

Time-Varying Incentives in the Mutual Fund Industry^{*}

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Abstract

We provide evidence that the convexity of the flow-performance relationship in the mutual fund industry varies with economic activity. This effect is strongly economically significant: a +/-1% change in GDP growth doubles/eliminates the degree of convexity of the flow-performance relationship. The effect of economic activity dominates that of market conditions and can be rationalized by the behavior of investors who smooth consumption while displaying a disposition effect. Our finding has two major implications: first, it rationalizes the risk-shifting behavior of mutual fund managers and provides support for the seminal flow-based tournament hypothesis over the more recent "career concern" explanation. Second, it explains why mutual fund performance varies with the business cycle.

JEL Classification codes: G11, G23

Key words: Mutual funds, Incentives, Economic activity, Risk-shifting, Performance

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INTRODUCTION

The mutual fund industry has grown remarkably over the past two decades. According to the Investment Company Institute¹, 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 literature² has confirmed the existence of a convex relationship between flows and past performance: investors 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.

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.

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 periods of weak economic activity. We show that the effect is economically large and that it is not driven by exceptional years. We also find that the time variation in the convexity of the flow performance relationship is indeed driven by macroeconomic fluctuations and not by

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). See also Berk and Green (2004) for a model with rational agents where the convex flow-performance relationship arises as an equilibrium outcome.

market conditions. This finding is important because it provides a clean test between flow-based and career-concern based hypotheses for the observed risk-shifting behavior of fund managers. It also provides an explanation for the relative performance of the mutual fund industry in good vs. bad times as observed by Kosowski (2006): the stronger the economic activity, the more misaligned are the incentives of the fund managers with the interests of investors. Finally, we contend that our result also carries some methodological implications.

The fact that economic activity affects the sensitivity of investor flows to past performance should not come as a surprise. However the new finding brought forward by this paper is that economic activity affects the *convexity* of the flow-performance relationship in a systematic way. One possible explanation for this finding is flow composition over the cycle. First, we know that gross outflows are less sensitive to past performance than gross inflows³. This is partly because investors hold concentrated portfolios of risky assets and are forced to liquidate their holdings, regardless of performance, whenever they need to finance consumption⁴. This may also be because investors suffer from a disposition effect, whereby they hold on to past losers and liquidate past winners⁵, which implies that outflows may actually become a decreasing concave function of past performance. Second, we know that aggregate flows into mutual funds are strongly correlated with economic activity⁶: because of consumption smoothing, agents invest money into mutual funds when the economy is booming and divest when economic activity is slowing down. As a consequence, the flow-performance relationship looks more like the "outflow-performance" relationship in bad times and more like the "inflow-performance" relationship in good times. In other words, it is more concave during bad times and more convex during good times.

An alternative channel through which economic activity could affect the flow-performance relationship is volatility⁷. It is well-known that stock market volatility is countercyclical⁸. 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

³ See evidence in Tables IV and V of Cashman et al. (2007)

⁴ 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.

⁵ 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)

⁶ See e.g. Kosowski (2006)

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)

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.

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. Regardless of the measure of performance we use, GDP growth is found to have a statistically significant impact on the flow-performance relationship. The effect is also economically large. Under most specifications, a drop in GDP growth by less than one standard deviation from its sample mean implies a flow-performance relationship which does not display any convexity whatsoever. Conversely, a GDP growth rate which is one standard deviation above its sample mean implies a flow-performance relationship which is more than twice as convex as the average convexity in our sample. This implies that moderate fluctuations in economic activity have a very significant impact on the nature of incentives faced by mutual fund managers. The result is found to be robust across sub-samples, including subsamples where we restrict the investment objective of the fund. More importantly, it is also robust to running a "horse-race" between economic fluctuations and market conditions as the main driver of time variation in the flow-performance relationship. This last result plays an important role in the analysis of risk-shifting by fund managers.

Next, we evaluate the two possible channels through which economic activity may indeed affect the flow-performance relationship: composition of investor flows and stock market volatility. In all specifications, we find strong evidence that years with high average flows (i.e. when 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, stock market volatility has no impact on the convexity of the relationship.

Our final set of results verifies the extent to which time variation in the convexity of the flow-performance relationship translates into time variation in risk-shifting by underperforming managers. Convexity of the flow-performance relationship implies that managers with poor mid-year performance have incentives to increase the risk of their portfolio. The results in the first part of our paper establish that the flow-performance relationship is convex if and only if economic activity is strong. Thus, we

should observe risk-shifting by underperforming managers only during such periods. In addition, we have established that market conditions have no impact on the convexity of the flow-performance relationship once the effect of economic activity is taken into account. This implies that market conditions should also have no impact on risk-shifting once the business cycle effect is accounted for. We test both propositions in the last part of the paper. We find strong evidence that economic activity affects risk-shifting in the way predicted by the theory. We report mixed results for the impact of market conditions, which seem to affect more the decomposition of risk into its idiosyncratic and systematic components than the total quantity of risk taken by underperforming managers.

Our paper is related to the 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 recessions⁹. Our focus here is different as we show that the flow-performance relationship is convex on average but may become concave during a recession. 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 nor by strong booms. Nonetheless, our results cast a new light on Kosowski's results as they 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 responsible for the underperformance of mutual funds during expansion phases documented by Kosowski¹⁰.

Our paper is also closely related to the empirical literature on the tournament hypothesis. Seminal papers in the field, namely Brown, Harlow and Starks (1996) and Chevalier and Ellison (1997), emphasized the role played by investor flows in shaping the incentives of fund managers. Following a series of mixed empirical results, most notably by Khorana (1996), Busse (2001) and Gorjaev, Nijman and Werker (2005), a second hypothesis based on career concerns by managers has emerged recently. Qiu (2003), Hu et al. (2007) and Kempf, Ruenzi and Thiele (2009) suggest that there are agency problems within mutual funds or mutual fund families which lead to a wedge between the fund's and

⁹ See also Cederburg (2008) for an investigation of the smart money effect over the cycle.

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.

the manager's interests. Career concerns may then tamper the incentives of underperforming managers to increase the risk of their portfolio. In particular, career concerns imply that the extent of risk-shifting by underperforming managers should vary according to market conditions because of the differential cost for a mutual fund manager to be fired under bad and under good market conditions. Our finding that the convexity of the flow-performance relationship varies with economic activity but not with market conditions provides a clean test between the flow-based and the career concerns hypotheses. Our results support the flow-based story as we find that risk-shifting by underperforming managers is primarily driven by economic activity.

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 misleading conclusions, as first pointed out in the asset pricing literature on the conditional CAPM¹¹.

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

¹¹ See e.g. Harvey (1989) and Jagannathan and Wang (1996)

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 because it is not clear how to treat load fees in a single period setting but also because of the evidence provided by Barber, Odean and Zheng (2005) of significant time variation in the way investors react to front loads over the past few decades. As our objective is to identify time-variation in the flow-performance relationship due to economic activity, we want to eliminate as much as possible any other source of time variation in our sample. 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 several 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 decreasing function of the fund's initial size. Third, time variation in the sensitivity of percentage flows to performance could arise either from a change in investors' behavior, which we are interested in, or from a mechanical effect of market prices on previous year's TNA, which we are not. Focusing on dollar flows eliminates the latter effect.

Numerous different measures of performance have been used in the literature on the flow-performance relationship. In this paper, we provide results based on:

- (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.
- (iv) Information ratio, defined as the ratio of excess return (as in i) divided by the standard deviation of excess returns. The information ratio is commonly used by practitioners in the mutual fund industry (see e.g. Goodwin, 1998)

These measures can be used directly, as in Gruber (1996), Chevalier and Ellison (1997), Lynch and Musto (2003), Barber, Odean and Zheng (2005). Alternatively, these measures can be used to rank funds within each year, and the ranks¹² used as a measure of performance, as in Sirri and Tufano (1998) and Huang, Wei and Yan (2007), among others. Given our focus on the tournament hypothesis in the second part of the paper, we concentrate on the ranks (which we refer to as *relative performance*) in most of the paper but we also provide robustness checks based on the actual alphas of the fund (which we refer to as *absolute performance*) for all the main results.

We use two types of control variables: cross-sectional variables of funds' characteristics that have been found by the existing literature to have an impact on flows from investors and 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 lagged fund flow, expenses expressed in percentage, the age of the fund in years, and the fund's initial size, which we define as $\ln(TNA_{i,t-1})$. 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

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

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. Table I includes summary statistics about the flow, performance, control, and interaction variables.

¹² The ranks within each year are normalized to lie between 0 and 1.

[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. 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 economic activity, 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 (2009), 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

Our primary objective in this section is to show that the sensitivity of investor flows to past performance changes in a systematic way with economic activity. We first reproduce with our sample the result obtained in the existing literature, namely that the flow-performance relationship is convex on average. We call this result *unconditional convexity*. We next allow the sensitivity of flows to performance to vary with economic activity, measured by GDP growth. We derive our main result, namely that convexity increases with economic activity, which we call *conditional convexity* and

quantify the effect. We finally conduct robustness checks and investigate possible explanations for the conditional convexity.

A) Unconditional convexity

Table II presents evidence that the flow-performance relationship is convex on average in our sample, as found to be in the existing literature. Regressions 1 to 3 in Table II are obtained with the methodology outlined in Sirri and Tufano (1998). We partition relative performance into three unbalanced quintiles: TOP refers to the top 20% performers of the year. BOTTOM refers to the bottom 20% and MIDDLE refers to the 60% left. This ranking is done year by year according to 1-factor alpha in Regression 1 (favored specification), using excess returns in Regression 2 and using 4-factor alphas in Regression 3. We then allow the sensitivity of flows to past performance to depend on the quintile the fund belongs to. In other words, we allow the relationship between flow and past performance to take the form of a piecewise linear function. As in Sirri and Tufano, 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 by running the regression:

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

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. The flow-performance is said to be convex if flows into

top-performing funds are more responding to performance than flows into the worse performing funds¹³. Statistically, this is tested by running a t-test on the positiveness of the difference $a_1 - a_3$.

Results of Regressions 1 to 3 in Table II confirm the results of the existing literature. First, looking at control variables, we find that lagged flows and age of the fund are strong predictors of future flows¹⁴. More importantly, we find 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 to past 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, the flow-performance relationship is significantly convex overall, even though the evidence is strongest when ranking funds according to their 1-factor alpha and weakest when ranking them over their 4-factor alphas.

(INSERT TABLE II AROUND HERE)

Regression 4 in Table II uses instead the same procedure as in Lynch and Musto (2003) and others. We partition (absolute) performance into two regions: positive and negative. A fund i is allocated to the positive (resp. negative) region during year t if its 1-factor alpha is positive (resp. negative), in which case a dummy variable $\delta_{i,t}^+$ (resp. $\delta_{i,t}^-$) takes value 1 for that fund and that year. We then run the regression:

$$FLOW_{i,t} = a_1 Performance_{i,t-1} * \delta_{i,t-1}^+ + a_2 Performance_{i,t-1} * \delta_{i,t-1}^- + (\text{time dummies}) + (\text{controls})$$

We say that the flow-performance relationship exhibits convexity if and only if flows are more sensitive to good than to bad performances, i.e. if the coefficient a_1 is significantly larger than the coefficient a_2 . The results of Regression 4 confirm those of Regressions 1 to 3: regardless of the performance measure, we find that the flow-performance relationship is convex on average in our sample.

¹³ Note that this definition ignores the coefficient of the middle quintile. It is worth pointing out that we never encounter a case where the coefficient of the middle group is either significantly larger than that of the top group or significantly smaller than that of the bottom group.

¹⁴ P-values are provided in parentheses in all tables.

B) Conditional Convexity

We now allow for the sensitivity of flows to past performance to vary with economic activity. For this purpose, we introduce a set of new variables, which are interaction variables between performance and economic activity measured by GDP growth. The advantage of testing for the impact of economic activity using interaction with GDP growth rather than 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.

We then augment the regressions we ran in the previous section with the interaction variables. For the case of relative performance (Regressions 1 to 3 in Table III), this yields the following specification:

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

This new specification is easily interpretable in the standard way. Using the chain rule, we can indeed decompose the total effect of a change in performance on investor flows as:

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

The first term in the RHS of (1) is equal to the coefficient of performance and the second term is equal to the coefficient on the interaction variable. When the growth rate of GDP is equal to its sample mean, the second term is equal to 0, which implies that the coefficient of flows on past performance can be interpreted 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 two statements which underlie 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

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

Thus the proposition that stronger economic activity increases the degree of convexity of the flow-performance relationship can be tested through a one-sided t-test on the difference of two coefficients¹⁵. Results of the test are reported in Table III with p-values in parentheses.

A similar specification is adopted for the absolute return regression (Regression 4 in Table 3) with:

$$\begin{aligned} FLOW_{i,t} = & a_1 Performance_{i,t-1} * \delta_{i,t-1}^+ + a_2 Performance_{i,t-1} * \delta_{i,t-1}^- \\ & + a_3 Performance_{i,t-1} * \delta_{i,t-1}^+ (g_{GDP,t} - \bar{g}_{GDP}) + a_4 Performance_{i,t-1} * \delta_{i,t-1}^- (g_{GDP,t} - \bar{g}_{GDP}) \\ & + (\text{time dummies}) + (\text{controls}) \end{aligned}$$

Using equation (1) and the same reasoning as previously, we get that:

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

[INSERT TABLE III AROUND HERE]

¹⁵ Note that any direct effect of economic activity on flows is captured by the year fixed effects.

Looking at the results of Table III, we find that the inclusion of the interaction variable does not affect the conclusions of the unconditional convexity regressions significantly: lagged fund flows and age remain very significant and we have a convex flow-performance relationship on average. However, we get a new and important result concerning the impact of economic activity on the convexity of the flow-performance relationship.

Looking at 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 relative to the coefficient a_1 . Using equation (1) and recalling that $(g_{GDP,t} - \bar{g}_{GDP})$ 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 between 1.45 (Regression 4) and 3.6 (regression 2) times the average sensitivity of flows to performance. Since at the same time we find a somewhat negative relationship between economic activity and the sensitivity to performance in the bottom region, the impact of economic activity on the convexity of the flow-performance relationship is unambiguous.

The effect of economic activity on convexity is strongly significant, with p-values ranging from 0.4% to 6.8%. It is also strongly economically significant as can be observed again by comparing the difference $a_4 - a_6$ with $a_1 - a_3$. In all regressions using relative performance (Regressions 1 to 3), a +1% change in GDP growth implies around three times as much convexity as the average convexity in the sample. On the other side, a -0.5% change in GDP growth suffices to imply an absence of convexity of the flow-performance relationship. 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 has a large impact on convexity. The effects are smaller when we use absolute performance (Regression 4) but a one-standard deviation change in economic activity is still enough to either double or eliminate convexity of the flow-performance relationship.

C) Robustness Checks

We now conduct a series of robustness checks in Table IV. The first two regressions are subsample analyses. Regression 1 looks at the subsample 1993-2006, which corresponds to the period most

frequently studied in the mutual fund literature because of availability of data on investment objectives and mutual fund families. Regression 2 looks at a sample where we remove all years with large economic fluctuations, either downward (recessions) or upwards (strong booms). Our objective is to check whether the findings of the previous section 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. Both regressions leave results virtually unaffected compared to the full sample. In particular, the p-value for the test of conditional convexity remains between 1% and 2%.

[INSERT TABLES IV AROUND HERE]

The last three robustness checks deal with our measure of performance. While alphas are widely used in the academic literature, two measures of performance which are widely looked at by practitioners are peer group ranking and information ratios. Looking first at peer group ranking, we look at funds and years for which ICDI fund objective code is available on the CRSP database. We then restrict our sample to funds whose objective code is "LG" (long-run growth), which is the most represented objective code in our sample¹⁶. This divides sample size by a factor of 3. It nevertheless leaves results qualitatively unchanged compared to the full sample. Looking next at information ratios, we use them either as a way to rank managers year by year (Regression 4) or as an absolute measure of performance (Regression 5). In both cases, conditional convexity shows up as statistically and economically significant.

¹⁶ The next two categories are "aggressive growth" and "growth and income". (Unreported) results for the aggressive growth subsample are similar to the "long run growth" subsample. Growth and income regressions on the other hand yield statistically insignificant results.

D) Sources of Conditional Convexity

Now that we have established the existence of conditional convexity, we need to understand where this effect comes from. With this objective in mind, we start by asking a simple question: is it really economic activity which is driving conditional convexity or is economic activity just playing the role of a proxy for market conditions?

The answer to that question is provided in Table V, where we run a "horse race" between economic activity and market conditions. To the extent that our sample is composed of domestic equity mutual funds, we use returns on the equally weighted market portfolio as our measure of market conditions. We then augment our base specification with interaction variables between fund performance and market return. To make the coefficients of the two sets of interaction variables directly comparable with one another we standardize both GDP growth and market return to yield:

$$\begin{aligned} Flow_{i,t} = & \text{time dummies} + \text{fund characteristics} + \\ & a_1 Rank_{i,t-1}^{TOP} + a_2 Rank_{i,t-1}^{MIDDLE} + a_3 Rank_{i,t-1}^{BOTTOM} \\ & + a_4 Rank_{i,t-1}^{TOP} * (g_{GDP,t}^*) + a_5 Rank_{i,t-1}^{MIDDLE} * (g_{GDP,t}^*) + a_6 Rank_{i,t-1}^{BOTTOM} * (g_{GDP,t}^*) \\ & + a_7 Rank_{i,t-1}^{TOP} * (r_{m,t}^*) + a_8 Rank_{i,t-1}^{MIDDLE} * (r_{m,t}^*) + a_9 Rank_{i,t-1}^{BOTTOM} * (r_{m,t}^*) + \varepsilon \end{aligned}$$

where $g_{GDP,t}^*$ and $r_{m,t}^*$ represent respectively standardized GDP growth and standardized market returns.

(INSERT TABLE V AROUND HERE)

Looking at the results of Table V, we observe that once the effect of economic activity is taken into account, market conditions hardly have an impact on the sensitivity of flows to performance. Actually, if anything, this impact is going the "wrong" way: good market conditions make flows somewhat less sensitive to performance and brings down the level of convexity. Thus, the horse race between economic activity and market conditions ends up being no race at all: economic activity is the sole driver of conditional convexity. It just remains to understand why this is so.

We consider two hypotheses. The first hypothesis is a flow composition hypothesis. 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 alphas¹⁷. Thus, it is optimal for investors to invest primarily only in the very best performers in the industry. However, this argument applies to new inflows and to portfolio rebalancing flows but not to outflows. This is because most investors invest only in very few assets¹⁸. When hit by negative income shocks such investors have little choice in terms of which asset to liquidate, regardless of past performance. The relationship between outflows and performance even goes in a counter-intuitive way when investors suffer from a disposition effect whereby they hold on past losers and liquidate past winners, as demonstrated for the stock market by Shefrin and Statman (1985) and by Odean (1998). With a high enough proportion of investors displaying a disposition effect, outflows become a decreasing and concave function of past performance. We observe neither inflows nor outflows in our dataset 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 be convex if and only if the relative weight of inflows relative to outflows is large enough. Because of consumption smoothing, the relative proportion of inflows vs. outflows is correlated with economic activity¹⁹. Thus, periods of strong economic activity are characterized by stronger convexity of the (net) flow-performance relationship²⁰.

An alternative explanation starts from the well-known observation that stock market volatility is countercyclical²¹. 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 another "horse race", this time between flow composition and volatility. We interact performance with (standardized) average flows for year t , $AFLOW_t^*$, and with lagged annual stock market volatility $\sigma_{m,t-1}^*$. That is, we run a regression of investor flows into individual funds on to: (i) fund characteristics, (ii) past performance, (iii) past performance interacted with average flows of the year, (iv) past performance interacted with past

¹⁷ See Barras, Scaillet and Wermers (2009), and Kosowski et al. (2006)

¹⁸ See e.g. Blume and Friend (1975), or Calvet, Campbell and Soldini (2007) for more recent evidence.

¹⁹ See e.g. Kosowski (2006)

²⁰ 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.

²¹ See e.g. Schwert (1989a and b), Hamilton and Lin (1996) or Mele (2007)

market volatility. As before, we do not need to include average flows and stock market volatility as independent variables as their direct effect on individual fund flows is captured by the year fixed effects. Results of the regressions are presented in Table VI.

[INSERT TABLE VI AROUND HERE]

The most striking feature of the regressions in Tables VI is the strong support they provide to the flow composition channel. For all 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. 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 between 2.35 (Regression 4) and 5.45 (Regression 2) times as steep as under average market conditions. In contrast, $AFLOW_t$ has either a negative (Regression 2) or no 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, which is both statistically and economically significant.

We find that stock market volatility has an impact on the sensitivity to performance of funds in the middle region. This effect is modest when relative performance measures are used (Regressions 1 to 3): comparing the coefficients a_2 and a_8 , we find that a one standard deviation increase in stock market volatility brings down the sensitivity to performance by a factor of around 1/3. The effect is more significant when using absolute alphas (Regression 4). However, we find no support for the hypothesis that periods with low stock market volatility are periods with high convexity of the flow-performance relationship. The point estimate of the effect of volatility on convexity is even of the wrong sign in all four specifications.

III) Conditional Convexity and the Tournament Hypothesis

A) Conditional Tournament Hypothesis

We now turn to the implications of conditional convexity for fund managers. The seminal papers of Brown, Harlow and Starks (1996) and Chevalier and Ellison (1997) suggest that a convex flow-performance relationship may induce fund managers who underperformed during the first part of the year to increase the risk of their portfolio. This is because 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. If flows are insensitive to performance below some threshold, increasing risk for funds below that threshold is a "free gamble"²².

However, recent empirical evidence does not seem to support this hypothesis. Busse (2001) challenges the methodology used by Brown, Harlow and Starks (1996) and argues that their results are 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 (2009).

How to explain the apparent lack of robustness of tests of the tournament hypothesis? Two answers are provided in the existing literature. The answer given 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 at high enough frequency. Another answer is provided by Qiu (2003), Hu et al (2007), and Kempf, Ruenzi and Thiele (2009) who argue that the reasoning 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,

²² Note that the same argument does not apply to hedge funds because of high-water marks (see e.g. Panageas and Westerfield, 2009)

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. Kempf, Ruenzi and Thiele (2009) provide empirical evidence supporting the "career concern" hypothesis using market conditions as a proxy for firing costs.

The evidence we provide of time variation in the convexity of the flow-performance suggests an alternative explanation, which resurrects the seminal flow-based story of Brown, Harlow and Starks (1996) and Chevalier and Ellison (1997). Our evidence shows that when economic activity is strong, there is strong convexity of the flow-performance relationship, which implies that the incentives for "underdogs" to increase the risk of their portfolio in the middle of the tournament are strong as well. In contrast, our point estimates suggest that the flow-performance relationship may become concave when economic activity slows down enough, which reverses 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 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.

It is important to point out that our results also provide a clean test between the flow-based and the career concern explanations for the risk-shifting behaviour of fund managers. We found in the previous section that the convexity of the flow-performance relationship is driven by economic activity but not by market conditions. The career concern hypothesis postulates that outside opportunities for fired managers depend on market conditions. Thus, a natural way to separate out the two hypotheses is to check whether it is economic activity or market conditions that drives risk-shifting by underperforming managers.

B) Empirical Evidence

Our methodology consists in augmenting the tournament regressions of Koski and Pontiff (1999) with the same interaction variables as in the previous section. 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 . Risk is measured by the standard deviation of

the (monthly) fund's returns in excess of the risk-free rate in Table VII (total risk). It is measured by the standard deviation of the residuals of a CAPM regression in Table VIII (idiosyncratic risk). It is measured by beta in Table IX (systematic risk). We then regress $\Delta Risk_{i,t}$ on the performance of fund i during the January-June period of year t (mid-year performance), that performance interacted with contemporaneous standardized GDP growth and performance interacted with contemporaneous standardized stock market return. As before, we allow for fixed year effects through a full set of year dummy variables and we use standard errors clustered by funds to allow for fund-specific effects.

In other words, we run the following regression:

$$\Delta Risk_{i,t} = \text{time dummies} + a_1 Rank_{i,t-1} + a_2 Rank_{i,t-1} * (g_{GDP,t}^*) + a_3 Rank_{i,t-1}^{TOP} * (r_{m,t}^*) + \varepsilon$$

where the interaction terms can be interpreted as in the previous section. The unconditional tournament hypothesis implies that the coefficient a_1 should be negative: the lower the interim performance of a fund the more it should increase risk during the second half of the year. Our conditional tournament hypothesis implies that the coefficient a_2 should be negative: the stronger is economic activity, the more convex is the flow-performance relationship and the more incentives underperforming fund managers have to increase the risk of their portfolio. Finally, the career concern hypothesis implies that the coefficient a_3 should be negative: the better the market conditions, the less afraid is an underperforming fund manager to lose his or her job and the more incentives he or she has to increase risk.

[INSERT TABLES VII TO IX AROUND HERE]

Table VII reports results of tests of the conditional tournament hypothesis for the four different performance measures we used in the previous section and where the dependent variable is defined as total risk. In all four regressions, we find that the coefficient a_2 is of the right sign and highly statistically significant. This is consistent with the conditional tournament hypothesis. By way of contrast, the coefficient a_3 is of the right sign and significant in only two of the four regressions. In addition, even focusing on the two specifications where a_3 is significant, i.e. Regressions 1 and 4, we find that the impact of market conditions on risk-shifting is small relative to that of economic activity:

a_3 is on average three times smaller than a_2 .²³ Thus, results in Table VII provide only mixed support for the career concern hypothesis.

We further investigate the differences between the conditional tournament and career concern hypotheses in Tables VIII and IX, where we look at, respectively, idiosyncratic and systematic risks. We find a sharp divide between the effects of market conditions and of economic activity on risk-taking. We find in Table VIII that, as predicted by the theory, underperforming managers take more idiosyncratic risk under strong than under weak economic activity. This can be seen by looking at the coefficient a_2 , which is always negative and significant at the 1% level. By contrast, we find that the coefficient a_3 is always *positive* and significant, which implies that underperforming managers take significantly more idiosyncratic risk under poor than under good market conditions, which contradicts the career concern hypothesis. The picture changes when looking at Table IX where we look at the impact of economic activity and market conditions on the beta of the portfolio of underperforming managers. We still find some evidence of higher risk-taking under strong economic activity but the bulk of the effect is driven by market conditions: underperforming managers increase the beta of the portfolio when the stock market is booming.

Collecting the results of Tables VII-IX together, we find that economic activity drives most of the extent to which underperforming fund managers increase the risk of their portfolio. As economic activity is the main driver behind the convexity of the flow-performance relationship, this provides strong support for the seminal flow-based incentives theory by Brown, Harley and Stark (1996) and of Chevalier and Ellison (1997). We find that most of this increase in risk-taking is driven by an increase in idiosyncratic risk, which is consistent with managers trying to generate "spurious" alphas. To the extent that this increased risk-taking is detrimental to performance as shown by Huang, Sialm and Zhang (2008), our results also provide a rationale for the findings reported by Kosowski (2006) of worse performance during booms than during recessions. Finally, we find that market conditions have only a marginal impact on the quantity of risk taken by underperforming managers but do affect the composition of that risk: underperforming managers take more systematic and less idiosyncratic risk when the stock market is booming.

²³ Note that the two coefficients are directly comparable to one another as r^* and g^* have been standardized.

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. The missing link is the fact that the convexity of the flow-performance relationship varies 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 countercyclical²⁴. 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.

²⁴ 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 $r_{i,t} - r_{m,t}$, 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.

| | 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 |
| TNA (\$mil) | 442.18 | 1231.0 |
| Age (years) | 7.862 | 5.778 |
| Expenses (%) | 1.218 | 0.512 |

Table II: Unconditional Convexity of the Flow-Performance Relationship

This table examines the unconditional impact of 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. Each year, funds are ranked between 0 (poorest performer) and 1 (best performer) based on $Performance_{i,t}$, where $Performance_{i,t}$ is measured by $r_{i,t} - r_{m,t}$, where r_m is the return on the equally weighted market portfolio (Excess return: Regression 2), or by residuals of a CAPM equation (1-factor alpha: Regressions 1 and 4) or by residuals of a 4-factor Carhart (1997) model (4-factor alpha: Regression 3), where factor loadings are estimated from 24 monthly observations. $Rank_{i,t-1}^{TOP}$, $Rank_{i,t-1}^{MIDDLE}$, 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. $\delta_{i,t-1}^-$ (resp. $\delta_{i,t-1}^+$) is a dummy variable which takes value 1 if $Performance_{i,t-1}$ is negative (resp. positive), and takes value 0 otherwise. Size is defined as $\ln(TNA_{i,t-1})$. Expenses are expressed in percentage. Lagged flow is equal to $FLOW_{i,t-1}$. 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. For regressions (1) to (3), 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. Similarly, we report the difference between the coefficients of positive and negative performance variables in Regression 4.

| Regression | (1) | (2) | (3) | (4) |
|---|--|--|--|--|
| Performance measure: | 1-factor alpha (relative performance) | Excess returns (relative performance) | 4-factor alpha (relative performance) | 1-factor alpha (absolute performance) |
| Size | -6.354 (0.227) | -1.263 (0.765) | -6.897 (0.191) | -7.197 (0.166) |
| Age | - 1.856 (**) (0.011) | -2.329 (***) (0.000) | - 1.955 (***) (0.007) | -1.697 (**) (0.017) |
| Expenses | -6.426 (0.188) | -10.560 (**) (0.035) | - 11.156 (**) (0.023) | -10.359 (**) (0.036) |
| Lagged Flow | 0.435 (***) (0.000) | 0.488 (***) (0.000) | 0.441 (***) (0.000) | 0.433 (***) (0.000) |
| | | | | |
| (a ₁): $Rank_{i,t-1}^{TOP}$ | 277.878 (0.112) | 129.877 (0.305) | 157.611 (0.395) | |
| (a ₂): $Rank_{i,t-1}^{MIDDLE}$ | 157.790 (***) (0.000) | 152.570 (***) (0.000) | 144.978 (***) (0.000) | |
| (a ₃): $Rank_{i,t-1}^{BOTTOM}$ | -62.250 (0.469) | -79.553 (0.236) | -123.564 (*) (0.070) | |
| a₁-a₃ | 340.13 (***) (0.008) | 209.43 (**) (0.026) | 281.17 (*) (0.095) | |
| | | | | |
| (a ₄): $Performance_{i,t-1} * \delta_{i,t-1}^+$ | | | | 498.767 (***) (0.003) |
| (a ₅): $Performance_{i,t-1} * \delta_{i,t-1}^-$ | | | | 140.814 (***) (0.002) |
| a₉-a₁₀ | | | | 357.95 (**) (0.028) |
| R ² | 24.9% | 26.0% | 24.2% | 24.8% |
| Observations | 4342 | 6146 | 4342 | 4342 |

Table III: Conditional Convexity of the Flow-Performance Relationship

This table examines the evolution over the business cycle of the impact of 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. Each year, funds are ranked between 0 (poorest performer) and 1 (best performer) based on $Performance_{i,t}$, where $Performance_{i,t}$ is measured by $r_{i,t} - r_{m,t}$, where r_m is the return on the equally weighted market portfolio (Regression 2), or by residuals of a CAPM equation (Regressions 1 and 4) or by residuals of a 4-factor Carhart (1997) model (Regression 3), where factor loadings are estimated from 24 monthly observations. $Rank_{i,t-1}^{TOP}$, $Rank_{i,t-1}^{MIDDLE}$, 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. $\delta_{i,t-1}^-$ (resp. $\delta_{i,t-1}^+$) is a dummy variable which takes value 1 if $Performance_{i,t-1}$ is negative (resp. positive), and takes value 0 otherwise. The variable $(g_{GDP,t} - \bar{g}_{GDP})$ measures deviations in percentage of the US real GDP growth rate from its sample mean. Size is defined as $\ln(TNA_{i,t-1})$. Expenses are expressed in percentage. Lagged flow is equal to $FLOW_{i,t-1}$. 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. For regressions (1) to (3), 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. Similarly, we report the difference between the coefficients of positive and negative performance variables in Regression 4.

| Regression | (1) | (2) | (3) | (4) |
|--|--|--|--|--|
| Performance measure: | 1-factor alpha (relative performance) | Excess returns (relative performance) | 4-factor alpha (relative performance) | 1-factor alpha (absolute performance) |
| Size | -6.859 (0.181) | -1.861 (0.657) | -6.997 (0.184) | -7.713 (0.133) |
| Age | - 1.778 (**) (0.014) | -2.335 (***) (0.000) | - 1.833 (***) (0.009) | -1.614 (**) (0.022) |
| Expenses | -6.873 (0.154) | -12.288 (**) (0.014) | - 11.293 (**) (0.022) | -10.570 (**) (0.034) |
| Lagged Flow | 0.434 (***) (0.000) | 0.487 (***) (0.000) | 0.440 (***) (0.000) | 0.428 (***) (0.000) |
| ----- | | | | |
| (a ₁): $Rank_{i,t-1}^{TOP}$ | 276.337 (0.109) | 129.741 (0.302) | 156.469 (0.390) | |
| (a ₂): $Rank_{i,t-1}^{MIDDLE}$ | 157.880 (***) (0.000) | 152.529 (***) (0.000) | 144.992 (***) (0.000) | |
| (a ₃): $Rank_{i,t-1}^{BOTTOM}$ | -62.035 (0.467) | -80.938 (0.227) | -122.988 (*) (0.071) | |
| a₁-a₃ | 338.37 (***) (0.007) | 210.68 (**) (0.025) | 279.46 (*) (0.092) | |
| ----- | | | | |
| (a ₄): $Rank_{i,t-1}^{TOP} * (g_{GDP,t} - \bar{g}_{GDP})$ | 439.836 (**) (0.048) | 336.008 (**) (0.016) | 392.742 (*) (0.089) | |
| (a ₅): $Rank_{i,t-1}^{MIDDLE} * (g_{GDP,t} - \bar{g}_{GDP})$ | 15.550 (0.617) | 13.026 (0.520) | 15.678 (0.597) | |
| (a ₆): $Rank_{i,t-1}^{BOTTOM} * (g_{GDP,t} - \bar{g}_{GDP})$ | -186.017 (0.121) | -140.315 (*) (0.062) | -31.483 (0.694) | |
| a₄-a₆ | 625.85 (**) (0.013) | 476.32 (***) (0.004) | 424.22 (**) (0.021) | |
| ----- | | | | |

(a₇) : $Performance_{i,t-1} * \delta_{i,t-1}^+$ 471.006 (***)
(0.003)

(a₈) : $Performance_{i,t-1} * \delta_{i,t-1}^-$ 117.294 (*)
(0.060)

a₇-a₈ **353.71 (**)**
(0.040)

(a₉) : $Performance_{i,t-1} * \delta_{i,t-1}^+ * (g_{GDP,t} - \bar{g}_{GDP})$ 212.564 (*)
(0.088)

(a₁₀) : $Performance_{i,t-1} * \delta_{i,t-1}^- * (g_{GDP,t} - \bar{g}_{GDP})$ -68.776
(0.296)

a₉-a₁₀ **281.34 (*)**
(0.068)

| | | | | |
|----------------|-------|-------|-------|-------|
| R ² | 25.5% | 26.5% | 24.7% | 25.3% |
| Observations | 4342 | 6146 | 4342 | 4342 |

Table IV: Robustness Checks of the Conditional Flow-Performance Relationship

This table examines the evolution over the business cycle of the impact of fund performance in year t-1 on the net flow of the fund in year t for alternative subsamples and performance measures. 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 performance measured by residuals of a CAPM equation (Regressions 1 to 3), with betas estimated from 24 monthly observations or by the information ratio defined as $E(r_i - r_m) / \sigma(r_i - r_m)$ where returns are measured at monthly frequency. $Rank_{i,t-1}^{TOP}$, $Rank_{i,t-1}^{MIDDLE}$, 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 is defined as $Ln(TNA_{i,t-1})$. Expenses are expressed in percentage. Lagged flow is equal to $FLOW_{i,t-1}$. Regressions also include one dummy variable for each year in the sample (coefficients unreported). The full sample is composed of 865 no-load US equity mutual funds appearing in the CRSP database between 1980 and 2006, with at least two years of return history and where we exclude index funds, multiple share classes, funds closed to investors, funds of funds and funds with TNA < 10M\$ for their entire existence. Regression 1 includes all funds but restricts the sample to years 1993 to 2006. Regression 2 further restricts the sample to the 335 funds in our sample whose ICDI fund objective code is "Long Term Growth" (LG). Regression 3 restricts the sample to years where $(g_{GDP,t} - \bar{g}_{GDP})$ 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.

| Regression | (1) | (2) | (3) | (4) | (5) |
|--|---------------------------------------|---------------------------------------|--------------------------------------|---------------------------------------|---------------------------------|
| Subsample: | 1993-2006 (all funds) | no outlier (all funds) | 1993-2006 (LG funds only) | full sample (all funds) | full sample (all funds) |
| Performance measure: | 1-factor alpha (relative) | 1-factor alpha (relative) | 1-factor alpha (relative) | information ratio (relative) | information ratio (absolute) |
| Size | -7.089 (0.177) | -10.247 (**) (0.021) | -7.539 (**) (0.024) | -1.463 (0.729) | -1.887 (0.653) |
| Age | -1.897 (**) (0.015) | -1.086 (0.107) | -1.156 (0.114) | -2.431 (***) (0.000) | -2.345 (***) (0.000) |
| Expenses | -7.722 (0.129) | -9.777 (**) (0.050) | -1.340 (0.807) | -12.696 (***) (0.010) | -11.876 (**) (0.018) |
| Lagged Flow | 0.433 (***) (0.000) | 0.549 (***) (0.000) | 0.623 (***) (0.000) | 0.490 (***) (0.000) | 0.488 (***) (0.000) |
| | | | | | |
| (a ₁): $Rank_{i,t-1}^{TOP}$ | 300.990 (*) (0.098) | 190.988 (0.101) | 272.553 (**) (0.027) | -1.030 (0.989) | |
| (a ₂): $Rank_{i,t-1}^{MIDDLE}$ | 160.765 (***) (0.000) | 114.055 (***) (0.000) | 113.205 (***) (0.000) | 144.346 (***) (0.000) | |
| (a ₃): $Rank_{i,t-1}^{BOTTOM}$ | -67.225 (0.443) | -97.859 (0.127) | 52.420 (0.727) | -74.373 (0.268) | |
| a₁-a₃ | 368.21 (***) (0.006) | 288.85 (***) (0.003) | 220.13 (**) (0.020) | 73.343 (0.143) | |
| | | | | | |
| (a ₄): $Rank_{i,t-1}^{TOP} * (g_{GDP,t} - \bar{g}_{GDP})$ | 594.801 (**) (0.041) | 624.624 (0.110) | 18.534 (0.886) | 125.228 (*) (0.084) | |
| (a ₅): $Rank_{i,t-1}^{MIDDLE} * (g_{GDP,t} - \bar{g}_{GDP})$ | 13.524 (0.722) | 82.346 (**) (0.031) | 82.981 (**) (0.0036) | 23.474 (0.241) | |
| (a ₆): $Rank_{i,t-1}^{BOTTOM} * (g_{GDP,t} - \bar{g}_{GDP})$ | -205.373 (0.123) | -163.724 (0.124) | -438.289 (*) (0.063) | -167.751 (**) (0.039) | |
| a₄-a₆ | 800.17 (**) (0.011) | 788.35 (**) (0.015) | 456.82 (*) (0.057) | 292.98 (***) (0.004) | |

| | | | | | |
|---|-------|-------|-------|-------|---------------------------------------|
| | | | | | |
| $(a_7) : Performance_{i,t-1} * \delta_{i,t-1}^+$ | | | | | 177.273 (***) (0.000) |
| $(a_8) : Performance_{i,t-1} * \delta_{i,t-1}^-$ | | | | | 63.122 (***) (0.000) |
| $a_7 - a_8$ | | | | | 114.15 (***) (0.001) |
| | | | | | |
| $(a_9) : Performance_{i,t-1} * \delta_{i,t-1}^+ * (g_{GDP,t} - \bar{g}_{GDP})$ | | | | | 33.948 (0.212) |
| $(a_{10}) : Performance_{i,t-1} * \delta_{i,t-1}^- * (g_{GDP,t} - \bar{g}_{GDP})$ | | | | | -35.347 (**) (0.050) |
| $a_9 - a_{10}$ | | | | | 69.295 (*) (0.065) |
| | | | | | |
| R^2 | 25.7% | 38.2% | 33.8% | 25.7% | 25.4% |
| Observations | 4166 | 1652 | 3953 | 6146 | 6146 |

Table V: Conditional Convexity of the Flow-Performance Relationship: Economic Activity vs. Market Returns

This table examines the evolution over business cycle and market conditions of the flow performance relationship. 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) and 1 (best) based on $Performance_{i,t}$, where $Performance_{i,t}$ is measured by $r_{i,t} - r_{m,t}$, where r_m is the return on the equally weighted market portfolio (Regr. 2) or by residuals of a CAPM equation (Regr. 1 and 4) or by residuals of a Carhart (1997) model (Regr. 3), where we estimate factor loadings from 24 monthly observations. We define: $Rank_{i,t-1}^{BOTTOM} = \min(Rank_{i,t-1}, 0.2)$, $Rank_{i,t-1}^{MIDDLE} = \min(Rank_{i,t-1} - Rank_{i,t-1}^{BOTTOM}, 0.6)$ 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. $\delta_{i,t-1}^{**}$ (resp. $\delta_{i,t-1}^{+}$) is a dummy variable which takes value 1 if $Performance_{i,t-1}$ is negative (resp. positive), and takes value 0 otherwise. The variable $g_{GDP,t}^* \equiv (g_{GDP,t} - \bar{g}_{GDP,t}) / \sigma(g_{GDP,t})$ measures standardized deviations of the US real GDP growth rate from its sample mean. and $r_{m,t}^* \equiv (r_{m,t} - \bar{r}_m) / \sigma(r_{m,t})$ standardized deviations of the EW market return in year t from its sample mean. Size is defined as: $Ln(TNA_{i,t-1})$. Expenses are expressed in percentage. Lagged flow is equal to $FLOW_{i,t-1}$. 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. For Regr. (1) to (3), 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. Similarly, we report the difference between the coefficients of positive and negative performance variables in Regr. 4.

| Regression | (1) | (2) | (3) | (4) |
|--|--|--|--|--|
| Performance measure: | 1-factor alpha (relative performance) | Excess returns (relative performance) | 4-factor alpha (relative performance) | 1-factor alpha (absolute performance) |
| Size | -6.847 (0.181) | -1.744 (0.678) | -6.983 (0.184) | -7.719 (0.133) |
| Age | -1.810 (**) (0.013) | -2.345 (***) (0.000) | -1.931 (***) (0.007) | -1.617 (**) (0.021) |
| Expenses | -6.903 (0.153) | -12.743 (**) (0.011) | -11.967 (**) (0.016) | -11.015 (**) (0.027) |
| Lagged Flow | 0.432 (***) (0.000) | 0.486 (***) (0.000) | 0.439 (***) (0.000) | 0.427 (***) (0.000) |
| ----- | | | | |
| (a ₁): $Rank_{i,t-1}^{TOP}$ | 275.487 (0.109) | 130.222 (0.299) | 156.574 (0.388) | |
| (a ₂): $Rank_{i,t-1}^{MIDDLE}$ | 158.091 (***) (0.000) | 152.628 (***) (0.000) | 144.996 (***) (0.000) | |
| (a ₃): $Rank_{i,t-1}^{BOTTOM}$ | -61.642 (0.470) | -81.776 (0.221) | -123.189 (*) (0.071) | |
| a₁-a₃ | 337.13 (***) (0.007) | 212 (**) (0.025) | 279.76 (*) (0.091) | |
| ----- | | | | |
| (a ₄): $Rank_{i,t-1}^{TOP} * (g_{GDP,t}^*)$ | 439.660 (**) (0.050) | 359.748 (**) (0.017) | 393.952 (*) (0.089) | |
| (a ₅): $Rank_{i,t-1}^{MIDDLE} * (g_{GDP,t}^*)$ | 15.801 (0.616) | 13.614 (0.535) | 15.848 (0.598) | |
| (a ₆): $Rank_{i,t-1}^{BOTTOM} * (g_{GDP,t}^*)$ | -187.216 (0.125) | -151.817 (*) (0.062) | -30.789 (0.705) | |
| a₄-a₆ | 626.88 (**) (0.013) | 511.57 (***) (0.004) | 424.74 (**) (0.021) | |
| ----- | | | | |
| (a ₇): $Rank_{i,t-1}^{TOP} * r_{m,t}^*$ | -206.850 (**) (0.037) | -111.533 (0.114) | -139.157 (0.180) | |
| (a ₈): $Rank_{i,t-1}^{MIDDLE} * r_{m,t}^*$ | -22.036 (0.227) | -25.217 (*) (0.053) | -21.730 (0.201) | |
| (a ₉): $Rank_{i,t-1}^{BOTTOM} * r_{m,t}^*$ | -29.513 (0.638) | -53.530 (0.196) | -37.277 (0.485) | |
| a₇-a₉ | -177.34 (0.973) | -58.004 (0.820) | -101.88 (0.826) | |

| | | | | |
|--------------------------------------|--|-------|-------|-------------------------------------|
| <hr/> | | | | |
| (a ₁₀) | $Performance_{i,t-1} * \delta_{i,t-1}^+$ | | | 376.612 (***) (0.001) |
| (a ₁₁) | $Performance_{i,t-1} * \delta_{i,t-1}^-$ | | | 142.379 (***) (0.008) |
| a₁₀-a₁₁ | | | | 234.23 (*) (0.063) |
| <hr/> | | | | |
| (a ₁₂) | $Performance_{i,t-1} * \delta_{i,t-1}^+ * (g_{GDP,t}^*)$ | | | 181.244 (0.119) |
| (a ₁₃) | $Performance_{i,t-1} * \delta_{i,t-1}^- * (g_{GDP,t}^*)$ | | | -76.946 (0.332) |
| a₁₂-a₁₃ | | | | 258.19 (*) (0.095) |
| <hr/> | | | | |
| (a ₁₄) | $Performance_{i,t-1} * \delta_{i,t-1}^+ * r_{m,t}^*$ | | | -341.843 (0.103) |
| (a ₁₅) | $Performance_{i,t-1} * \delta_{i,t-1}^- * r_{m,t}^*$ | | | 47.814 (0.234) |
| a₁₄-a₁₅ | | | | -389.66 (0.951) |
| R ² | 25.7% | 26.6% | 24.8% | 25.4% |
| Observations | 4342 | 6146 | 4342 | 4342 |

Table VI: Source of the Effect of Economic Activity: Flow Composition vs. Stock Market Volatility

This table examines how the flow-performance relationship varies with average flows and market volatility. 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) and 1 (best) based on $Performance_{i,t}$, which is measured by $r_{i,t} - r_{m,t}$, where r_m is the return on the equally weighted market portfolio (Regr. 2) or by residuals of a CAPM equation (Regr. 1 and 4) or by residuals of a Carhart model (Regr. 3), where we estimate factor loadings from 24 monthly observations. We define $Rank_{i,t-1}^{BOTTOM} = \min(Rank_{i,t-1}, 0.2)$, $Rank_{i,t-1}^{MIDDLE} = \min(Rank_{i,t-1} - Rank_{i,t-1}^{BOTTOM}, 0.6)$, 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 $t-1$. $\delta_{i,t-1}^*$ (resp. $\delta_{i,t-1}^{**}$) is a dummy variable which takes value 1 if $Performance_{i,t-1}$ is negative (resp. positive), and takes value 0 otherwise. We define: $AFLOW_t = (1/n(t)) \sum_{i=1}^{n(t)} FLOW_{i,t}$, 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 sample mean and $\sigma_{M,t}^*$ standardized deviations of the volatility of the equally weighted market portfolio from its sample mean. Size is defined as: $Ln(TNA_{i,t-1})$. Expenses are expressed in percentage. Lagged flow is equal to $FLOW_{i,t-1}$. 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. For regressions (1) to (3), 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. Similarly, we report the difference between the coefficients of positive and negative performance variables in Regr. 4.

| Regression | (1) | (2) | (3) | (4) |
|---|--|--|--|--|
| Performance measure: | 1-factor alpha (relative performance) | Excess returns (relative performance) | 4-factor alpha (relative performance) | 1-factor alpha (absolute performance) |
| Size | -7.059 (0.173) | -1.936 (0.642) | -6.845 (0.193) | -8.025 (0.117) |
| Age | -1.706 (**) (0.019) | -2.115 (***) (0.001) | -1.820 (**) (0.011) | -1.478 (**) (0.034) |
| Expenses | -8.017 (0.103) | -11.765 (**) (0.019) | -11.870 (**) (0.018) | -9.894 (*) (0.052) |
| Lagged Flow | 0.431 (***) (0.000) | 0.483 (***) (0.000) | 0.436 (***) (0.000) | 0.426 (***) (0.000) |
| ----- | | | | |
| (a ₁): $Rank_{i,t-1}^{TOP}$ | 269.512 (0.107) | 129.774 (0.297) | 150.701 (0.389) | |
| (a ₂): $Rank_{i,t-1}^{MIDDLE}$ | 158.440 (***) (0.000) | 152.769 (***) (0.000) | 145.297 (***) (0.000) | |
| (a ₃): $Rank_{i,t-1}^{BOTTOM}$ | -63.880 (0.458) | -79.010 (0.239) | -121.829 (*) (0.076) | |
| a₁-a₃ | 333.39 (***) (0.007) | 208.78 (**) (0.024) | 272.53 (*) (0.088) | |
| ----- | | | | |
| (a ₄): $Rank_{i,t-1}^{TOP} * (AFLOW_t^*)$ | 631.925 (0.103) | 579.593 (**) (0.028) | 804.089 (**) (0.047) | |
| (a ₅): $Rank_{i,t-1}^{MIDDLE} * (AFLOW_t^*)$ | 35.200 (0.298) | 13.744 (0.564) | -21.303 (0.528) | |
| (a ₆): $Rank_{i,t-1}^{BOTTOM} * (AFLOW_t^*)$ | -129.992 (0.188) | -122.730 (**) (0.030) | 42.932 (0.622) | |
| a₄-a₆ | 761.92 (**) (0.023) | 702.32 (***) (0.003) | 761.16 (**) (0.022) | |
| ----- | | | | |
| (a ₇): $Rank_{i,t-1}^{TOP} * \sigma_{m,t-1}^*$ | 118.942 (0.410) | 121.997 (0.275) | 185.071 (0.231) | |
| (a ₈): $Rank_{i,t-1}^{MIDDLE} * \sigma_{m,t-1}^*$ | -39.895 (**) (0.038) | -48.906 (***) (0.005) | -49.083 (***) (0.009) | |
| (a ₉): $Rank_{i,t-1}^{BOTTOM} * \sigma_{m,t-1}^*$ | 79.600 (0.186) | 35.432 (0.479) | 35.503 (0.514) | |
| a₇-a₉ | -39.342 (0.607) | -86.565 (0.798) | -149.57 (0.829) | |

| | | | | |
|--------------------------------------|---|-------|-------|-------------------------------------|
| <hr/> | | | | |
| (a ₁₀) | $Performance_{i,t-1} * \delta_{i,t-1}^+$ | | | 329.128 (***) (0.003) |
| (a ₁₁) | $Performance_{i,t-1} * \delta_{i,t-1}^-$ | | | 245.167 (***) (0.001) |
| a₁₀-a₁₁ | | | | 83.96 (0.289) |
| <hr/> | | | | |
| (a ₁₂) | $Performance_{i,t-1} * \delta_{i,t-1}^+ * (AFLOW_i^*)$ | | | 447.159 (**) (0.046) |
| (a ₁₃) | $Performance_{i,t-1} * \delta_{i,t-1}^- * (AFLOW_i^*)$ | | | -56.272 (0.647) |
| a₁₂-a₁₃ | | | | 503.43 (*) (0.066) |
| <hr/> | | | | |
| (a ₁₄) | $Performance_{i,t-1} * \delta_{i,t-1}^+ * \sigma_{m,t}^*$ | | | 162.264 (0.378) |
| (a ₁₅) | $Performance_{i,t-1} * \delta_{i,t-1}^- * \sigma_{m,t}^*$ | | | -166.289 (***) (0.001) |
| a₁₅-a₁₄ | | | | -328.55 (0.936) |
| R ² | 26.2% | 27.1% | 25.7% | 26.4% |
| Observations | 4342 | 6146 | 4342 | 4342 |

**Table VII: Change in Total Risk as a Function of Interim Performance:
Impact of Economic Activity and Market Conditions**

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 $\Delta RISK_{i,t} = RISK_{i,Jul-Dec\ yr\ t} - RISK_{i,Jan-Jun\ yr\ t}$, where $RISK_{i,t}$ is measured by the standard deviation of monthly excess returns (total risk) expressed in percentage. Each year, funds are ranked between 0 (poorest performer) and 1 (best performer) based on $Performance_{i,t}$, where $Performance_{i,t}$ is measured by $r_{i,t} - r_{m,t}$, where r_m is the return on the equally weighted market portfolio (Regression 2), or by residuals of a CAPM equation (Regressions 1 and 4) or by residuals of a 4-factor Carhart (1997) model (Regression 3), where factor loadings are estimated from 24 monthly observations. $Rank_{i,t-1}^{TOP}$, $Rank_{i,t-1}^{MIDDLE}$, 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 $t-1$. $\delta_{i,t-1}^-$ (resp. $\delta_{i,t-1}^+$) is a dummy variable which takes value 1 if $Performance_{i,t-1}$ is negative (resp. positive), and takes value 0 otherwise. The variable $g_{GDP,t}^* \equiv (g_{GDP,t} - \bar{g}_{GDP,t}) / \sigma(g_{GDP,t})$ measures standardized deviations of the US real GDP growth rate from its sample mean. $r_{m,t}^* \equiv (r_{m,t} - \bar{r}_m) / \sigma(r_{m,t})$ measures standardized deviations of the market return in year t 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. 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.

| Regression: | (1) | (2) | (3) | (4) |
|--|-------------------------|-------------------------|-------------------------|-------------------------|
| Relative / absolute performance | Relative | Relative | Relative | Absolute |
| Based on: | 1-factor | Excess Returns | 4-factor | 1-factor |
| (a ₁) : $Rank_{i, Jan-Jun\ year\ t}$ | 0.234 (***) (0.010) | 0.325 (***) (0.000) | -0.363 (***) (0.000) | -2.033 (***) (0.000) |
| (a ₂) : $Rank_{i, Jan-Jun\ year\ t} * (g_{GDP, Jan-Jun\ year\ t}^*)$ | -0.827 (***) (0.000) | -0.746 (***) (0.000) | - 0.194 (**) (0.047) | -4.048 (***) (0.000) |
| (a ₃) : $Rank_{i, Jan-Jun\ year\ t} * (r_{m, Jan-Jun\ year\ t}^*)$ | -0.299 (**) (0.014) | 0.144 (0.208) | 0.024 (0.823) | -1.212 (*) (0.091) |
| R ² | 58.6% | 56.4% | 57.8% | 59.6% |
| Observations | 4342 | 6146 | 4342 | 4342 |

**Table VIII: Change in Idiosyncratic Risk as a Function of Interim Performance:
Impact of Economic Activity and Market Conditions**

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 $\Delta RISK_{i,t} = RISK_{i,Jul-Dec\ yr\ t} - RISK_{i,Jan-Jun\ yr\ t}$, where $RISK_{i,t}$ is measured by the standard deviation of the residuals of a 1-factor CAPM regression expressed in percentage. Each year, funds are ranked between 0 (poorest performer) and 1 (best performer) based on $Performance_{i,t}$, where $Performance_{i,t}$ is measured by $r_{i,t} - r_{m,t}$, where r_m is the return on the equally weighted market portfolio (Regression 2), or by residuals of a CAPM equation (Regressions 1 and 4) or by residuals of a 4-factor Carhart (1997) model (Regression 3), where factor loadings are estimated from 24 monthly observations. $Rank_{i,t-1}^{TOP}$, $Rank_{i,t-1}^{MIDDLE}$, 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 $t-1$. $\delta_{i,t-1}^-$ (resp. $\delta_{i,t-1}^+$) is a dummy variable which takes value 1 if $Performance_{i,t-1}$ is negative (resp. positive), and takes value 0 otherwise. The variable $g_{GDP,t} = (g_{GDP,t} - \bar{g}_{GDP,t}) / \sigma(g_{GDP,t})$ measures standardized deviations of the US real GDP growth rate from its sample mean. $r_{m,t}^* = (r_{m,t} - \bar{r}_m) / \sigma(r_{m,t})$ measures standardized deviations of the market return in year t 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. 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.

| Regression: | (1) | (2) | (3) | (4) |
|--|-------------------------|-------------------------|-------------------------|-------------------------|
| Relative / absolute performance | Relative | Relative | Relative | Absolute |
| Based on: | 1-factor | Excess Returns | 4-factor | 1-factor |
| (a ₁) : $Rank_{i, Jan-Jun\ year\ t}$ | 0.483 (***) (0.010) | 0.360 (***) (0.000) | 0.202 (**) (0.013) | 0.868 (*) (0.067) |
| (a ₂) : $Rank_{i, Jan-Jun\ year\ t} * (g_{GDP, Jan-Jun\ year\ t})$ | -1.140 (***) (0.000) | -1.101 (***) (0.000) | -0.707 (***) (0.000) | -4.807 (***) (0.000) |
| (a ₃) : $Rank_{i, Jan-Jun\ year\ t} * (r_{m, Jan-Jun\ year\ t})$ | 0.647 (***) (0.000) | 0.403 (***) (0.000) | 0.227 (**) (0.034) | 2.213 (***) (0.001) |
| R ² | 44.1% | 44.1% | 40.2% | 48.1% |
| Observations | 4342 | 6146 | 4342 | 4342 |

**Table IX: Change in Systematic Risk as a Function of Interim Performance:
Impact of Economic Activity and Market Conditions**

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 $\Delta RISK_{i,t} = RISK_{i,Jul-Dec\ yr\ t} - RISK_{i,Jan-Jun\ yr\ t}$, where $RISK_{i,t}$ is measured by the by the 1-factor CAPM beta. Each year, funds are ranked between 0 (poorest performer) and 1 (best performer) based on $Performance_{i,t}$, where $Performance_{i,t}$ is measured by $r_{i,t} - r_{m,t}$, where r_m is the return on the equally weighted market portfolio (Regression 2), or by residuals of a CAPM equation (Regressions 1 and 4) or by residuals of a 4-factor Carhart (1997) model (Regression 3), where factor loadings are estimated from 24 monthly observations. $Rank_{i,t-1}^{TOP}$, $Rank_{i,t-1}^{MIDDLE}$, 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. $\delta_{i,t-1}^*$ (resp. $\delta_{i,t-1}^{**}$) is a dummy variable which takes value 1 if $Performance_{i,t-1}$ is negative (resp. positive), and takes value 0 otherwise. The variable $g_{GDP,t}^* \equiv (g_{GDP,t} - \bar{g}_{GDP,t}) / \sigma(g_{GDP,t})$ measures standardized deviations of the US real GDP growth rate from its sample mean. $r_{m,t}^* \equiv (r_{m,t} - \bar{r}_m) / \sigma(r_{m,t})$ measures standardized deviations of the market return in year t 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. 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.

| Regression: | (1) | (2) | (3) | (4) |
|--|-------------------------|-------------------------|-------------------------|-------------------------|
| Relative / absolute performance | Relative | Relative | Relative | Absolute |
| Based on: | 1-factor | Excess Returns | 4-factor | 1-factor |
| (a ₁) : $Rank_{i, Jan-Jun\ year\ t}$ | -0.436 (***) (0.000) | 0.003 (0.167) | -0.307 (***) (0.000) | -2.026 (***) (0.000) |
| (a ₂) : $Rank_{i, Jan-Jun\ year\ t} * (g_{GDP, Jan-Jun\ year\ t}^*)$ | -0.111 (***) (0.000) | -0.059 (***) (0.001) | 0.028 (0.180) | -1.036 (***) (0.000) |
| (a ₃) : $Rank_{i, Jan-Jun\ year\ t} * (r_{m, Jan-Jun\ year\ t}^*)$ | -0.568 (***) (0.000) | 0.163 (***) (0.000) | -0.332 (**) (0.000) | -2.915 (***) (0.001) |
| R ² | 30.6% | 21.3% | 25.4% | 32.0% |
| Observations | 4342 | 6146 | 4342 | 4342 |