII to X. Remember that relative performance is by construction always between 0 and 1, with 0 corresponding to the worse performer and 1 to the best performer. Remember also that GDP growth is expressed in percentage. The coefficients of the interaction variable in Regressions (4) in Tables VIII to X then imply that the impact of a 1% increase in GDP growth is a difference in terms of (monthly) idiosyncratic risk between bottom and top performers equal going from 0.73% to 0.95%. To put these numbers in perspectives, we can compare them to the average level of idiosyncratic risk for funds in our sample, which is slightly above 2%. Our point estimates thus imply that during a mild expansion, the bottom performer in our sample shifts the level of idiosyncratic risk in his portfolio relative to that of the top performer by a factor between 1.3 and 1.4, which is not huge but is nevertheless economically significant[20].

Results regarding the conditional tournament hypothesis for total risk (Regressions 2) are still fairly strong in terms of statistical significance: the interaction variable is always of the right sign, it is significant at the 0.01 level of confidence in three out of six specifications of the measure of performance, and it is significant at the 0.05 level of confidence in all specifications. Economic significance is however more modest than for idiosyncratic risk: doing similar computations as above yields that during a mild expansion, the bottom performer in our sample shifts the level of total risk in his portfolio relative to that of the top performer by a factor between 1.07 and 1.25.

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[20] These numbers are comparable to those obtained by Chevalier and Ellison (1997)

Given the decomposition of total risk in between systematic and idiosyncratic risk and given the results above, it should come as no surprise that our weakest results hold for systematic risk. Actually, if one looks at statistical significance only, the conditional tournament hypothesis seems to hold for systematic risk as well: the coefficient of the interaction variable is again negative and significant in 5 out 6 specifications. However, performing the same test of economic significance as above reveals that the effect of mid-year performance on the change in beta by fund managers is trivial in terms of magnitude. For instance, point estimates of regression (6) in Table VI suggest that the bottom performer increases the beta of his portfolio relative to that of the top performer by an amount equal to 0.07.

To summarize our results, we find strong statistical support for the conditional tournament hypothesis in all specifications of the tournament regressions. In terms of economic significance, the strongest effect is found when looking at idiosyncratic risk. This should not come as a surprise. The reason why managers of poorly performing funds want to increase the risk of their portfolio is in the hope of being lucky and to generate "spurious alphas", so as to fool investors into believing that the manager possesses high skill. This can only be done by raising idiosyncratic risk. Thus, to get back to the issue that initially motivated the literature on the tournament hypothesis, our results suggest that mutual fund managers do respond to incentives provided to them by the (time-varying) convexity of the flow-performance relationship.

IV Concluding Remarks

In the past few years, there has been formidable growth in the literature on investor flows in the mutual fund industry, and on the tournament hypothesis. We believe that this paper provides an important link that bridges many of the results in the existing literature that have so far remained unconnected. This missing link is the fact that the convexity of the flow-performance relationship varies strongly with economic activity. Our point estimates suggest that a plus or minus 1% variation in GDP growth entails respectively, twice as much convexity as average, or no convexity whatsoever. Our finding provides a quantitatively plausible solution to different issues in the mutual fund literature such as:

(i) Why there is significant time variation in the extent of risk-shifting by mutual fund managers, as in Brown, Harlow and Starks (1996)

(ii) Why mutual funds seem to deliver worse performance during booms than during recessions, as in Kosowski (2006)

(iii) How different qualitative properties of gross inflows and gross outflows, as identified by Cashman et al. (2007), affect fund managers decisions

More generally, our results point toward a complex interaction between real activity and incentives of market participants. Asset pricing theory has long recognized that time-varying risk premia and shocks to risk aversion are central for our understanding of asset prices. In a very modest way, this paper provides a very specific channel through which shocks to economic activity translate into shocks to the risk appetite of agents. As economic activity intensifies, mutual fund managers see their incentives biased toward more risk taking, which is qualitatively consistent with the long established stylized fact that risk premia are countercyclical[21]. We leave it to future research to discover if this channel, or channels like it, can contribute quantitatively to our understanding of time-varying risk premia.

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[21] See e.g. Ferson and Harvey (1991) and references in Campbell and Cochrane (1999).

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Table I Summary Statistics

This table contains summary statistics of the flow, performance, and control variables. $FLOW_{i,t}$ is defined as:

$$FLOW_{i,t} = TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1}$$

where $TNA_{i,t}$ represents the total net assets of fund i at the end of year t (in M\$) and where $r_{i,t}$ is the net return of fund i during year t. Performance is measured either by excess return $r_{i,t-1} - r_{m,t-1}$, where r_m is the return on the equally weighted market portfolio, or by residuals of a CAPM equation (1-factor alpha) or of a Carhart (1997) model (4-factor alpha), where factor loadings have been estimated from 24 monthly observations. Size and expenses are expressed in percentage, where Size is defined by $TNA_{i,t-1} / \Sigma_j (TNA_{j,t-1})$. Real GDP growth is computed as 100 times the difference of the log of annual GDP measured in billions of chained 2000 dollars. Average flow $AFLOW_t$ is the year by year average dollar flows, that is $AFLOW_t = (1/n_t)\Sigma_i FLOW_{i,t}$ where n_t is the number of funds in our sample in year t. For annual market volatility $\sigma_{M,t}$, we use realized volatility calculated as $\sigma_{M,t} = \sqrt{\sum_\tau r_{M,t,\tau}^2}$ where $r_{M,t,\tau}$ is daily returns in year t, with distributions, of an equal weighted portfolio of stocks listed on NYSE/AMEX.

	Mean	S.D
Flow ($mil)	21.12	287.47
Performance		
Excess Returns	-0.071	0.196
One-Factor Alphas	-0.034	0.171
Four-Factor Alphas	-0.036	0.136
Size (%)	0.408	1.816
Age (years)	7.862	5.778
Expenses (%)	1.218	0.512
Real GDP Growth	2.900	1.769
Average Net Flow ($mil)	35.21	54.71
Realized Volatility	0.148	0.054

Table II: Flow-Performance Relationship: the relative performance case

This table examines the evolution over the business cycle of the impact of relative fund performance (i.e. Rank) in year t-1 on the net flow of the fund in year t. For each regression, the dependent variable, $FLOW_{i,t}$ is defined as: $FLOW_{i,t} = TNA_{i,t} - (1+r_{i,t})TNA_{i,t-1}$, where $TNA_{i,t}$ represents the total net assets of fund i at the end of year t (in M\$) and where $r_{i,t}$ is the net return of fund i during year t. Each year, funds are ranked between 0 (poorest performer) and 1 (best performer) based on their previous year performance, where performance is either measured by excess return $r_{i,t-1} - r_{m,t-1}$, where r_m is the return on the equally weighted market portfolio, or by residuals of a CAPM equation (1-factor alpha) or of a Carhart (1997) model (4-factor alpha), where factor loadings have been estimated from 24 monthly observations. The variables $Rank_{i,t-1}^{TOP}$, $Rank_{i,t-1}^{MIDDLE}$, and $Rank_{i,t-1}^{BOTTOM}$, are defined as $Rank_{i,t-1}^{BOTTOM} = \min(Rank_{i,t-1}, 0.2)$, $Rank_{i,t-1}^{MIDDLE} = \min(Rank_{i,t-1} - Rank_{i,t-1}^{BOTTOM}, 0.6)$, and $Rank_{i,t-1}^{TOP} = \min(Rank_{i,t-1} - Rank_{i,t-1}^{BOTTOM} - Rank_{i,t-1}^{MIDDLE}, 0.2)$, where $Rank_{i,t-1}$ refers to the rank of fund i in year t-1. The variable $(g_{GDP,t} - \bar{g}_{GDP})$ measures deviations in percentage of the US real GDP growth rate from its sample mean. Size and expenses are expressed in percentage, where Size is defined by $TNA_{i,t-1} / \Sigma_j (TNA_{j,t-1})$. Regressions also include one dummy variable for each year in the sample (coefficients unreported). The sample is composed of 942 no-load US equity mutual funds appearing in the CRSP database between 1980 and 2006, where we exclude index funds, multiple share classes, funds closed to investors, funds of funds and funds with TNA < 10M\$ for their entire existence. For regressions where the dependent variable is 1-factor or 4-factor alpha, we require funds to have at least 2 years of full return history, which further restricts the sample to 865 funds. Standard errors are clustered by funds. P-values are reported in parentheses. ***, ** and * indicate, respectively, significance at the 1%, 5% and 10% level. We report below each triplet of rank variables the difference between the coefficient of the top quintile rank variable and that of the corresponding bottom quintile rank variable and the p-value resulting from a one-sided t-test of the sign of that difference predicted by the theory.

Rank based on:	Excess returns		1-factor alpha		4-factor alpha	
Regression	(1)	(2)	(3)	(4)	(5)	(6)
Size	34.214 (***)	33.868 (***)	21.531 (**)	21.552 (**)	21.017 (**)	21.142 (**)
	(0.003)	(0.003)	(0.042)	(0.039)	(0.044)	(0.041)
Age	- 5.399 (***)	-5.362 (***)	- 4.497 (***)	-4.367 (***)	-4.656 (***)	-4.575 (***)
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Expenses	-10.356	-11.490	- 0.377	0.520	-6.518	-6.240
	(0.275)	(0.225)	(0.968)	(0.955)	(0.484)	(0.507)
(a₁) : $Rank_{i,t-1}^{TOP}$	219.675	279.777 (*)	390.755 (*)	485.497 (*)	332.778	406.660
	(0.142)	(0.057)	(0.079)	(0.059)	(0.159)	(0.141)
(a₂) : $Rank_{i,t-1}^{MIDDLE}$	187.629 (***)	192.182 (***)	202.400 (***)	207.740 (***)	158.819 (***)	164.650 (***)
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(a₃) : $Rank_{i,t-1}^{BOTTOM}$	-82.598	-90.761	-69.403	-73.006	-53.684	-53.709
	(0.301)	(0.282)	(0.503)	(0.502)	(0.568)	(0.596)
a₁-a₃	**302.27 (**)**	**370.54 (**)**	**460.16 (**)**	**558.5 (**)**	**386.46 (*)**	**460.37 (*)**
	(0.020)	**(0.014)**	**(0.014)**	**(0.013)**	**(0.056)**	**(0.052)**
(a₄) : $(g_{GDP,t} - \bar{g}_{GDP})*Rank_{i,t-1}^{TOP}$		352.072 (**)		494.002 (**)		387.524
		(0.023)		(0.049)		(0.127)
(a₅) : $(g_{GDP,t} - \bar{g}_{GDP})*Rank_{i,t-1}^{MIDDLE}$		26.823		26.860		29.657
		(0.176)		(0.404)		(0.313)
(a₆) : $(g_{GDP,t} - \bar{g}_{GDP})*Rank_{i,t-1}^{BOTTOM}$		-39.280		- 26.135		-3.639
		(0.558)		(0.779)		(0.967)
a₄-a₆		**391.35 (**)**		**520.14 (**)**		**391.16 (*)**
		(0.014)		**(0.032)**		**(0.052)**

Table III: Flow-Performance Relationship: the absolute performance case

This table examines the evolution over the business cycle of the impact of absolute fund performance in year t-1 on the net flow of the fund in year t. For each regression, the dependent variable, $FLOW_{i,t}$ is defined as:

$$FLOW_{i,t} = TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1}$$

where $TNA_{i,t}$ represents the total net assets of fund i at the end of year t (in M\$) and where $r_{i,t}$ is the net return of fund i during year t. Performance is measured either by excess return $r_{i,t-1} - r_{m,t-1}$, where r_m is the return on the equally weighted market portfolio, or by residuals of a CAPM equation (1-factor alpha) or of a Carhart (1997) model (4-factor alpha), where factor loadings have been estimated from 24 monthly observations. $\delta_{i,t-1}^-$ (resp. $\delta_{i,t-1}^+$) takes value 1 if the past year performance of the fund is negative (resp. positive), and takes value 0 otherwise. ($g_{GDP,t}$ - $\overline{g}_{GDP}$) measures deviations in percentage of the US real GDP growth rate from its sample mean. Size and expenses are expressed in percentage, where Size is defined by $TNA_{i,t-1} / \Sigma_j (TNA_{j,t-1})$. Regressions also include one dummy variable for each year in the sample (coefficients unreported). The sample is composed of 942 no-load US equity mutual funds appearing in the CRSP database between 1980 and 2006, where we exclude index funds, multiple share classes, funds closed to investors, funds of funds and funds with TNA < 10M\$ for their entire existence. For regressions where the dependent variable is 1-factor or 4-factor alpha, we require funds to have at least 2 years of full return history, which further restricts the sample to 865 funds. Standard errors are clustered by funds. P-values are reported in parentheses. ***, ** and * indicate, respectively, significance at the 1%, 5% and 10% level. We report below each triplet of rank variables the difference between the coefficient of the top quintile rank variable and that of the corresponding bottom quintile rank variable and the p-value resulting from a one-sided t-test of the sign of that difference predicted by the theory.

Performance measured by:	Excess returns		1-factor alpha		4-factor alpha	
Regression	(1)	(2)	(3)	(4)	(5)	(6)
Size	34.604 (***)	34.199 (***)	20.479 (**)	20.424 (**)	21.145 (**)	21.085 (**)
	(0.003)	(0.003)	(0.048)	(0.044)	(0.045)	(0.041)
Age	- 5.450 (***)	-5.361 (***)	- 4.314 (***)	-4.189 (***)	-4.565 (***)	-4.372 (***)
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Expenses	-11.215	-11.509	- 4.143	-2.745	-6.747	-7.307
	(0.243)	(0.232)	(0.661)	(0.773)	(0.474)	(0.443)
....						
$(a_1): Performance_{t-1} * \delta_{i,t-1}^+$	335.143 (***)	350.490 (***)	672.063 (***)	678.399 (***)	396.449 (**)	820.647 (**)
	(0.002)	(0.004)	(0.001)	(0.002)	(0.013)	(0.020)
$(a_2): Performance_{t-1} * \delta_{i,t-1}^-$	278.621 (***)	295.841 (***)	209.303 (***)	202.747 (**)	417.716 (***)	406.478 (***)
	(0.000)	(0.000)	(0.000)	(0.013)	(0.000)	(0.000)
a_1-a_2	*56.222*	*54.649*	*462.76 (**)*	*475.65 (**)*	*-21.267*	*414.17*
	(0.321)	*(0.363)*	*(0.021)*	*(0.041)*	*(0.555)*	*(0.148)*
....						
$(a_3): Performance_{t-1} * (g_{GDP,t} - \overline{g}_{GDP}) * \delta_{i,t-1}^+$		151.110 (**)		309.193 (**)		358.602 (**)
		(0.021)		(0.025)		(0.045)
$(a_4): Performance_{t-1} * (g_{GDP,t} - \overline{g}_{GDP}) * \delta_{i,t-1}^-$		46.694		- 19.190		173.266 (**)
		(0.871)		(0.793)		(0.014)
a_3-a_4		*104.15*		*328.38 (*)*		*185.34*
		(0.175)		*(0.054)*		*(0.195)*

Table IV: Decomposition of the business cycle effect: the relative performance case

This table examines how the impact of relative fund performance (i.e. Rank) in year t-1 on the net flow of the fund in year t varies with aggregate flows and market volatility of the year. For each regression, the dependent variable, $FLOW_{i,t}$ is defined as: $FLOW_{i,t} = TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1}$, where $TNA_{i,t}$ represents the total net assets of fund i at the end of year t (in M\$) and where $r_{i,t}$ is the net return of fund i during year t. Each year, funds are ranked between 0 (poorest performer) and 1 (best performer) based on their previous year performance, where performance is either measured by excess return $r_{i,t-1} - r_{m,t-1}$, where r_m is the return on the equally weighted market portfolio, or by residuals of a CAPM equation (1-factor alpha) or of a Carhart (1997) model (4-factor alpha), where factor loadings have been estimated from 24 monthly observations. The variables $Rank_{i,t-1}^{TOP}$, $Rank_{i,t-1}^{MIDDLE}$, and $Rank_{i,t-1}^{BOTTOM}$, are defined as $Rank_{i,t-1}^{BOTTOM} = \min(Rank_{i,t-1}, 0.2)$, $Rank_{i,t-1}^{MIDDLE} = \min(Rank_{i,t-1} - Rank_{i,t-1}^{BOTTOM}, 0.6)$, and $Rank_{i,t-1}^{TOP} = \min(Rank_{i,t-1} - Rank_{i,t-1}^{BOTTOM} - Rank_{i,t-1}^{MIDDLE}, 0.2)$, where $Rank_{i,t-1}$ refers to the rank of fund i in year t-1. The variable $AFLOW_t$ is defined as:

$$AFLOW_t = (1 / n(t))\sum_{i=1}^{n(t)} FLOW_{i,t} ,$$

where n(t) represents the number of funds in our sample in year t. $AFLOW_t^* \equiv (AFLOW_t - E(AFLOW)) / \sigma(AFLOW)$ measures standardized deviations of the average flow in year t from its full sample mean. $\sigma_{M,t}^*$ similarly measures standardized deviations of the volatility of the equally weighted market portfolio from its full sample mean. Size and expenses are expressed in percentage, where Size is defined by $TNA_{i,t-1} / \Sigma_j (TNA_{j,t-1})$. Regressions also include one dummy variable for each year in the sample (coefficients unreported). The sample is composed of 942 no-load US equity mutual funds appearing in the CRSP database between 1980 and 2006, where we exclude index funds, multiple share classes, funds closed to investors, funds of funds and funds with TNA < 10M\$ for their entire existence. For regressions where the dependent variable is 1-factor or 4-factor alpha, we require funds to have at least 2 years of full return history, which further restricts the sample to 865 funds. Standard errors are clustered by funds. P-values are reported in parentheses. ***, ** and * indicate, respectively, significance at the 1%, 5% and 10% level. We report below each triplet of rank variables the difference between the coefficient of the top quintile rank variable and that of the corresponding bottom quintile rank variable and the p-value resulting from a one-sided t-test of the sign of that difference predicted by the theory.

Rank based on:	Excess returns	1-factor alpha	4-factor alpha
Size	32.424 (***)	20.746 (**)	20.048 (**)
	(0.004)	(0.042)	(0.043)
Age	- 5.121 (***)	-4.308 (***)	- 4.453 (***)
	(0.000)	(0.001)	(0.000)
Expenses	-11.404	-1.334	- 7.495
	(0.228)	(0.886)	(0.421)
(a$_1$): $Rank_{i,t-1}^{TOP}$	220.524	380.411 (*)	324.377
	(0.125)	(0.067)	(0.137)
(a$_2$): $Rank_{i,t-1}^{MIDDLE}$	187.676 (***)	202.710 (***)	158.805 (***)
	(0.000)	(0.000)	(0.000)
(a$_3$): $Rank_{i,t-1}^{BOTTOM}$	-81.408	-69.379	-50.526
	(0.303)	(0.501)	(0.589)
a_1-a_3	*301.93 (**)*	*449.79 (**)*	*374.9 (*)*
	(0.017)	*(0.012)*	*(0.051)*
(a$_4$): $\left(AFLOW_t^*\right) * Rank_{i,t-1}^{TOP}$	615.240 (**)	705.502 (*)	885.312 (**)
	(0.015)	(0.087)	(0.031)
(a$_5$): $\left(AFLOW_t^*\right) * Rank_{i,t-1}^{MIDDLE}$	14.434	35.694	-17.063
	(0.597)	(0.392)	(0.624)
(a$_6$): $\left(AFLOW_t^*\right) * Rank_{i,t-1}^{BOTTOM}$	-69.824	- 61.767	76.557
	(0.327)	(0.559)	(0.518)
a_4-a_6	*685.06 (***)*	*767.27 (**)*	*808.76 (**)*
	(0.004)	*(0.031)*	*(0.022)*
(a$_7$): $\left(\sigma_{M,t-1}^*\right) * Rank_{i,t-1}^{TOP}$	130.418	125.587	233.131 (*)
	(0.197)	(0.326)	(0.098)
(a$_8$): $\left(\sigma_{M,t-1}^*\right) * Rank_{i,t-1}^{MIDDLE}$	-58.403 (***)	-53.571 (***)	-49.653 (**)
	(0.005)	(0.007)	(0.012)
(a$_9$): $\left(\sigma_{M,t-1}^*\right) * Rank_{i,t-1}^{BOTTOM}$	9.593	59.096	-12.435
	(0.876)	(0.440)	(0.181)

Table V: Decomposition of the business cycle effect: the absolute performance case

This table examines how the impact of absolute fund performance in year t-1 on the net flow of the fund in year t varies with aggregate flows and market volatility of the year. For each regression, the dependent variable, $FLOW_{i,t}$ is defined as:

$$FLOW_{i,t} = TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1}$$

where $TNA_{i,t}$ represents the total net assets of fund i at the end of year t (in M\$) and where $r_{i,t}$ is the net return of fund i during year t. Performance is measured either by excess return $r_{i,t-1} - r_{m,t-1}$, where r_m is the return on the equally weighted market portfolio, or by residuals of a CAPM equation (1-factor alpha) or of a Carhart (1997) model (4-factor alpha), where factor loadings have been estimated from 24 monthly observations. $\delta_{i,t-1}^-$ (resp. $\delta_{i,t-1}^+$) takes value 1 if the past year performance of the fund is negative (resp. positive), and takes value 0 otherwise. $AFLOW_t$ is defined as: $AFLOW_t = (1/n(t))\sum_{i=1}^{n(t)} FLOW_{i,t}$, where n(t) represents the number of funds in our sample in year t.

$$AFLOW_t^* \equiv (AFLOW_t - E(AFLOW))/\sigma(AFLOW)$$

measures standardized deviations of the average flow in year t from its full sample mean. $\sigma_{M,t}^*$ similarly measures standardized deviations of the volatility of the equally weighted market portfolio from its full sample mean. Size and expenses are expressed in percentage, where Size is defined by $TNA_{i,t-1} / \Sigma_j (TNA_{j,t-1})$. Regressions also include one dummy variable for each year in the sample (coefficients unreported). The sample is composed of 942 no-load US equity mutual funds appearing in the CRSP database between 1980 and 2006, where we exclude index funds, multiple share classes, funds closed to investors, funds of funds and funds with TNA < 10M\$ for their entire existence. For regressions where the dependent variable is 1-factor or 4-factor alpha, we require funds to have at least 2 years of full return history, which further restricts the sample to 865 funds. Standard errors are clustered by funds. P-values are reported in parentheses. ***, ** and * indicate, respectively, significance at the 1%, 5% and 10% level. We report below each triplet of rank variables the difference between the coefficient of the top quintile rank variable and that of the corresponding bottom quintile rank variable and the p-value resulting from a one-sided t-test of the sign of that difference predicted by the theory.

Performance measured by:	Excess returns	1-factor alpha	4-factor alpha
Size	33.779 (***)	19.770 (**)	19.374 (**)
	(0.003)	(0.044)	(0.046)
Age	- 5.182 (***)	-4.041 (***)	- 4.292 (***)
	(0.000)	(0.001)	(0.000)
Expenses	-11.064	-1.833	- 7.467
	(0.255)	(0.850)	(0.434)
(a_1) : $Performance_{t-1} * \delta_{i,t-1}^+$	151.216 (**)	428.668 (***)	435.206 (***)
	(0.023)	(0.002)	(0.008)
(a_2) : $Performance_{t-1} * \delta_{i,t-1}^-$	416.654 (***)	371.123 (***)	511.960 (***)
	(0.000)	(0.000)	(0.000)
a_1-a_2	*-265.44*	*57.545*	*-76.754*
	(0.994)	*(0.376)*	*(0.651)*
(a_3) : $Performance_{t-1} * (AFLOW_t^*) * \delta_{i,t-1}^+$	370.787 (***)	533.282 (**)	1067.626 (**)
	(0.007)	(0.020)	(0.024)
(a_4) : $Performance_{t-1} * (AFLOW_t^*) * \delta_{i,t-1}^-$	-79.275	23.998	-92.023
	(0.423)	(0.860)	(0.555)
a_3-a_4	*450.06* (**)	*509.28* (*)	*1159.6* (**)
	(0.017)	*(0.068)*	*(0.025)*
(a_5) : $Performance_{t-1} * (\sigma_{M,t-1}^*) * \delta_{i,t-1}^+$	80.485	8.010	210.413
	(0.419)	(0.960)	(0.310)
(a_6) : $Performance_{t-1} * (\sigma_{M,t-1}^*) * \delta_{i,t-1}^-$	-242.485 (***)	-184.306 (***)	-268.217 (***)
	(0.000)	(0.000)	(0.000)

Table VI: Flow-Performance Relationship: the relative performance case - Restricted sub-sample to years with small fluctuations of economic activity

This table examines the evolution over the business cycle of the impact of relative fund performance (i.e. Rank) in year t-1 on the net flow of the fund in year t. For each regression, the dependent variable, $FLOW_{i,t}$ is defined as: $FLOW_{i,t} = TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1}$, where $TNA_{i,t}$ represents the total net assets of fund i at the end of year t (in M\$) and where $r_{i,t}$ is the net return of fund i during year t. Each year, funds are ranked between 0 (poorest performer) and 1 (best performer) based on their previous year performance, where performance is either measured by excess return $r_{i,t-1} - r_{m,t-1}$, where r_m is the return on the equally weighted market portfolio, or by residuals of a CAPM equation (1-factor alpha) or of a Carhart (1997) model (4-factor alpha), where factor loadings have been estimated from 24 monthly observations. The variables $Rank_{i,t-1}^{TOP}$, $Rank_{i,t-1}^{MIDDLE}$, and $Rank_{i,t-1}^{BOTTOM}$, are defined as $Rank_{i,t-1}^{BOTTOM} = \min(Rank_{i,t-1}, 0.2)$, $Rank_{i,t-1}^{MIDDLE} = \min(Rank_{i,t-1} - Rank_{i,t-1}^{BOTTOM}, 0.6)$, and $Rank_{i,t-1}^{TOP} = \min(Rank_{i,t-1} - Rank_{i,t-1}^{BOTTOM} - Rank_{i,t-1}^{MIDDLE}, 0.2)$ where $Rank_{i,t-1}$ refers to the rank of fund i in year t-1. The variable (g_{GDP} -$\overline{g}_{GDP}$) measures deviations in percentage of the US real GDP growth rate from its sample mean. Size and expenses are expressed in percentage, where Size is defined by $TNA_{i,t-1} / \Sigma_j (TNA_{j,t-1})$. Regressions also include one dummy variable for each year in the sample (coefficients unreported). The sample is composed of 942 no-load US equity mutual funds appearing in the CRSP database between 1980 and 2006, where we exclude index funds, multiple share classes, funds closed to investors, funds of funds and funds with TNA < 10M\$ for their entire existence. For regressions where the dependent variable is 1-factor or 4-factor alpha, we require funds to have at least 2 years of full return history, which further restricts the sample to 865 funds. Finally, we restrict the sample to years where ($g_{GDP,t}$ - $\overline{g}_{GDP}$) is comprised between -2 and 2, which implies to exclude years 1980, 1982, 1984, 1991 and 2001. Standard errors are clustered by funds. P-values are reported in parentheses. ***, ** and * indicate, respectively, significance at the 1%, 5% and 10% level. We report below each triplet of rank variables the difference between the coefficient of the top quintile rank variable and that of the corresponding bottom quintile rank variable and the p-value resulting from a one-sided t-test of the sign of that difference predicted by the theory.

Rank based on:	Excess returns	1-factor alpha	4-factor alpha
Size	47.883 (***)	30.705 (**)	30.745 (**)
	(0.001)	(0.036)	(0.036)
Age	-5.675 (***)	-4.459 (***)	-4.657 (***)
	(0.000)	(0.001)	(0.001)
Expenses	-11.108	0.886	-6.432
	(0.259)	(0.929)	(0.513)
(a_1) : $Rank_{i,t-1}^{TOP}$	232.185 (*)	444.538 (**)	368.487
	(0.098)	(0.046)	(0.121)
(a_2) : $Rank_{i,t-1}^{MIDDLE}$	182.383 (***)	195.274 (***)	155.446 (***)
	(0.000)	(0.000)	(0.000)
(a_3) : $Rank_{i,t-1}^{BOTTOM}$	-79.747	-61.374	-50.336
	(0.335)	(0.569)	(0.605)
a_1-a_3	*311.93 (**)*	*505.91 (**)*	*419.02 (**)*
	(0.018)	*(0.013)*	*(0.046)*
(a_4) : $(g_{GDP,t}$ - $\overline{g}_{GDP})*Rank_{i,t-1}^{TOP}$	513.047 (**)	788.243 (*)	602.212
	(0.038)	(0.064)	(0.187)
(a_5) : $(g_{GDP,t}$ - $\overline{g}_{GDP})*Rank_{i,t-1}^{MIDDLE}$	57.781 (**)	71.764	76.558 (*)
	(0.048)	(0.118)	(0.087)
(a_6) : $(g_{GDP,t}$ - $\overline{g}_{GDP})*Rank_{i,t-1}^{BOTTOM}$	-100.092	- 75.357	-63.966
	(0.259)	(0.556)	(0.612)
a_4-a_6	*613.14 (***)*	*863.6 (**)*	*666.18 (*)*
	(0.010)	*(0.024)*	*(0.067)*

Table VII: Flow-Performance Relationship: the absolute performance case - Restricted sub-sample to years with small fluctuations of economic activity

This table examines the evolution over the business cycle of the impact of absolute fund performance in year t-1 on the net flow of the fund in year t. For each regression, the dependent variable, $FLOW_{i,t}$ is defined as:

$$FLOW_{i,t} = TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1}$$

where $TNA_{i,t}$ represents the total net assets of fund i at the end of year t (in M$) and where $r_{i,t}$ is the net return of fund i during year t. Performance is measured either by excess return $r_{i,t-1} - r_{m,t-1}$, where r_m is the return on the equally weighted market portfolio, or by residuals of a CAPM equation (1-factor alpha) or of a Carhart (1997) model (4-factor alpha), where factor loadings have been estimated from 24 monthly observations. δ_- (resp. δ_+) takes value 1 if the past year performance of the fund is negative (resp. positive), and takes value 0 otherwise. ($g_{GDP,t} - \overline{g}_{GDP}$) measures deviations in percentage of the US real GDP growth rate from its sample mean. Size and expenses are expressed in percentage, where Size is defined by $TNA_{i,t-1} / \Sigma_j (TNA_{j,t-1})$. Regressions also include one dummy variable for each year in the sample (coefficients unreported). The sample is composed of 942 no-load US equity mutual funds appearing in the CRSP database between 1980 and 2006, where we exclude index funds, multiple share classes, funds closed to investors, funds of funds and funds with TNA < 10M$ for their entire existence. For regressions where the dependent variable is 1-factor or 4-factor alpha, we require funds to have at least 2 years of full return history, which further restricts the sample to 865 funds. Finally, we restrict the sample to years where ($g_{GDP,t} - \overline{g}_{GDP}$) is comprised between -2 and 2, which implies to exclude years 1980, 1982, 1984, 1991 and 2001. Standard errors are clustered by funds. P-values are reported in parentheses. ***, ** and * indicate, respectively, significance at the 1%, 5% and 10% level. We report below each triplet of rank variables the difference between the coefficient of the top quintile rank variable and that of the corresponding bottom quintile rank variable and the p-value resulting from a one-sided t-test of the sign of that difference predicted by the theory.

Performance measured by:	Excess returns	1-factor alpha	4-factor alpha
Size	48.461 (***)	29.532 (**)	30.604 (**)
	(0.000)	(0.037)	(0.034)
Age	-5.706 (***)	-4.311 (***)	-4.561 (***)
	(0.000)	(0.001)	(0.000)
Expenses	-10.062	-2.111	-6.561
	(0.313)	(0.833)	(0.510)
....			
(a_1) : $Performance_{t-1} * \delta_{i,t-1}^{+}$	-69.535	239.724	109.278
	(0.598)	(0.124)	(0.489)
(a_2) : $Performance_{t-1} * \delta_{i,t-1}^{-}$	337.616 (***)	245.187 (***)	417.330 (***)
	(0.000)	(0.000)	(0.000)
a_1-a_2	**-407.15**	**-5.463**	**-308.05**
	(0.995)	**(0.512)**	**(0.950)**
....			
(a_3) : $Performance_{t-1} * (g_{GDP,t} - \overline{g}_{GDP}) * \delta_{i,t-1}^{+}$	694.346 (***)	953.522 (**)	1838.963 (**)
	(0.007)	(0.025)	(0.029)
(a_4) : $Performance_{t-1} * (g_{GDP,t} - \overline{g}_{GDP}) * \delta_{i,t-1}^{-}$	59.262	- 7.669	86.796
	(0.313)	(0.917)	(0.385)
a_3-a_4	**635.08 (**)**	**961.19 (**)**	**1752.2 (**)**
	(0.016)	**(0.024)**	**(0.027)**

Table VIII: Change in Levels of Risk as a Function of Interim Performance:
Case (i): Relative performance based on excess returns

This table examines the impact of performance during the first six months of a calendar year on the change in risk variable between the first and the last six months of the year. For each regression, the dependent variable, is defined as $\Delta RISK_{i,t} = RISK_{i,Jul-Dec\ yr\ t} - RISK_{i,Jun-Jan\ yr\ t}$, where $RISK_{i,t}$ is measured either by the standard deviation of excess returns (total risk) expressed in percentage, by the standard deviation of the residuals of a 1-factor CAPM regression (idiosyncratic risk) expressed in percentage or by the 1-factor CAPM beta (systematic risk). Each year, funds are ranked between 0 (poorest performer) and 1 (best performer) based on their performance during the first six months of the year, where performance is measured by excess return $r_{i,Jan-Jun\ yr\ t} - r_{m,Jan-Jun\ yr\ t}$, and where r_m is the return on the equally weighted market portfolio. $(g_{GDP,t} - \bar{g}_{GDP})$ measures deviations in percentage of the US real GDP growth rate from its sample mean. Regressions also include one dummy variable for each year in the sample (coefficients unreported). The sample is composed of 942 no-load US equity mutual funds appearing in the CRSP database between 1980 and 2006, where we exclude index funds, multiple share classes, funds closed to investors, funds of funds and funds with TNA < 10M\$ for their entire existence. Standard errors are clustered by funds. P-values are reported in parentheses. ***, ** and * indicate, respectively, significance at the 1%, 5% and 10% level.

RISK variable:	Total Risk		Idiosyncratic Risk		Systematic Risk	
Business Cycle Effect:	No	Yes	No	Yes	No	Yes
Year dummy variables	Yes	Yes	Yes	Yes	Yes	Yes
Regression	(1)	(2)	(3)	(4)	(5)	(6)
$Rank_{i,Jan-Jun\ yr\ t}$	0.295 (***)	0.217 (**)	0.277 (***)	0.129 (*)	0.002	-0.013
	(0.002)	(0.024)	(0.000)	(0.067)	(0.934)	(0.634)
$Rank_{i,Jan-Jun\ yr\ t} * (g_{GDP,t} - \bar{g}_{GDP})$		- 0.467 (***)		-0.880 (***)		- 0.070 (***)
		(0.000)		(0.000)		(0.000)

Table IX: Change in Levels of Risk as a Function of Interim Performance:
Case (ii): Relative performance based on 1-factor alpha

This table examines the impact of performance during the first six months of a calendar year on the change in risk variable between the first and the last six months of the year. For each regression, the dependent variable, is defined as $\Delta RISK_{i,t} = RISK_{i,Jul-Dec\ yr\ t} - RISK_{i,Jun-Jan\ yr\ t}$, where $RISK_{i,t}$ is measured either by the standard deviation of monthly excess returns (total risk) expressed in percentage, by the standard deviation of the residuals of a 1-factor CAPM regression (idiosyncratic risk) expressed in percentage or by the 1-factor CAPM beta (systematic risk). Each year, funds are ranked between 0 (poorest performer) and 1 (best performer) based on their performance during the first six months of the year, where performance is measured by residuals of a CAPM equation (1-factor alpha) where factor loadings have been estimated from 24 monthly observations. $(g_{GDP,t} - \bar{g}_{GDP})$ measures deviations in percentage of the US real GDP growth rate from its sample mean. Regressions also include one dummy variable for each year in the sample (coefficients unreported). The sample is composed of 865 no-load US equity mutual funds appearing in the CRSP database with at least 2 years of full return history between 1980 and 2006, where we exclude index funds, multiple share classes, funds closed to investors, funds of funds and funds with TNA < 10M\$ for their entire existence. Standard errors are clustered by funds. P-values are reported in parentheses. ***, ** and * indicate, respectively, significance at the 1%, 5% and 10% level.

RISK variable:	Total Risk		Idiosyncratic Risk		Systematic Risk	
Business Cycle Effect:	No	Yes	No	Yes	No	Yes
Year dummy variables	Yes	Yes	Yes	Yes	Yes	Yes
Regression	(1)	(2)	(3)	(4)	(5)	(6)
$Rank_{i,Jan-Jun\ yr\ t}$	-0.167 (*)	-0.289 (***)	0.338 (***)	0.153 (*)	-0.301 (***)	-0.316 (***)
	(0.075)	(0.003)	(0.000)	(0.068)	(0.000)	(0.000)
$Rank_{i,Jan-Jun\ yr\ t} * (g_{GDP,t} - \bar{g}_{GDP})$		- 0.623 (***)		-0.948 (***)		- 0.032 (*)
		(0.000)		(0.000)		(0.080)

Table X: Change in Levels of Risk as a Function of Interim Performance:
Case (iii): Relative performance based on 4-factor alpha

This table examines the impact of performance during the first six months of a calendar year on the change in risk variable between the first and the last six months of the year. For each regression, the dependent variable, is defined as $\Delta RISK_{i,t} = RISK_{i,Jul-Dec\ yr\ t} - RISK_{i,Jun-Jan\ yr\ t}$, where RISK$_{i,t}$ is measured either by the standard deviation of monthly excess returns (total risk) expressed in percentage, by the standard deviation of the residuals of a 1-factor CAPM regression (idiosyncratic risk) expressed in percentage or by the 1-factor CAPM beta (systematic risk). Each year, funds are ranked between 0 (poorest performer) and 1 (best performer) based on their performance during the first six months of the year, where performance is measured by residuals of a Carhart (1997) model (4-factor alpha), where factor loadings have been estimated from 24 monthly observations. $(g_{GDP,t} - \overline{g}_{GDP})$ measures deviations in percentage of the US real GDP growth rate from its sample mean. Regressions also include one dummy variable for each year in the sample (coefficients unreported). The sample is composed of 865 no-load US equity mutual funds appearing in the CRSP database with at least 2 years of full return history between 1980 and 2006, where we exclude index funds, multiple share classes, funds closed to investors, funds of funds and funds with TNA < 10M\$ for their entire existence. Standard errors are clustered by funds. P-values are reported in parentheses. ***, ** and * indicate, respectively, significance at the 1%, 5% and 10% level.

RISK variable:	Total Risk		Idiosyncratic Risk		Systematic Risk	
Business Cycle Effect:	No	Yes	No	Yes	No	Yes
Year dummy variables	Yes	Yes	Yes	Yes	Yes	Yes
Regression	(1)	(2)	(3)	(4)	(5)	(6)
$Rank_{i,Jan-Jun\ yr\ t}$	-0.369 (***)	-0.408 (***)	0.151 (**)	0.008	-0.232 (***)	-0.223 (***)
	(0.000)	(0.000)	(0.049)	(0.917)	(0.000)	(0.000)
$Rank_{i,Jan-Jun\ yr\ t} * (g_{GDP,t} - \overline{g}_{GDP})$		-0.202 (**)		-0.731 (***)		0.045 (**)
		(0.041)		(0.000)		(0.017)

This table examines the impact of performance during the first six months of a calendar year on the change in risk variable between the first and the last six months of the year. For each regression, the dependent variable, is defined as $\Delta RISK_{i,t} = RISK_{i,Jul-Dec\ yr\ t} - RISK_{i,Jun-Jan\ yr\ t}$, where $RISK_{i,t}$ is measured either by the standard deviation of monthly excess returns (total risk) expressed in percentage, by the standard deviation of the residuals of a 1-factor CAPM regression (idiosyncratic risk) expressed in percentage or by the 1-factor CAPM beta (systematic risk). Performance is measured by excess return $r_{i,Jan-Jun\ yr\ t} - r_{m,Jan-Jun\ yr\ t}$, where r_m is the return on the equally weighted market portfolio. $(g_{GDP,t} - \overline{g}_{GDP})$ measures deviations in percentage of the US real GDP growth rate from its sample mean. Regressions also include one dummy variable for each year in the sample (coefficients unreported). The sample is composed of 942 no-load US equity mutual funds appearing in the CRSP database between 1980 and 2006, where we exclude index funds, multiple share classes, funds closed to investors, funds of funds and funds with TNA < 10M$ for their entire existence. Standard errors are clustered by funds. P-values are reported in parentheses. ***, ** and * indicate, respectively, significance at the 1%, 5% and 10% level.

RISK variable:	Total Risk		Idiosyncratic Risk		Systematic Risk	
Business Cycle Effect:	No	Yes	No	Yes	No	Yes
Year dummy variables	Yes	Yes	Yes	Yes	Yes	Yes
Regression	(1)	(2)	(3)	(4)	(5)	(6)
$Performance_{i,Jan-Jun\ yr\ t}$	0.060 (0.945)	-0.929 (0.357)	0.772 (0.256)	-1.168 (0.102)	0.003 (0.979)	-0.122 (0.376)
$Performance_{i,Jan-Jun\ yr\ t} * (g_{GDP,t} - \overline{g}_{GDP})$		- 2.043 (***) (0.001)		-4.006 (***) (0.000)		- 0.259 (***) (0.003)

Table XII: Change in Levels of Risk as a Function of Interim Performance:
Case (v): Absolute performance based on 1-factor alpha

This table examines the impact of performance during the first six months of a calendar year on the change in risk variable between the first and the last six months of the year. For each regression, the dependent variable, is defined as $\Delta RISK_{i,t} = RISK_{i,Jul-Dec\ yr\ t} - RISK_{i,Jun-Jan\ yr\ t}$, where $RISK_{i,t}$ is measured either by the standard deviation of monthly excess returns (total risk) expressed in percentage, by the standard deviation of the residuals of a 1-factor CAPM regression (idiosyncratic risk) expressed in percentage or by the 1-factor CAPM beta (systematic risk). Performance is measured by residuals of a CAPM equation (1-factor alpha) where factor loadings have been estimated from 24 monthly observations. $(g_{GDP,t} - \bar{g}_{GDP})$ measures deviations in percentage of the US real GDP growth rate from its sample mean. Regressions also include one dummy variable for each year in the sample (coefficients unreported). The sample is composed of 865 no-load US equity mutual funds appearing in the CRSP database with at least 2 years of full return history between 1980 and 2006, where we exclude index funds, multiple share classes, funds closed to investors, funds of funds and funds with TNA < 10M$ for their entire existence. Standard errors are clustered by funds. P-values are reported in parentheses. ***, ** and * indicate, respectively, significance at the 1%, 5% and 10% level.

RISK variable:	Total Risk		Idiosyncratic Risk		Systematic Risk	
Business Cycle Effect:	No	Yes	No	Yes	No	Yes
Year dummy variables	Yes	Yes	Yes	Yes	Yes	Yes
Regression	(1)	(2)	(3)	(4)	(5)	(6)
$Performance_{i,Jan-Jun\ yr\ t}$	0.562	-2.147 (***)	3.703 (***)	0.039	-1.119 (***)	-1.701 (***)
	(0.285)	(0.001)	(0.000)	(0.944)	(0.000)	(0.000)
$Performance_{i,Jan-Jun\ yr\ t} * (g_{GDP,t} - \bar{g}_{GDP})$		- 3.077 (***)		-4.162 (***)		- 0.596 (***)
		(0.000)		(0.000)		(0.000)

This table examines the impact of performance during the first six months of a calendar year on the change in risk variable between the first and the last six months of the year. For each regression, the dependent variable, is defined as $\Delta RISK_{i,t} = RISK_{i,Jul-Dec\ yr\ t} - RISK_{i,Jun-Jan\ yr\ t}$, where $RISK_{i,t}$ is measured either by the standard deviation of monthly excess returns (total risk) expressed in percentage, by the standard deviation of the residuals of a 1-factor CAPM regression (idiosyncratic risk) expressed in percentage or by the 1-factor CAPM beta (systematic risk). Performance is measured by residuals of a Carhart (1997) model (4-factor alpha), where factor loadings have been estimated from 24 monthly observations. $(g_{GDP,t} - \bar{g}_{GDP})$ measures deviations in percentage of the US real GDP growth rate from its sample mean. Regressions also include one dummy variable for each year in the sample (coefficients unreported). The sample is composed of 865 no-load US equity mutual funds appearing in the CRSP database with at least 2 years of full return history between 1980 and 2006, where we exclude index funds, multiple share classes, funds closed to investors, funds of funds and funds with TNA < 10M$ for their entire existence. Standard errors are clustered by funds. P-values are reported in parentheses. ***, ** and * indicate, respectively, significance at the 1%, 5% and 10% level.

RISK variable:	Total Risk		Idiosyncratic Risk		Systematic Risk	
Business Cycle Effect:	No	Yes	No	Yes	No	Yes
Year dummy variables	Yes	Yes	Yes	Yes	Yes	Yes
Regression	(1)	(2)	(3)	(4)	(5)	(6)
$Performance_{i,Jan-Jun\ yr\ t}$	-1.255 (*)	-1.790 (**)	1.994 (***)	0.189	-1.114 (***)	-1.070 (***)
	(0.091)	(0.025)	(0.007)	(0.757)	(0.000)	(0.000)
$Performance_{i,Jan-Jun\ yr\ t} * (g_{GDP,t} - \bar{g}_{GDP})$		- 1.278 (**)		-4.310 (***)		0.1015
		(0.036)		(0.000)		(0.376)