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L'évaluation de la performance des fonds mutuels

par

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Résumé

Cette thèse aborde en trois chapitres des questions relatives à l'évaluation de la performance des fonds mutuels. Les deux premières parties offrent une analyse approfondie de la performance et des caractéristiques des nouveaux fonds mutuels. La troisième partie s'intéresse au phénomène de l'inversion du risque adopté par les gestionnaires de portefeuille entre la première et la deuxième partie de l'année pour les fonds mutuels américains investis en actions.

Le premier essai analyse la performance et les caractéristiques des fonds mutuels nouvellement lancés. Le développement spectaculaire qu'a connu le secteur des fonds mutuels durant les deux dernières décennies (1990 et 2000) a fait émerger un grand nombre de fonds dont l'historique de placement ne dépasse guère les trois ans. Ces fonds sont par définition moins connus que les autres et doivent de ce fait adopter une stratégie plus agressive que la moyenne pour acquérir des parts de marché. Ils sont alors incités à prendre plus de risque pour atteindre une performance supérieure. Celle-ci leur permettra d'accroitre le volume des flux, et de garantir ainsi la survie du fonds. Nous étudions la performance et les caractéristiques de 828 nouveaux fonds mutuels américains sur la période 1991-2005. Ces fonds ont initialement, un rendement absolu et un rendement anormal élevés. La performance ajustée au risque est aussi supérieure à celle observée chez les fonds établis de plus longue date. Les fonds appartenant aux déciles les plus élevés montrent des signes de persistance de leur performance à court terme. Néanmoins, une fraction non négligeable des fonds change des déciles les

plus élevés vers les déciles les moins élevés et vice-versa. Nous avons analysé les caractéristiques des portefeuilles et avons mis en lumière que les rendements des nouveaux fonds ont un ratio de risque idiosyncratique sur risque total plus élevé. Les portefeuilles des fonds nouvellement lancés, sont typiquement moins diversifiés, contiennent un nombre moindre d'actifs et sont investis dans des actions moins liquides et à faible capitalisation.

Le deuxième essai propose de nouvelles mesures de performance pour les fonds mutuels nouvellement lancés. Conséquence de la spécificité de ces fonds, que nous avons montrée au premier chapitre de la thèse, cette partie propose de nouvelles mesures de performance et de risque qui permettent de mieux apprécier le potentiel d'un fonds. Afin, d'atteindre cet objectif nous utilisons les concepts d'économétrie Bayesienne pour 'améliorer' notre estimation de la performance. Afin d'affiner notre estimation de la performance, nous extrayons de l'information à partir d'autres fonds appartenant à la même famille ou au même style. Cette technique nous permet d'accroitre l'information dont nous disposons et d'améliorer ainsi notre évaluation du fonds. Les mesures que nous offrons sont plus efficientes que les mesures standards utilisées. Les résultats trouvés dans cette étude sont pertinents pour l'estimation de la performance de fonds et le choix d'investissement.

Le troisième essai aborde le phénomène de l'altération du risque des fonds mutuels entre le début et la fin de l'année sur un échantillon de 1233 fonds mutuels américains investis en actions. Nous vérifions si les fonds qui ont accusé une mauvaise performance en début d'année augmentent leur risque dans la seconde moitié de l'année. Utilisant un tableau de contingence, nous avons trouvé des résultats contrastés quant à l'existence du phénomène de changement de risque: les fonds perdants (gagnants) n'augmentent (diminuent) pas systématiquement leurs risques en seconde moitié d'année. De plus,

le fait d'ordonner les fonds sur la base de leur rendement souffre d'un biais à la hausse (à la baisse) pour le changement de risque si la relation entre le risque et le rendement est positive (négative). Si les fonds sont ordonnés selon des rendements orthogonaux par rapport au risque, les phénomènes de persistance et de changement de risque sont moins souvent observés. En effet, nous trouvons que 10% de corrélation additionnelle ente le risque et le rendement ajoute artificiellement 1% de plus dans les fréquences de changement de risque observé. D'autre part, le ratio du risque ajusté est plus grand pour les fonds qui ont une faible sensibilité flux-performance, un rendement élevé, un risque faible et des flux élevés. Les variables âge et taille des actifs du fonds sont négativement reliées au ratio du risque ajusté. Finalement, analysant les positions des fonds, nous n'avons pas trouvé que les fonds perdants (gagnants) augmentent (diminuent) significativement leur allocations dans les actifs risqués dans la deuxième moitié d'année. Les managers ne changent pas non plus d'une façon significative leurs pondérations actions/obligations.

Classification JEL: G11, G12, G14

Mots clés: nouveaux fonds mutuels, performance, estimation bayesienne, persistence, changement de risque

Abstract

This thesis comprises three essays that explore several empirical features related to the performance of mutual funds. The first two essays focus on the evaluation of the performance of new mutual funds, while the third one tackles the issue of tournament behavior among U.S. equity funds.

The first essay investigates the performance and the characteristics of mutual fund starts. A large number of new equity mutual funds has emerged over the past two decades (1990's and 2000's). We advocate that new funds present specific features compared with seasoned funds. The short track record of returns available to investors and the pressure to have a good start induce a particular risk-taking behavior among managers of new funds. We study the performance and portfolio characteristics of 828 newly launched U.S. equity mutual funds over the period 1991-2005. These fund starts initially earn, on average, higher excess returns and higher abnormal returns. Their risk-adjusted performance is also superior to existing funds. Furthermore, we provide evidence for short-term persistence among top performing fund starts, however, a substantial fraction of funds drop from the top to the bottom decile over two subsequent periods. Analyzing portfolio characteristics, we find that returns of fund starts exhibit higher ratios of unsystematic to total risk. Portfolios of new funds are typically also less diversified in terms of number of stocks and industry concentration, and are invested in smaller and less liquid stocks.

The second essay offers new measures of performance for newly launched funds. We have shown in the first essay that new funds have significantly different characteristics compared to seasoned funds particularly in term of risk taking behavior. Thereby, traditional measures of performance may fail to capture different features of portfolio management among new fund starts. Applying a Bayesian approach, we provide new

measures of performance and risk that take into account the shortage of data. More specifically, we incorporate prior information from fund family, fund style and fund industry to improve the estimation of the performance measures. The efficiency tests confirm the superiority of the combined-sample and the Bayesian estimator over the traditional measures. These results have many implications in assessing the performance of new funds.

The third essay tackles the question of risk tournaments among 1,233 active U.S. equity funds over the period 1991-2005. We verified whether poorly performing funds in the first part of the year increase their risk in the second half year to improve their final ranking. Using a contingency methodology, we reach mixed results related to the existence of tournament phenomenon: loser (winner) funds do not systematically increase (decrease) their risk in the second half year. Sorting on cumulative returns suffers from an upward (downward) tournament bias and downward (upward) inverse tournament bias if the correlation between risk and return is positive (negative). When we sort funds on an orthogonalized measure of cumulative returns, we observe less evidence of tournament and persistence as well. Moreover, we find that about 10% of additional correlation between risk and returns artificially adds 1% in tournament frequencies. Furthermore, we link risk adjusted ratio (RAR) to fund characteristics. We find that RAR is higher for funds that exhibit weak flow-performance dependence, high mean returns, low total risk and high inflows. Age and TNA are also negatively related to RAR. Finally analyzing holdings of funds, we do not find evidence that loser (winner) funds increase (decrease) the allocation in riskier stocks for the second half year.

JEL Classification: G11, G12, G14

KeyWords: mutual fund starts, new funds, performance, bayesian estimation,

combined-sample, persistence, fund tournament

A mes grands-parents

Mes parents

Mes frères et ma belle-soeur

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Contribution des Auteurs

Parmi les trois articles de la thèse, je suis co-auteur du premier article intitulé "Performance and Characteristics of mutual fund starts", avec Dr. Iwan Meier, et du troisième article, intitulé "Mutual fund tournaments", avec Dr. Iwan Meier. Tous les auteurs ont apporté une contribution égale.

Je suis seul responsable du deuxième article intitulé " Performance analysis of new mutual funds: a Bayesian approach "

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Chapter 1

Introduction

Cette thèse se compose de trois parties qui traitent différents aspects de la performance des fonds mutuels. Pour les deux premiers essais, nous nous concentrons sur les nouveaux fonds mutuels comme une classe d'actifs spécifique, alors que pour le troisième essai nous étudions le phénomène de changement de risque parmi les gestionnaires de fonds.

Un grand nombre de nouveaux fonds a émergé pendant la décennie passée. La valeur totale des actifs nets contrôlés par les fonds communs de placement dans le monde entier est passée de 9.6 trillions en 1998 à 17.8 trillions de 2005 et le nombre de fonds est passé de 50.266 à 56.863 durant la même période. Dans le premier essai, nous analysons la performance et les caractéristiques des fonds communs de placement américains qui sont principalement investis en actions. L'étude de nouveaux fonds par opposition aux fonds plus âgés offre des interrogations de recherche intéressantes. D'abord, comme les investisseurs disposent de moins d'informations sur les nouveaux fonds, ces derniers sont habituellement perçus comme un investissement plus risqué que les fonds déjà établis. Deuxièmement, les nouveaux fonds subissent une pression plus élevée pour atteindre une performance supérieure à la moyenne. En effet, une bonne performance au lancement du fonds est synonyme d'un accroissement des flux et donc d'une garantie de survie pour le fonds. Par contre, une mauvaise performance annuelle sur un historique de trois ans par exemple aura plus de conséquences qu'une mauvaise année sur un historique de dix ans. Troisièmement, l'interaction entre les nouveaux fonds et leurs familles respectives offre une autre dimension au problème de l'évaluation de la performance des nouveaux fonds. Avec un lien élevé entre les fonds nouvellement lancés et leur famille d'origine, il est difficile d'évaluer le potentiel intrinsèque des nouveaux fonds. Nous essayons dans la première partie de mettre en lumière ces aspects par une analyse profonde de la performance et des caractéristiques des nouveaux fonds mutuels. Nous mettons en évidence que les nouveaux fonds ont un meilleur rendement et attirent de ce fait des flux élevés comparativement à la taille de leurs actifs nets. Bien qu'un certain nombre d'articles ait abordé la question de la performance des fonds, seulement une attention limitée a été accordée à l'évaluation des nouveaux fonds (Blake et Timmerman, 1996). Khorana et Servaes (1996) ont également étudié les déterminants du lancement des fonds, alors que dans notre travail nous étudions les caractéristiques des fonds nouvellement lancés. Enfin, récemment avec la crise financière de 2008, la question de lancer de nouveaux produits sur le marché revient incontestablement comme un sujet important auprès de tous les gestionnaires de projets.

Dans la première partie nous avons mis en évidence la spécificité des nouveaux fonds et nous les avons comparés aux fonds établis sur le marché. Nous essayons dans le deuxième essai de remédier au problème d'asymétrie d'information en recourant à une approche bayésienne. La première source d'information pour un investisseur est la performance historique du fonds. Typiquement, les investisseurs ont une plus grande confiance pour les fonds avec des données historiques plus longues et les perçoivent comme moins risqués. La méthode bayésienne vise à rééquilibrer le point de vue de l'investisseur et à combler le déficit informationnel des nouveaux fonds. L'adéquation de l'approche bayésienne pour la performance des fonds communs de placement et en particulier pour les fonds avec un court historique a été défendue par Baks et al. (2001), et Pastor et Stambaugh (2002). Pourtant jusqu'ici, aucune étude n'a été spécifiquement consacrée à l'amélioration des mesures de performance des fonds nouvellement lancés. L'opinion qu'on a au sujet de la performance future des fonds peut être perçue comme une combinaison de deux éléments: un élément observé, et un élément à priori généralement pas directement observé. L'élément observé est la performance historique des fonds. L'élément non observé est toute information utile qui peut donner une idée sur le potentiel du fonds. L'élément à priori peut apporter un niveau d'information variable et peut être subjectif (image des fonds, des rumeurs) ou basé sur des données observées (famille de fonds, secteur, modèle, ou tout autre indice de référence). La combinaison de toute l'information (observée et non observée) donne la distribution postérieure de la performance. Offrir une mesure de performance adaptée aux fonds de courte durée est un vrai défi pour la littérature de fonds communs de placement et aura assurément des conséquences significatives sur l'industrie de fonds.

La troisième partie aborde la question du changement de risque entre le début et la fin de l'année parmi les fonds communs de placement. Est-ce que les gestionnaires qui ont mal (bien) performé en début d'année augmentent (diminuent) le risque de leurs fonds en seconde moitié d'année ? Cette question incorpore implicitement deux hypothèses: d'abord, les gestionnaires de fonds changent les positions de leur portefeuille conditionnellement à la performance réalisée. Deuxièmement, le classement relatif des fonds est un élément important pour les gestionnaires de fonds. Brown, Harlow et Starks (1996) sont les premiers à découvrir ce phénomène de tournament parmi des fonds mutuels aux États-Unis. Cependant, des études suivantes comme celle de (Busse,

2001) et plus récemment (Elton et autres 2006) trouvent une faible évidence de ce dit phénomène. Un deuxième groupe d'auteurs défend au contraire l'idée de l'existence d'un phénomène de persistance. Taylor (2003) montre qu'en présence de joueurs actifs de fonds communs, les gestionnaires qui ont gagné en première partie de l'année ont une plus grande incitation à prendre du risque. Récapitulant la littérature entière, les résultats portant sur le changement actif du risque des gestionnaires de fonds semblent être en contradiction. Nous essayons de réconcilier en partie les deux approches en contrôlant un biais potentiel découlant de l'estimation du risque au premier semestre. En effet, si nous orthogonalisons le critère de tri sur le risque observé en première moitié de l'année, nous observons moins d'évidence d'altération de risque. Une partie du tournament/ tournament inverse peut être artificiellement amplifiée par la corrélation observée entre les deux premiers moments des rendements dans le premier semestre. Néanmoins quelques questions demeurent non résolues : comment pourrions-nous expliquer la variation des résultats d'une année à une autre? Pourquoi certains fonds qui ont une gestion passive montrent aussi des changements de risque entre le début et la fin de l'année? Et en conclusion, pourquoi le changement de risque aurait lieu à une date donnée (le milieu de l'année) et ne serait pas une notion dynamique. Les fonds qui ont observé une mauvaise performance ne vont pas nécessairement attendre six mois pour changer leurs vues et leur stratégies.

Chapter 2

Performance and Characteristics of Mutual Fund Starts

2.1 Introduction

A large number of new equity mutual funds has emerged over the past two decades. Total net assets managed by domestic U.S. open-end equity funds increased from 239 billion at the end of 1990 to 6.9 trillion in 2007. Despite the slowdown of net inflows into equity funds after the downturn on stock markets in 2000, net inflows over this period total $2.3 trillion, which corresponds to 136 billion per year. The number of funds increased over the same time span from 1,191 to 4,767 and substantial dollar amounts flowed into recently launched funds[1]. An investor typically attempts to infer manager skill from past performance. However, this task is complicated in the case of fund starts as they provide, by definition, only a short track record of returns. For delegated portfolio management it is therefore important to learn whether there exist systematic patterns in risk-adjusted performance, risk taking, or portfolio characteristics after the inception of new funds. In this study we analyze the performance and characteristics, such as the ratio of unsystematic risk to total risk, diversification, and liquidity of the portfolio holdings of 828 equity fund starts over the period from 1991 to 2005.

[1] ICI Mutual Fund Factbook 2008: www.ici.org, "Data Tables"; "Section 1: U.S. Mutual Fund Totals"; Tables 3, 5 and 48.

Starting with the seminal work of Jensen (1968) a large literature has discussed the performance of mutual funds. However, relatively little attention has been paid to the performance evaluation of emerging funds over the first months after inception. One notable exception is Blake and Timmerman (1998) who study a large sample of U.K. open-end mutual funds. They find weak evidence for superior performance of new funds and report an average, risk-adjusted excess return of 0.8% over the first year. For U.K. data on mutual funds Cuthbertson et al. (2008) indirectly draw a similar conclusion. When excluding younger funds (less than three years old) the average alpha in their sample decreases slightly. A number of studies examine the relationship between fund age and performance in a multivariate regression framework. Ferreira et al. (2006) study a large sample of actively managed open-end equity funds in 19 countries and find evidence for a negative relation between fund age and abnormal performance, in particular for foreign and global funds. For a survivorship-bias controlled sample of 506 funds from five important European fund countries (United Kingdom, Germany, France, Netherlands, and Italy) Otten and Bams (2002) draw the same conclusion[2]. Similarly, Liang (1999) finds a negative relationship for a sample of hedge funds. Two studies on socially responsible investments (or ethical funds) report an underperformance of fund starts: Gregory et al. (1997) for 18 U.K. funds, and Bauer et al. (2002) using a database of 103 German, U.K. and U.S. ethical mutual funds[3]. We find that the mean fund return over the first year after inception, net of fees and in excess of the 1-month Treasury bill rate, exceeds the mean return over the subsequent year by 0.12% per month. When we estimate the risk-adjusted performance as the intercept

[2] Another strand of literature studies the impact of fund family affiliation. For example, Berzins (2006) analyzes institutional money managers and finds that the performance of a newly launched fund tends to fall into the same performance decile than the existing funds of the same family.

[3] Peterson et al. (2001) and Prather et al. (2004) report no significant difference in the performance of new and existing mutual funds.

of the Carhart (1997) 4- factor model, we report a decrease in the means over two non-overlapping 3 year windows after inception of 0.08% per month. Both results are significantly different from zero at the 5% level. Fund starts also outperform older funds on a risk-adjusted basis over the first 12 and 36 months after the launch date by 0.10% and 0.12% per month, respectively. When we look at unsystematic risk and estimates of factor loadings, we observe that fund starts are typically exposed to a higher fraction of unsystematic risk, are less sensitive to market risk, and load up on small stocks. We provide evidence that the observed decrease in excess returns and risk-adjusted performance is driven by changes in risk-taking and not a mere effect of diseconomies of scale.

Hendricks, Patel, and Zeckhauser (1993) triggered a series of studies on the performance persistence in mutual fund returns. They document that skilled managers persistently provide superior performance relative to their peers ("hot hands" phenomenon). Other studies, such as Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), and Gruber (1996) also associate the existence of persistence over one to three year horizons with manager skill. Grinblatt, Titman, and Wermers (1995) and Carhart (1997) contest these results. Carhart (1997) concludes that the short-term persistence in fund returns disappears after controlling for the momentum anomaly discussed in Jegadeesh and Titman (1993). More recently, Bollen and Busse (2004) measure returns over intervals much shorter than monthly and find that the persistence is statistically significant – although they question the economic significance. We document that fund starts, using monthly returns and including a momentum factor, exhibit some degree of persistence. However, a relatively high fraction of funds drop from the decile of top performing funds to the lowest decile over two subsequent 3-year windows, which indicates a high degree of risk-taking by fund starts. Another result of Carhart's (1997) study is that there exists more likely an "icy hands" phenomenon. We find only weak evidence of persistence among poorly performing fund starts.

Another contribution of our paper is the analysis of individual portfolio holdings of fund starts. For each fund in our sample we observe quarterly holdings and compute two measures of diversification: We count the number of different stock positions in the portfolio and compute the industry concentration index of Kacperczyk et al. (2005). To measure the liquidity of the reported portfolio we calculate for all individual stock positions the Amihud (2002) illiquidity ratio and aggregate using market capitalization weights. This enables us to draw conclusions regarding changes in the selection of stocks over time not only from estimated factor loadings but also directly from portfolio holdings. We find that fund starts typically hold a smaller number of stocks, hold more industry concentrated portfolios, invest more in small-cap stocks, and the stock positions tend to be less liquid[4].

Our results are consistent with several explanations:

(i) Berk and Green (2004) propose a model where managers have differential skills to generate positive excess returns. They assume that with increasing fund size future expected fund returns become competitive and no longer exceed a passive benchmark. In their model, rational investors infer manager skill from past performance and allocate money to funds with superior past performance. This behavior generates inflows to those funds and causes excess returns to deteriorate. These diseconomies of scale are consistent with small startup funds outperforming larger incumbent funds. A number of empirical studies such as Indro et al. (1999) and Chen et al. (2004) corroborate their

[4] The focus of Khorana and Servaes (1999), who study 1,163 emerging funds over the period 1979-1992 (including other fund classes than equity funds), is on the determinants of mutual fund starts. They conclude that generating additional fees is the driving factor for fund openings. Fund families that outperformed their peers, larger fund families, and those who added new funds in the recent past are more likely to create a new fund. Fund families also more likely add a new fund when the largest fund families open new funds in a given investment style category.

conjecture that excess performance decreases with size. Chen et al. (2004) attribute this negative relationship between size and performance to increased indirect costs of price impact when larger volumes are traded. This view is contested by Otten and Bams (2002) and Ferreira et al. (2006) who report a positive coefficient for the impact of size on abnormal performance (economies of scale).

(ii) Managers of emerging funds have a particularly high incentive to devote a lot of effort to the portfolio selection process as they build their career and reputation. In fact, the fund flow literature shows that top performing funds are disproportionally rewarded with high inflows, which in turn will likely have a positive impact on the fund manager's salary. Chevalier and Ellison (1999a) find that younger fund managers tend to outperform their older peers. They attribute some of the superior performance to a survivorship bias due to the higher likelihood of being fired for poor performance when you are a young manager with short tenure. To explain the residual superior performance by younger managers, the authors put forward effort and career concerns. On the other hand, one might argue that new funds have less favorable terms to execute trades, limited research resources, and that new fund managers may lack experience and are more likely to commit costly mistakes.

(iii) Prendergast and Stole (1996) suggest that young managers exaggerate their own opinion and take risk to signal high ability. With longer tenure managers become increasingly reluctant to take on risk. Our finding that fund starts are subject to a higher fraction of unsystematic risk is consistent with their argument. However, this decrease in the ratio of unsystematic to total risk differs from Chevalier and Ellison (1999b). Their results show that managers of young age are more likely to be replaced or demoted to a smaller fund if they do not deliver satisfying performance. They argue that this gives an incentive to young managers to avoid unsystematic risk and to herd. Our study, though, does not directly evaluate manager age (and education) but rather fund age. Moreover, our dataset with 828 fund starts (1,374 funds in total) over a 15 year period 1991-2005 is hardly comparable with their total of 1,320 annual observations on the two investment objective categories growth and growth and income over the period from 1993 to 1995. Most importantly, Chevalier and Ellison (1999b) define unsystematic risk as the fraction of the variance that cannot be explained by the market beta (Jensen's model) whereas in our analysis unsystematic risk is one minus the R-square from the Carhart 4-factor model.

(iv) Reuter (2006) shows that funds paying substantial commissions to lead underwriters benefit from larger allocations of underpriced IPOs. If fund families favor newly launched funds in an attempt to build a successful return history, attract fund inflows, and increase fee income, this would result in superior performance of young funds. Gaspar, Massa and Matos (2006) test whether fund complexes offer preferential treatment to young funds in IPO allocations but find no conclusive evidence.

(v) Malkiel (1995) discusses the issue of survivorship bias. He annotates that even after correcting for survivorship bias his dataset may still suffer from an incubation bias. Fund families often allocate seed money to a number of newly created portfolios ("incubator" funds). After these portfolios have established an initial track record the fund complex decides which ones of these incubator portfolios will be opened and advertized to the public. The return series of the portfolios that are terminated are typically not added to mutual fund databases because these portfolios were never assigned a ticker. Evans (2008) estimates that 39.4% of his sample compiled from the CRSP Survivor-Bias-Free Mutual Fund Database are incubated. Artega et al. (1998) provide another example of the existence of an incubation bias. Our findings that funds start out as less diversified portfolios, take sector bets, and carry more unsystematic risk are consistent with the existence of an incubation bias. If the strategy is successful and the fund is made publicly available, the fund further diversifies its portfolio and reduces unsystematic risk in an attempt to maintain a good track record and attain a favorable Sharpe ratio.

The remainder of the paper is organized as follows. Section 2 describes the sample. The performance of new funds is analyzed in Section 3. Section 4 examines the characteristics of fund starts and Section 5 concludes.

The remainder of the paper is organized as follows. Section 2 describes our sample. The performance of new funds is analyzed in Section 3. The characteristics of these new funds are documented in Section 4. Moreover, in Section 5, we do the link between Section 3 and Section 4 by analyzing the determinants of the performance and the flows of new mutual funds using their characteristics. In Section 6, we investigate whether funds starts have an impact on stock markets. Section 7 concludes.

2.2 Data

Morningstar provided quarterly portfolio holdings of U.S. domestic equity mutual funds going back to January 1991 and ending in December 2005. Monthly fund returns are retrieved from the Survivor-Bias-Free Mutual Fund Database compiled by the Center for Research in Security Prices (CRSP). We match the two databases and for each fund portfolio we retain the return series of the oldest share class. Zhao (2002) and Nanda et al. (2005) stress the importance to differentiate between the decision to start a new fund portfolio and the decision to introduce new share classes. We consider the first appearance of a new ICDI number, the primary and unique identifier in the CRSP mutual fund database, as a fund start. If a fund changes its name it will keep the ICDI number as long as it corresponds to essentially the same fund portfolio. The fund may also change its style orientation and/or fund manager and continue to be recorded under the same ICDI. The final sample comprises 1,374 U.S. domestic equity mutual funds and 828 fund starts over the period 1991-2005. Sixty-four fund starts stop operation during our sample period, 24 funds within three years. While the CRSP database is free of survivorship bias (but does not include holdings prior to 2003), the Morningstar database suffers from this bias to some extent (Blake et al. 2001). We include dead funds in our merged dataset, however, coverage may not be comprehensive.

All returns are net of fees and we subtract the 1-month Treasury bill rate as a proxy for the risk-free rate to compute excess returns. To assess the risk-adjusted performance we estimate the intercept (alpha) of the 4-factor model introduced by Carhart (1997). The returns on these four factors are downloaded from Kenneth French's website[5].

Fund characteristics are compiled from three sources: (i) Monthly total net assets under management (TNA), annual fees and turnover are from the CRSP mutual fund database, (ii) the general industry classification (GIC) for each stock held in the portfolio is from the Morningstar database, and (iii) and the size quantile rankings of stocks and the Amihud (2002) liquidity ratios are from Joel Hasbrouck's website[6]. For each fund portfolio we compute the industry concentration index of Kacperczyk et al. (2005), using the GICs of individual stock positions along with their portfolio weights, the average market capitalization rankings of reported stock positions, and the average illiquidity measure of Amihud (2002). Details on the computation of these measures follow in Section 4 where we discuss the characteristics of fund starts.

Table 1 is split into two panels. Panel A shows the style classification of the sample firms. For each style classification we tabulate number of funds, percentage of funds,

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[5]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french; Section "Data Library", "U.S. Research Returns Data". The website also details the portfolio formation methodology to construct these factor returns.

[6]http://pages.stern.nyu.edu/~jhasbrou; Section "Research and Working Papers".

and the market capitalization at the beginning and end of the sample period. When funds are sorted by these self-reported investment styles, it is evident that growth funds constitute almost one third of the sample (30.9%). Panel B summarizes the size of the fund families in our sample. We count a total of 388 fund family affiliations. Most families count of 2-5 funds. Only 26 families are represented with more than 11 equity funds. However, the sum of the TNA of the 26 largest families exceeds the market capitalization of all other 362 families, which underlines the domination of the mutual fund industry by large fund families.

[Table 1]

2.3 The Performance of Mutual Fund Starts

In this section we analyze the returns of fund starts. First, we study the evolution of cumulative monthly excess returns and cumulative abnormal returns over the first six years after inception. Second, we compare the performance over two subsequent time windows. Third, instead of comparing the fund to any benchmark, we compare the risk-adjusted performance over time to test whether the performance of fund starts declines. Fourth, we compare the risk-adjusted performance of each fund start to the average risk-adjusted performance of all incumbent funds over the same time period. Finally, we study whether the decrease in (risk-adjusted) performance we find is driven by diseconomies of scale or change in risk exposure.

2.3.1 Estimating the Performance of Mutual Fund Starts

For each fund we regress the fund returns net of fees, $\mathrm{R}_{i,t}$, and in excess of the 1-month Treasury bill rate, RF, on a constant and the returns of the standard four factors as in Carhart (1997). RMRF denotes the excess return of the CRSP value-weighted index over the 1 month T-bill rate, SMB and HML the returns on the factor-mimicking portfolios for small-cap minus large cap and high book-to-market minus low book-to-market as defined by Fama and French (1993), and MOM captures the momentum anomaly documented by Jegadeesh and Titman (1993).

$$R_{it} - RF_t = \alpha_i + \beta_{1i} Rmt_t + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} MOM_t + \xi_{it} \tag{2.1}$$

We choose a 2-year estimation period. Using the estimated coefficients of the four factors, $\beta_{j,i}$ for $j=$ 1 to 4, we compute monthly expected returns. The abnormal return is the difference between the observed fund return and the expected return.

$$AR_{i,t} = R_{i,t} - (\beta_{1i} Rmt_t + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} MOM_t) \tag{2.2}$$

We use the same factor loadings estimated over the first two years to compute abnormal returns for months $t = 1$ to $t = 24$. Thus, by construction the abnormal returns over the first two years are determined in-sample. The abnormal returns of months $t = 25$ to $t = 72$ are based on the factor loadings estimated from returns over months $t - 24$ to $t - 1$. Similar to Aggarwal and Jorion (2008), who study the performance of emerging hedge fund managers, we consider each fund start as an event. We take the first appearance of the fund in the CRSP Survivor-Bias-Free Mutual Fund Database as the inception date. Cumulative excess and cumulative abnormal returns over the first k months after inception are computed as:

$$CAR_{i,k} = \sum_{t=1}^{k} \frac{1}{N(t)} \sum_{i=1}^{N(t)} R^{*}_{i,t} \tag{2.3}$$

where $R^{*}_{i,t}$ is alternatively the excess return, $R_{it} - RF_t$, or the abnormal return, AR_{it} of fund i over month t after inception, and $N(t)$ the number of fund starts. The number of fund starts is slightly decreasing with k due to the 64 fund exits in our sample. Figure 1 shows the cumulative excess returns and cumulative abnormal returns of the 828 fund starts in our sample[7].

[Insert Figure 1]

Cumulative excess returns begin to flatten out after four years. The cumulative abnormal return over the first 12 months of 0.72% is similar to the 0.8% that Blake and Timmermann (1998) find for U.K. open-end mutual funds. Cumulative abnormal returns become negative after four years. Table 2 displays the mean abnormal returns for each of the first eight years after inception. Mean returns are significantly positive at the 10% level for the first two years and then become negative in the third year which is consistent with the drop in cumulative abnormal returns in Figure 1.

[Table 2]

To formally test whether the initial risk-adjusted performance is significantly larger we estimate the intercept of the Carhart 4 factor model (1) over two subsequent

[7]To check whether sample selection has an impact on our results on cumulative performance we also tested with an alternative sample where we select funds from the CRSP Survivors-Bias-Free Mutual Fund Database following the sample selection methodology of Pastor and Stambaugh (2002). The authors provide a list of ICDI (named ICDI_Obj in MFDB), Wiesenberger (Obj) and Strategic Insight (SI_obj) classifications to identify U.S. equity mutual funds in the CRSP mutual fund database and eliminate balanced funds, bond funds, flexible funds, international funds, mortgage-backed funds, money market funds, multi-manager funds and specialized funds. Multiple share classes have been introduced starting in the 1990s and we use a name algorithm to exclude share classes as in Nanda et al. (2005). Qualitatively, the results are similar: The performance declines rather quickly after the initial three years and the difference is significant over two subsequent 3 year windows.

36-months periods. This time window corresponds to the cutoff point that is also used e.g. by Cuthbertson et al. (2008). We trim the top and bottom 1% before reporting means and performing tests in means to mitigate the impact of potential outliers. The mean difference for alpha is 0.08% per month which is significantly different from zero at the 1% level ($t-statistic$ 2.73). To check the robustness of this result, we relax the assumption of a 36-months window and vary the length from k = 12 to 48 months. Figure 2 shows the mean difference (first minus second period) and the corresponding 95% confidence intervals. The mean difference, plotted as a solid line, gradually decreases as we increase the length of the time window. With an increasing window size the precision of the mean estimate increases and the confidence bounds narrow. The line graph illustrates that for windows shorter than 27 months, the hypothesis that the performance over the first period is superior to the performance over the subsequent window of equal length can no longer be rejected at the 5% level. This finding is in line with Figure 1. The positive abnormal returns of fund starts begin to deteriorate after three years. Therefore, if we compare two windows shorter than 27 months, the second window still includes many observations of the period of high abnormal returns and we find no significant difference in performance. Hence, testing the decline in fund performance crucially depends on the selected window size.

[Insert Figure 2]

2.3.2 Persistence in the Returns of Mutual Fund Starts

So far we have documented a decrease in initial fund performance. Next, we address the question whether some fund starts persistently outperform their peers. Following Carhart (1997) we construct a contingency table of the decile rankings over two subsequent intervals. We rank the fund starts into deciles over an initial and subsequent time window based on their risk-adjusted performance. Then, we count the frequencies that a fund ends up in one of the deciles over the second period conditional on its ranking over the first period. This exercise is different from Carhart (1997) in that we sort funds into deciles based on event time. Instead of forming performance deciles over e.g. years 1991 and 1992 (calendar time), we construct the deciles over each of the two years after inception (event time).

Figure 3 illustrates the frequencies for 1 year (Panel A) and 3 year (Panel B) windows. The corner bar lined up with decile 10 for the initial period and decile 10 for the subsequent period represents the number of funds whose performance persistently ranks among the top 10 percent over both intervals. Both graphs illustrate the existence of short-term persistence among top performing funds ("hot hands"). There is only weak evidence for persistence among poorly performing fund starts ("icy hands"). The general pattern for different window sizes is fairly robust. The most important observation is a decrease of the persistent top performers when we move from a 1 year to a 3 year window. Coupled with the substantial fraction of funds that drop from the top decile 10 to the bottom decile 1 these findings indicate that some funds earn a high alpha over the initial period due to luck or risk taking and not necessarily due to manager skill.

[Insert Figure 3]

2.3.3 The Performance of New versus Old Funds

We proceed by testing whether fund starts outperform existing funds over the first three years after inception. As before, we focus on alpha estimates from Carhart (1997) 4 factor regressions. The difference in means of 0.15% per month is statistically significant at the 1% level ($t - statistic$ 2.77). Similar to Section 3.1 we check the robustness of this result and change the size of the time window after inception. Figure 4 plots the difference in means between alphas of new funds minus alphas of existing funds. The results are very robust to the selection of the window length and the differences start to decline beyond 48 months.

[Insert Figure 4]

In the introduction we discussed the literature on the performance of young funds. Blake and Timmermann (1998) plot the cumulative abnormal return of fund starts. In addition, two alternative methodologies were proposed to analyze the relationship between fund age and performance. Otten and Bams (2002) run a panel regression of risk-adjusted performance on fund age (in addition to assets under management and expense ratio) to study the performance of 506 funds from five European countries. However, this linear relationship between fund alphas and fund age is too restrictive. While it appears plausible that new funds exhibit superior performance initially, it is not clear why a 30-year old fund should perform worse compared to a 20-year old fund. This relationship between fund age and performance is not expected to be linear for all fund ages. The second approach by Huij and Verbeek (2007) separates funds into two groups. One group contains all fund starts (defined as funds with an inception date less than five years ago) and the remainder forms the second group. The authors then compare the risk-adjusted performance of the two groups. This approach provides a snapshot for the given sample period and fund returns of new and existing funds are not evaluated over the same time span as new funds will be introduced throughout the sample period. We estimate the alpha of a given fund start over a specific period. To illustrate the evolution over time we select three periods: the first year, years 2 and 3, and years 4 and 5. Over the same calendar time window as the fund start, we then compute the alphas of all existing funds and sort them into deciles. Finally, we assign the fund start to one of the deciles formed by the existing funds. We repeat these steps for all 828 fund starts in our sample. This nonparametric ranking methodology is not influenced by outliers and avoids the criticisms raised above. The bar chart in Figure 5 shows the frequencies of the decile rankings of new funds among existing funds.

[Insert Figure 5]

The proportion of new funds is higher among top performing deciles (especially decile 10) over the first 12 months, and to some smaller degree during the period 12-36 months. Overall, the histogram shows a U-shaped pattern for the first year. Fund starts are not only more frequently ranked among the top performing funds (decile 10) but also among the worst performing funds (decile 1). A $\varkappa^2$-test rejects the null hypothesis that all the proportions are equal for the first 12 months ($\varkappa^2$-statistic 49.93) and the period 12-36 months (29.10) at the 1% level. However, the null hypothesis of equality cannot be rejected over the period 36-60 months (p-value of 0.24). Hence, while funds initially are more prominent among top winners and, to some lesser extent, bottom losers, the effect fades away after five years.

2.3.4 What Return Characteristics Can Explain the Pattern?

We further examine whether this U-shape pattern in Figure 5 is explained by risk taking of young funds. We use the loadings on the four factors of the Carhart (1997) model and one minus the R-square from the 4 factor regression to capture the fraction of unsystematic risk relative to total risk. Panel A of Table 3 reports means return and risk characteristics for each of the first eight years after inception. The top part of Panel B tabulates the differences in means for 12-months and 36-months windows and tests for significant differences. The lower part of Panel B tests for differences in means between fund starts and existing funds over the first 12 and 36 months after inception. To avoid distortions by outliers we trim again the top and bottom 1% of the observations when reporting means and testing whether the means are drawn from the same population.

[Table 3]

The exposure to market risk, quantified by the average coefficient of RMRF, increases gradually over time (with the exception of year 2). The loadings on SMB decrease while those on HML increase over time and change signs. Overall, the explanatory power of the 4-factor model increases. There is no consensus in the literature on the exposure of mutual funds to small/large and value/growth stocks. Gruber (1996) and Carhart (1997) argue that funds tend to invest more often in small growth stocks, whereas Falkenstein (1996) documents a preference for large value stocks.

The top part of Panel B in Table 3 tests whether these changes over time are statistically significant. We repeat the comparison of two subsequent windows after inception with window lengths of 12 and 36 months. Excess returns are significantly different (0.15% per month) between subsequent 36-months windows. As discussed in Section 3.1, for fund starts the decline in alpha becomes significant at the 5% level beyond a time window with a length of 27 months. The difference in the mean loadings over two subsequent 36-months windows significantly increases for RMRF (at the 10% level) and HML (at the 1% level). The difference for SMB is positive, indicating that fund starts invest more in small stocks, but not significant. The difference in HML indicates that in the longer run young funds increase their investments in high book-to-market stocks. There is no evident pattern in the exposure to the momentum factor (MOM). The increase in R-square means that a higher percentage of the variation in mutual fund returns is explained by the four factors, corresponding to a decrease in unsystematic risk.

The bottom part of Panel B compares the means of fund starts with the means of existing funds. We check for robustness by comparing means over the first 12 and 36 months after inception. New funds have somewhat less market risk. In this comparison, the difference in SMB is significant (at the 1% level) at both horizons. Coupled with the positive but insignificant difference for SMB in the previous analysis this reflects the slow but gradual decrease in the exposure to small cap stocks. Again, the mean coefficient for HML is lower for fund starts and also the exposure to RMRF slightly increases over time. When comparing the R-square to existing funds the difference is statistically different at the 1% level for the 12 month horizon and at the 10% level for 36 months which corroborates our finding that the fraction of unsystematic to total risk decreases after inception.

Next, we apply again the methodology that we introduced in the previous section and sort new funds into the deciles formed by old funds based on these return and risk measures. Table 4 reports the frequencies of the decile rankings. $\varkappa^2$-statistics along with the p-values for testing the null hypothesis of equality of the proportions are added at the bottom of the table.

[Table 4]

2.3.5 Does Alpha Decrease Due to Fund Inflows?

In their model with rational investors Berk and Green (2004) illustrate how fund performance is competed away by new funds flowing to recently successful managers. The predictions of their model reproduce two empirical results we find; a decrease in alpha and the lack of performance persistence for most funds – even though it would not explain why the most successful funds in the top decile exhibit some degree of performance persistence. In the previous section we suggest that changes in risk-taking are associated with the decrease in excess performance of fund starts. The following panel regression analysis attempts to differentiate whether the decrease in performance is an effect of inflows and/or due to systematic changes in the risk exposure of new funds. We follow a recent methodology proposed by Amihud and Goyenko (2008) that essentially regresses alpha from the Carhart 4-factor model on size, the R-square from the 4 factor model, and control variables such as turnover, expenses, and fund age. They find that R square is negatively related to alpha. This is consistent with our results that young funds have higher alphas and higher degrees of unsystematic risk relative to total risk (lower R-squares).

We run panel regressions with fund fixed effects and year dummies to explore the impact of fund flows, fund age, and unsystematic risk on alpha. Fund flows are measured as a percentage of TNA (see Section 4.1 for more details). Our focus is on the behavior of fund starts and we therefore define an age dummy variable that takes zero for funds up to three years and one if the fund is older than three years. As in Amihud and Goyenko (2008) we use a logistic transform of the R squares from the Carhart 4-factor regressions to proxy for the ratio of unsystematic to total risk. This transformation is necessary as these R-squares are clustered around 0.90 and the transformation produces the preferred symmetric distribution.

$$TR^2 = \log\left(\frac{\sqrt[2]{R^2}}{1-\sqrt[2]{R^2}}\right) \tag{2.4}$$

When regressing alternatively alpha on one-year lagged fund flows or the age dummy variable both coefficients are negative but only significantly negative in the case of age. Table 5, models (1) and (2), presents the results. Assuming that the negative effect of fund size on alpha, or the negative impact of large inflows, is not linear in size, we include in the fund flow regression (3) not only size, measured by the logarithm of total net assets (TNA), but also the square of it. Indeed, as in Amihud and Goyenko (2008), the coefficient for $\log(\text{TNA})^2$ is positive which mitigates the negative relation with alpha for the largest funds. TNA and flows simultaneously are both negative and significant at the 5% level.

[Table 5]

Next, we compare the effect of flows and the age dummy in model (4). Both coefficients remain negative as in the individual regressions (1) and (2). The interaction term between age and flows does not add any explanatory power. We avoid including TNA in the estimation as TNA and age are highly correlated (Spearman rank order correlation of 0.35). Specification (5) shows that part of the age dummy proxies for the higher unsystematic risk of young funds. Amihud and Goyenko (2008) document that higher TR^2 has a negative predictive effect on alpha. Our previous results show that young funds are subject to higher unsystematic risk and thus lower TR^2. To check whether our finding that both, flows and the age dummy, are negatively related to alpha we include control variables for expenses, turnover, diversification and liquidity. We discuss these variables in more detail in the next section. The only control variables that show up significantly are expenses and average market capitalization of stock positions (size). Highly actively managed funds typically charge higher fees and have low R-squares in a Carhart 4-factor regression (low TR^2). Thus, the positive coefficient for expenses is likely related to the effect of unsystematic risk on alpha.

In summary, we find that flows have a negative and young fund age a positive impact on fund performance. Part of the young age effect may be attributed to their lower R-squares in the Carhart 4-factor regressions.

2.4 Characteristics of Mutual Fund Starts

In this section we examine the portfolio characteristics of new funds: Total net asset values (TNA), fund flows, management fees, turnover, number of stocks in reported portfolios, industry concentration, and illiquidity ratio. So far, we have shown that new funds initially outperform existing funds and from exploring these characteristics we gain further insight on the main determinants of this superior performance. Table 6 shows descriptive statistics of the characteristics for the full sample. The increase in TNA reflects the growth in the mutual fund industry. For the other variables we observe no particular trend over the period 1991-2005[8].

[Table 6]

2.4.1 Variable Definitions and Hypotheses

Successful fund starts typically receive large inflows relative to their assets under management. This facilitates shifting portfolio allocations as these funds do not need to sell off positions to substantially change the portfolio composition. Chen et al. (2004) argue that larger fund entities additionally suffer from indirect costs of price impact as they need to execute larger trades. Therefore, we expect to find economically relevant changes for fund starts over the first few years after inception.

We measure monthly fund flow as a percentage of fund size, where TNA is total net asset under management at time t and R_t the fund return from month $t-1$ to t.

$$Flows_t = \frac{TNA_t - TNA_{t-1}(1+R_t)}{TNA_{t-1}} \tag{2.5}$$

[8]When we consider the trend starting in 1962, then average fees have increased over time.

As a new fund enters the market, its size is typically relatively small compared to existing funds. Given the favorable performance we documented previously, we expect that fund starts will succeed in attracting higher than average fund inflows.

Next, we define the following holdings-based fund characteristics: the industry concentration index (ICI) of Kacperczyk et al. (2005), the average size quantile rankings of stock positions, and the Amihud (2002) illiquidity ratio. Similar to the Herfindahl-Hirschman index, ICI quantifies the degree of diversification across j = 10 broadly defined industries, where wj,t is the weight of the reported mutual fund holdings in industry j at time t.

$$ICI_t = \sum_{j=1}^{10} (\omega_{j,t})^2 \tag{2.6}$$

By construction, ICI varies between 0.1 (perfect diversification) and 1.0 (the portfolio is fully invested in one industry). Thus, higher values of ICI indicate a lower degree of diversification. Another proxy for portfolio diversification is the number of different stock positions. In an attempt to outperform their peers it appears plausible that new funds will invest in a less diversified portfolio and take bets on individual stocks or sectors. We therefore expect portfolios of new funds to have a smaller number of stocks and a higher concentration in a few industries. This view is also consistent with the higher total and unsystematic risk we documented in the previous section. Furthermore, failure of the timing of sector bets or stock picks could help to explain the lack of long-term persistence in the return pattern of new funds. In fact, the literature does not provide much evidence of market timing skills of fund managers. An exception is Bollen and Busse (2001) who find some timing ability in the very short run. Shawky and Smith (2005) discuss the tradeoff to decide on the optimal number of stocks from the perspective of a mutual fund. On one hand, the diversification argument encourages managers to increase the number of stocks in their portfolio. On the other hand, improving analyst coverage favors a smaller number of stocks. Fund starts may have limited research resources and focus on covering fewer stocks or industries.

The estimated coefficients of the Carhart (1997) 4 factor regressions may not fully capture the premium earned by small, illiquid stocks due to estimation errors. To corroborate our previous result that fund starts have a higher exposure to small stocks we study the portfolio composition of new and incumbent funds using the average size quantile rankings of stock positions, and the Amihud (2002) illiquidity ratio. Hasbrouck (2006) sorts all stocks in CRSP into 20 quantiles (where the stocks in quantile 1 are micro-cap and in quantile 20 stocks issued by the largest firms). We assess the value-weighted average of all stock positions in the reported portfolio. On average, we succeed to match 94.1% of the holdings. The Amihud ratio measures the impact of dollar volume on returns.

$$IR_{it} = \frac{|R_{it}|}{T_{it} * P_{it}} \tag{2.7}$$

where $R_{i,t}$ is the daily return on stock i from t − 1 to t, $T_{i,t}$ the number of stocks traded over the same day, and $P_{i,t}$ the stock price at the end of the day. We use aggregated and annualized illiquidity ratios and compute a value-weighted average over all stock positions in the quarterly holdings.

2.4.2 Persistence in Fund Characteristics

First, we examine whether managers of fund starts systematically adjust the portfolio characteristics over time. Figure 6 shows the changes in average characteristics over the first five years after inception. Average TNA and fees exhibit a smooth upward trend. Fund flows as a percentage of TNA decay a few months after inception. Turnover decreases with fund age. Given the growth in assets under management the absolute turnover in dollars may still increase but the annual turnover as a percentage of TNA decreases. The number of stocks increases along with a decrease in ICI over time. Thus, funds become more diversified which is consistent with the reduction in unsystematic risk we observed in Section 3.4. The last two plots at the bottom of Figure 6 support our earlier finding that young funds initially exhibit larger coefficient estimates for the factor small-cap minus large-cap (SMB). The average size quantile ranking of all stock positions in the reported portfolios is initially lower. In line with this finding, managers allocate a larger fraction of their assets to illiquid stocks, i.e. the average Amihud (2002) illiquidity ratio is higher.

[Figure 6]

2.4.3 Differences in Characteristics of New versus Old Funds

In order to test whether these changes in the fund characteristics are significant, we analyze the changes over two subsequent 3 year windows. Table 7 reports the results. Rows 2 and 3 show the differences in mean characteristics over two subsequent 3 year periods (along with t-statistics in brackets) and the last two rows the differences between fund starts and existing funds over the first three years after inception. Not surprisingly, the size of new funds is smaller and they attract higher percentage inflows (significant at the 5% level). Fees are also significantly higher, however, economically hardly relevant and more an artifact of the low dispersions in fees. Fund portfolios of young funds are typically less diversified. However, the average number over three years does not exceed the number of stocks held by incumbent funds. The reason is that fund starts adjust their low number of stocks over a relatively short period and the difference over a 3-year period does not capture this effect. Similarly, the major decrease in ICI and the illiquidity ratio occurs over the first three years (as Figure 6 illustrates). When we compare the difference over the first year only (not reported here) the difference is significant. New funds are also more actively managed than existing funds (turnover is statistically significantly higher).

[Table 7]

As a final step, we apply our ranking methodology outlined in Section 3.4. We take the average fund characteristic of each fund start over the first three years of existence and compare it to the cross-section of all existing funds over the same time period. We do this by sorting existing funds over the same three years into deciles based on a given characteristic and determine the rank of the decile to which the fund start belongs to. Table 8 reports the frequencies of the decile rankings along with a $\varkappa^2$-statistic for an equality test of these frequencies across all deciles. Most fund starts rank in the lower TNA deciles and only three are classified in the top decile within three years. However, most emerging funds grow quickly in relative terms. Management fees tend to be above the median of old funds and young funds are also more prominent in the top two deciles for turnover. The majority of new funds hold a smaller number of stocks and the stock positions tend to be less liquid. The evidence for industry concentration is mixed.

[Table 8]

2.5 Conclusions

We study the returns and matched portfolio holdings of U.S. domestic equity mutual fund starts over the period from 1991 to 2005. In particular, we investigate how performance and risk characteristics of fund starts change over the first years after inception. Our results show that, on average, new U.S. equity mutual funds outperform their peers by 0.15% per month over the first three years. However, cumulative abnormal returns of fund starts decline after the initial three years. This decline in performance cannot be explained by diseconomies of scale alone as these funds mature and grow in size. We find distinct patterns in superior risk-adjusted performance estimated using Carhart's (1997) 4 factor model. There is some performance persistence among top performing fund starts. However, a relatively large number of top performing funds over the first three years also drop directly to the bottom decile rankings over the next 3-year period. These results suggest that the initially favorable performance is to some extent due to risk taking and not necessarily superior manager skill. Scrutinizing the returns further confirms that fund starts exhibit higher unsystematic risk that cannot be explained by the risk exposure to the four factors of the Carhart model. Active management in the form of sector bets, rotation in factor loadings, and holding undiversified portfolios reduces the R-squares from these 4 factor regressions. Based on factor loadings and characteristics of portfolio holdings we find that fund starts invest more actively in small cap stocks and hold less diversified portfolios. They gradually increase their exposure to market risk and reduce unsystematic risk relative to total risk.

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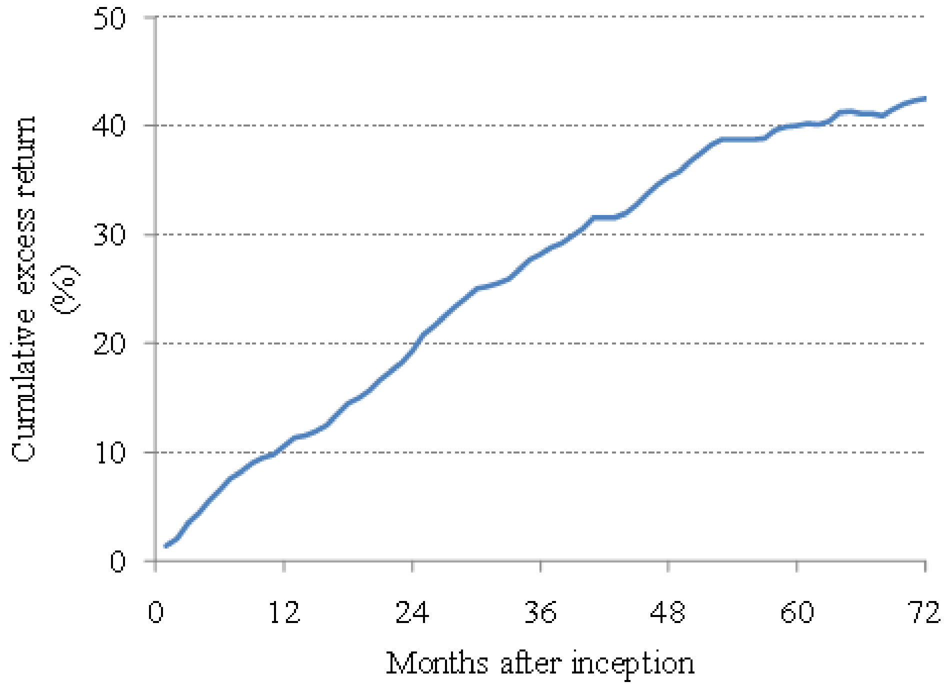
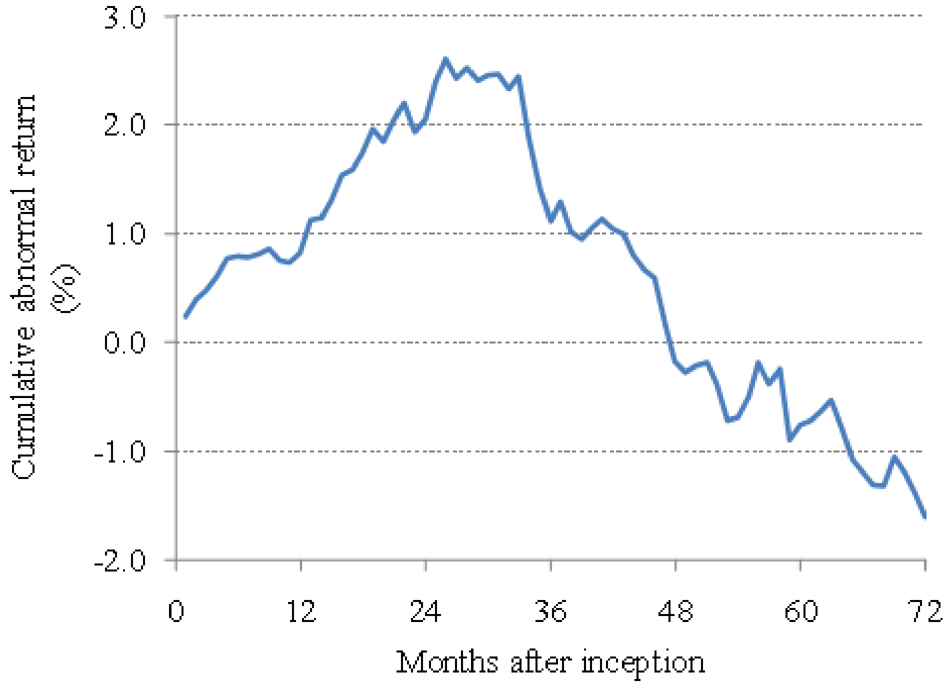
2.6 Appendix

Figure 2-1: **Cumulative excess returns and cumulative abnormal returns of fund starts.**



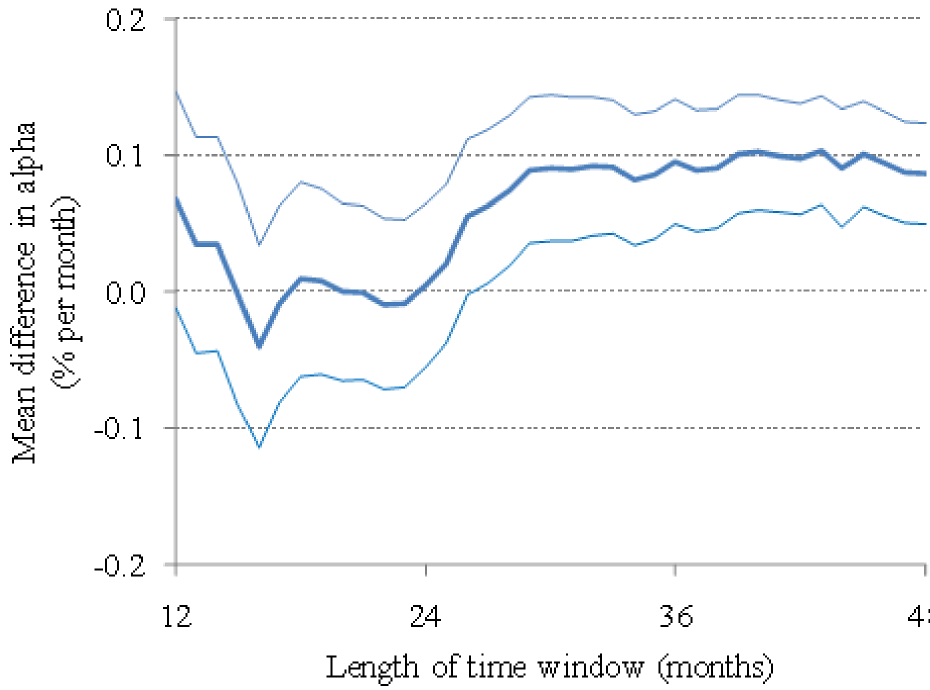
Panel A: Cumulative excess return.

Panel B: Cumulative abnormal return.



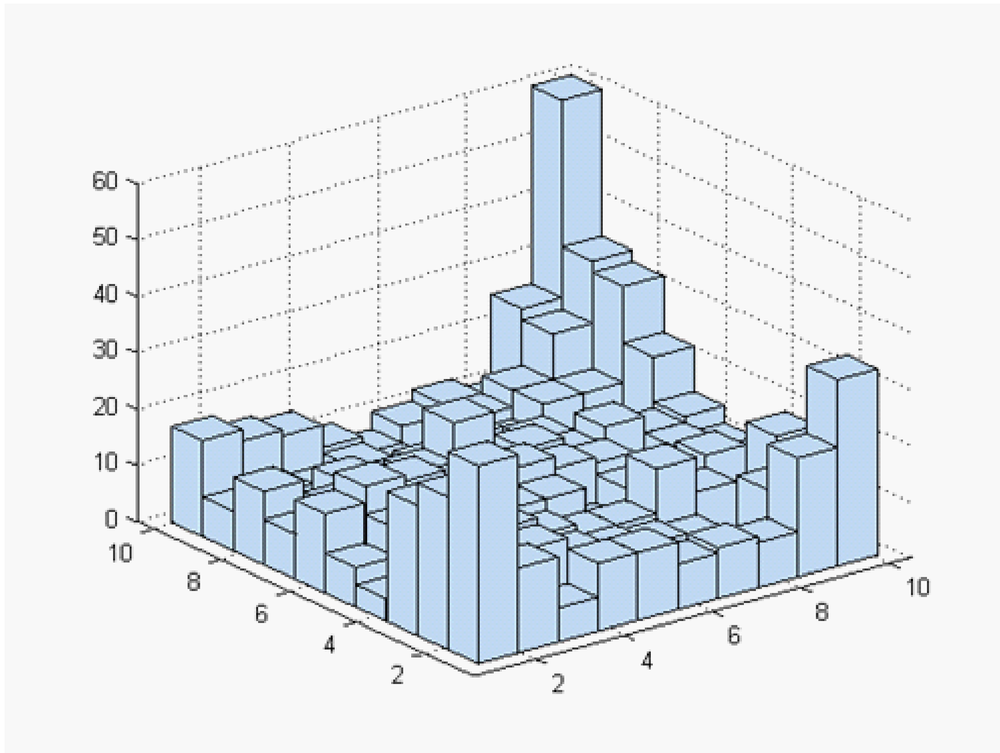
The graphs show the cumulative average excess return (Panel A) and cumulative average abnormal return (Panel B) of fund starts over the first six years. Excess returns equal fund returns net of management fees minus the 1-month Treasury bill rate. For each fund we estimate the coefficients of a Carhart 4 factor regression over a 2-year window. Abnormal returns are computed as net fund return minus expected return, where the expected return is the sum of the returns on the four factors multiplied by the coefficient estimates. Monthly averages are equally-weighted portfolio returns of all fund starts aligned by inception date. The sample covers 828 fund starts over the period 1991-2005.

Figure 2-2: **The difference in the risk-adjusted performance over two subsequent non-overlapping time windows of increasing length.**



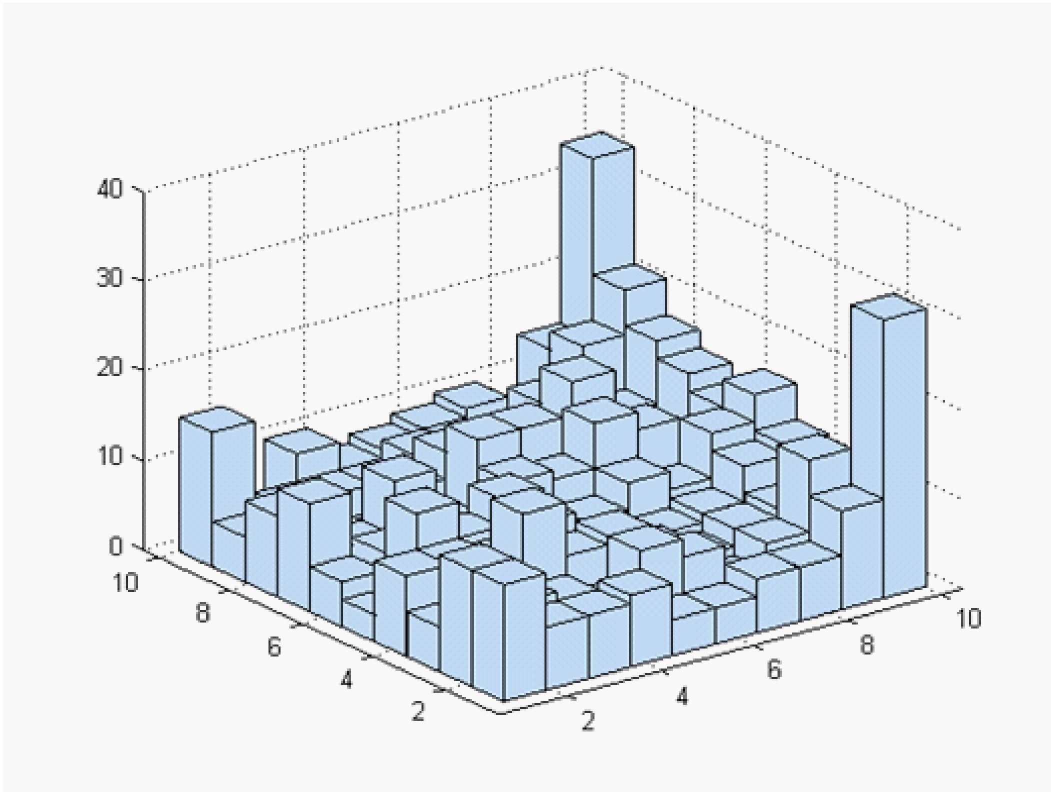
The graph shows the difference in the mean risk-adjusted performance over two subsequent, non-overlapping time windows after inception (mean over the first interval minus mean over the second interval). We vary the window lengths from k = 12 to 48 months. Risk-adjusted performance is measured by the alpha from the Carhart 4 factor model and reported in % per month. The thin lines indicate the upper and lower bounds of the 95% confidence interval. The sample covers 828 fund starts over the period 1991-2005.

Figure 2-3: **Performance persistence of fund starts**



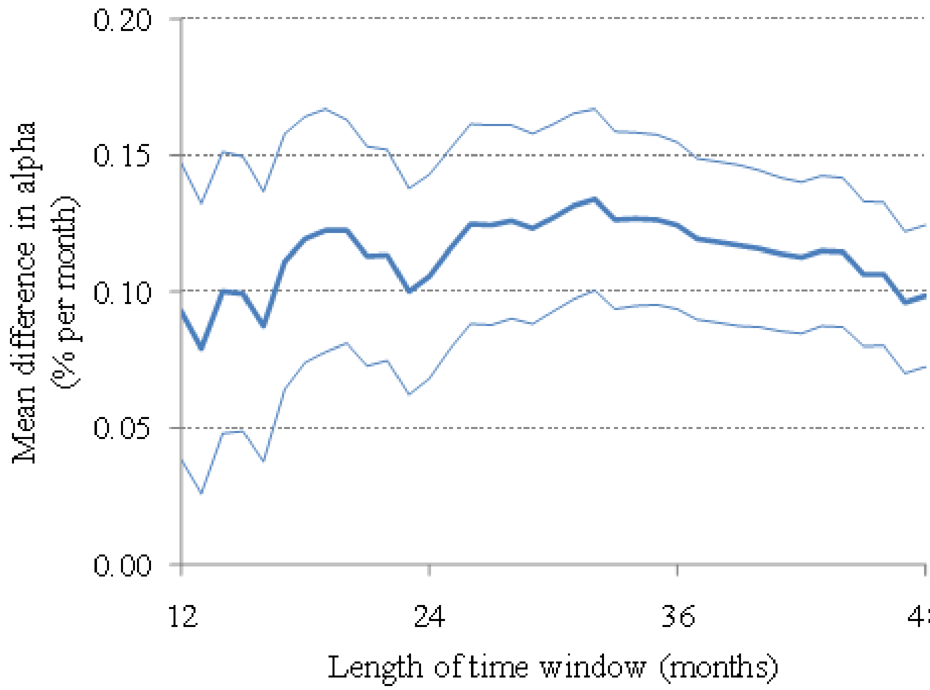
Panel A: Transition frequencies for decile rankings over years 1 and 2.

Panel B: Transition frequencies for decile rankings over years 1-3 and 4-6.



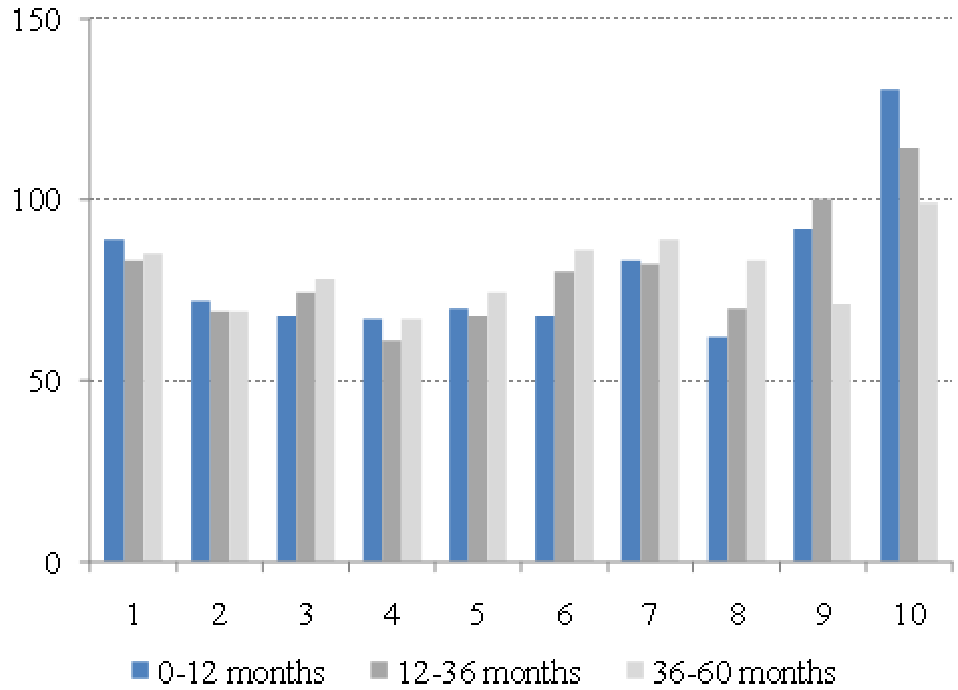
The 828 fund starts over the period 1991-2005 are ranked into deciles based on their average risk-adjusted performance. The risk-adjusted performance is measured by the alpha from the Carhart 4 factor model. The bar chart plots the transition frequencies f(l,m) that a fund with an initial decile rank l over the first period (initial rank) is sorted into decile m over the subsequent period (subsequent ranking). Panel A shows the conditional frequencies for a window length of one year, and Panel B the results for a 3-year window. Decile 1 comprises the funds with the lowest risk-adjusted performance and decile 10 the top performing funds.

Figure 2-4: **The difference in the risk-adjusted performance of fund starts vs. existing funds for an increasing time windows after inception.**



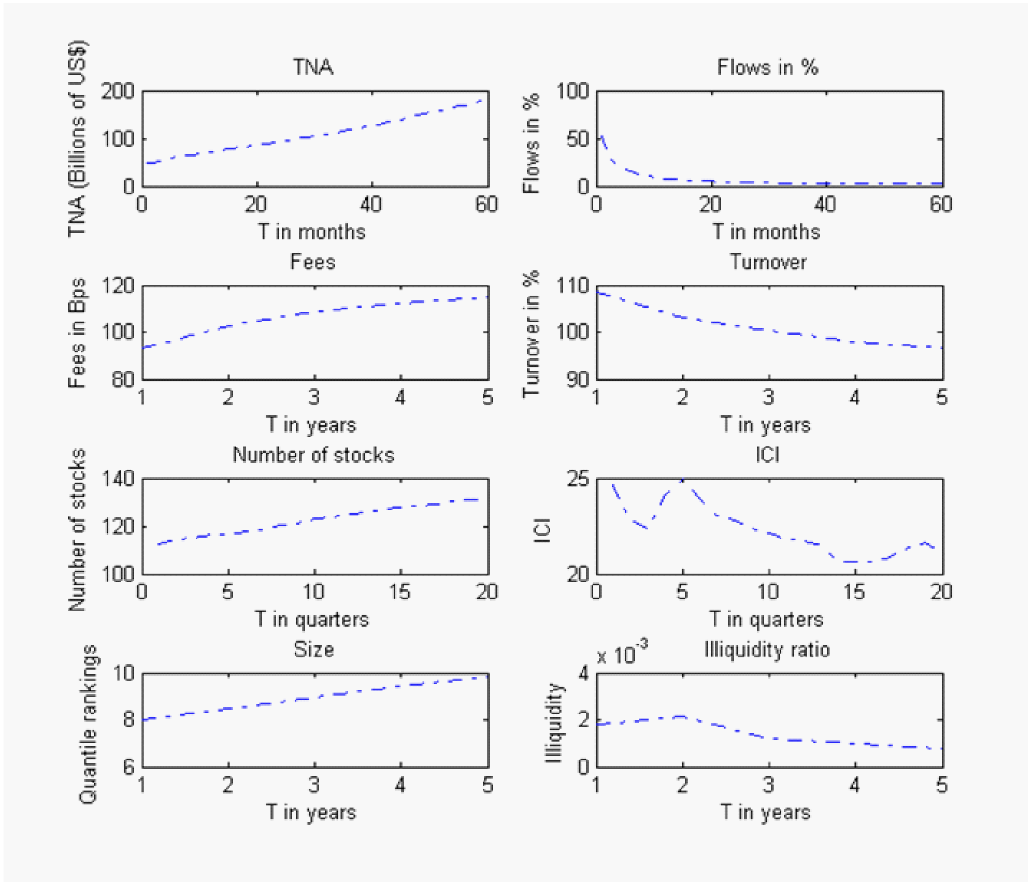
After each fund start we estimate the alpha of the Carhart 4-factor model over the first k months and subtract the mean alpha of all existing funds over the same time span. The bold line plots the mean difference between the alphas and the thin lines indicate the upper and lower bounds of the 95% confidence interval for time windows from k = 12 to 48 months. The sample includes 1,374 funds and 828 fund starts over the period 1991-2005.

Figure 2-5: **Histogram of the rankings of fund starts among the deciles of existing funds.**



For a fund start we estimate the alpha of the Carhart 4 factor model for the first year, years 2 and 3, and years 4 and 5. Next, we sort existing funds into deciles within each of the same three time spans and assign the fund start to one of the deciles in each period. We repeat this procedure for all 828 fund starts in the sample of 1,374 funds from 1991 to 2005. The bar chart illustrates the frequencies of the rankings over the three time windows after inception. Decile 1 comprises the funds with the lowest risk-adjusted performance and decile 10 the top performing funds.

Figure 2-6: **Persistence in characteristics of fund starts.**



We report the development of the average characteristics of fund starts over the first five years after inception. Total net assets (TNA) and fund flows (as a % of TNA) are available monthly. Fees and turnover are annual. Number of stocks in the fund portfolio, the Kacperczyk et al. (2005) industry concentration (ICI), the average size quantile rankings of all stock positions (from 1 for micro-cap to 20 for giant-cap), and the average Amihud (2002) illiquidity ratio are computed from quarterly holdings.

Table 2.1: Style classification and fund family affiliations.

Panel A reports the number of funds, the percentage of funds, and total net assets under management (TNA) sorted by self-declared investment style. Panel B reports the number of fund families for each category of family size (number of portfolios) and the TNA at the beginning and end of the sample period. The sample covers 1,374 U.S. equity mutual funds over the period 1991-2005.

Panel A: Style classifications.

Type of the fund	Number of funds	Percentage	TNA(in millions of US$) 1970	1980	1991	2005
Small Company Growth	248	18.05%	354.9	810.1	6,530.3	214,772.0
Other Aggressive Growth	195	14.19%	1,964.3	1,757.9	11,974.1	153,412.3
Growth	424	30.86%	7,592.1	6,418.3	63,544.5	676,040.0
Income	48	3.49%	3,599.4	2,785.6	21,314.8	110,621.4
Growth and Income	284	20.67%	14,941.5	13,079.0	64,155.3	719,644.4
Sector Funds	170	12.37%	514.9	491.4	9,613.7	102 947.1
Not Specified	5	0.36%	0	0	1,269.4	134.2
Total	1374	100.00%	28,967.3	25,342.6	178,402.3	1,977,571.4

Panel B: Fund family characteristics.

Number of Portfolios	Number of families	TNA(in millions of US$) 1991	2005
1	171	4,313	111,675
2-5	153	21,488	258,008
6-10	38	43,350	459,468
11-50	25	80,818	732,084
>50	1	28,431	416,333
Total	388	178,402	1,977,571

Table 2.2: Annualized abnormal returns after inception.

Annualized average monthly abnormal returns are presented for the first eight years after inception and expressed in percentage per year. For each fund we estimate the coefficients of a Carhart 4 factor regression. Abnormal returns are computed as net fund return minus expected return, where the expected return is the sum of the returns on the four factors multiplied by the coefficient estimates. ** and * indicate significance at the 5% and 10% level, respectively.

# of years after inception	Mean	t-statistic
1	0.63*	1.81
2	0.72**	2.08
3	-0.40	-0.69
4	-0.25	-1.80
5	-0.72	-0.51
6	-0.32	-1.18
7	-0.44	-0.94
8	-0.95**	-3.41

Table 2.3: Tests of differences in the performance of fund starts over time and between fund starts and existing funds.

Panel A tabulates average monthly excess returns and average coefficient estimates from the Carhart 4-factor model for each of the first eight years after inception. Excess returns are fund returns net of management fees minus the 1-month Treasury bill rate. α is the intercept of the Carhart 4 factor regression, RMRF is the exposure to the CRSP value-weighted market index minus the 1-month T-bill rate, SMB the small-cap minus big-cap factor, HML the high minus low book-to-market factor, and MOM the 1 year momentum factor. All means are in percentages per month and the top and bottom 1% of the differences are trimmed. The top part of Panel B tests for differences in means between first minus the second period. The period length is alternatively 12 or 36 months. The bottom part of Panel B test for differences between fund starts and existing funds over the first 12 and 36 months after inception. The values in brackets show the t-statistic for a two-sided t-test on the equality of the means. ***, ** and * indicates significance at the 1%, 5% and 10% level respectively. The sample period is from 1991 to 2005

Panel A: Monthly mean excess returns, coefficient estimates, and R^2 over time.

	Carhart (1997) 4-factor model							
# of years after inception	Excess return	α	RMRF	SMB	HML	MOM	R^2	# of obs.
1	0.87	0.04	93.28	28.68	-3.42	5.95	84.92	828
2	0.75	-0.02	96.11	26.64	-3.78	5.32	86.71	824
3	0.97	0.12	94.59	25.44	-2.32	2.13	86.69	820
4	0.81	-0.02	95.39	25.45	4.10	4.86	87.30	816
5	0.64	-0.09	97.94	27.20	5.98	3.71	88.44	784
6	0.56	-0.02	97.21	24.59	8.65	4.37	88.83	735
7	0.45	-0.04	96.95	23.20	8.31	3.83	88.15	678
8	0.26	-0.05	97.14	23.55	8.11	6.80	89.11	569

Panel B: Differences over 12-months and 36-months horizons.

	Carhart (1997) 4-factor model						
Difference	Excess returns	α	RMRF	SMB	HML	MOM	R^2
1^{st} vs. 2^{nd} 12 mths	0.12	0.06	-2.85	2.08	0.34	0.63	-1.78**
	(1.48)	(1.17)	(-1.56)	(0.82)	(0.12)	(0.30)	(-2.54)
1^{st} vs. 2^{nd} 36 mths	0.15***	0.08***	-2.22*	2.68	-8.81***	-0.93	-2.36***
	(2.77)	(2.73)	(-1.75)	(1.30)	(-3.85)	(-0.79)	(-3.11)
New vs. old funds	0.03	0.09**	-1.92	14.43***	-6.51***	2.49*	-1.23***
12 mths	(0.41)	(2.29)	(-1.43)	(7.73)	(-3.20)	(1.77)	(-3.02)
New vs. old funds	0.15**	0.12***	-1.66*	14.59***	-8.88***	0.39	-0.68*
36 mths	(2.23)	(5.63)	(-1.95)	(9.61)	(-5.34)	(0.43)	(-1.70)

Table 2.4: Frequency table for the rankings of fund starts among the deciles formed by existing funds based on return and risk characteristics.
After the inception of a new fund all existing U.S. equity mutual funds are sorted into decile portfolios based on fund characteristics over the first three years. The new fund is then attributed to one of the deciles. The table reports the frequencies of fund starts among the deciles of existing funds for the mean excess return over three years after inception and the loadings of the Carhart (1997) 4 factor model. Decile 1 contains the funds with the lowest values for the returns, risk measures, or loadings, decile 10 the ones with the highest values. RMRF is the excess return of the CRSP value-weighted stock market portfolio over the 1 month Treasury bill rate. α represents the intercept of the four-factor model. SMB, HML, and MOM are the factor-mimicking size, book-to-market and 1 year momentum portfolios as defined by Fama and French (1993) and in the case of MOM by Carhart (1997). The last two rows report the $\varkappa^2$-statistic along with the p-values for testing the null hypothesis that the frequencies across all deciles are equal. The sample includes returns from 1,374 funds (828 fund starts) over the period 1991-2005.

		Carhart (1997) 4-factor model					
Decile	Excess return	α	RMRF	SMB	HML	MOM	R^2
1	87	66	90	88	114	106	95
2	74	57	80	75	87	78	75
3	78	77	85	76	69	73	117
4	82	63	82	51	79	83	98
5	76	77	81	61	88	73	75
6	64	69	79	81	76	72	60
7	75	62	74	81	73	64	65
8	80	82	64	70	56	72	59
9	74	90	87	99	71	76	67
10	132	155	76	116	85	101	87
$\varkappa^2 - Statistic$	37.49	90.30	6.11	38.42	26.79	20.40	40.75
$p - value$	0.00	0.00	0.73	0.00	0.00	0.02	0.00

Table 2.5: Determinants of fund alpha.

Panel regression with fund fixed effects and year dummies. The dependent variable is the intercept (α) from the Carhart 4-factor model. α is regressed on lagged flow, age, risk, and control variables. Flows are in percentage of total net assets (TNA). Age is a dummy variable that is zero for funds that are up to three years old, and one otherwise. TR^2 is the logistic transformation of the R^2 for the Carhart 4-factor model: $TR^2 = \log[(\sqrt[2]{R^2}\ )/(1-\sqrt[2]{R^2}\ )]$. The control variables include the number of different stock positions, the industry concentration index (ICI) of Kacperczyk et al. (2005), the average size quantile rankings of all stock positions (from 1 for micro-cap to 20 for giant-cap), and the illiquidity ratio is defined as in Amihud (2002). t statistics are in brackets. ***, ** and * indicates significance at the 1%, 5% and 10% level respectively. The sample period is 1991-2005.

Lagged variables	(1)	(2)	(3)	(4)	(5)	(6)
Log(TNA)			-0.154***			
			(-4.14)			
Log(TNA)2			0.003			
			(0.74)			
Flows	-0.057		-0.323***	-0.133**	-0.227***	-0.554***
	(-1.27)		(-5.19)	(-2.69)	(-3.01)	(-3.26)
Age		-0.091***		-0.128***	-0.126*	-0.136***
		(-3.75)		(-4.50)	(-1.73)	(-3.29)
Age × flows				0.001	0.006	
				(0.05)	(0.33)	
TR^2					-0.113***	
					(-5.53)	
Age × TR2					0.007	
					(0.34)	
Expenses						26.01***
						(4.36)
Turnover						-0.002
						(-0.35)
# of stocks						0.000
						(-0.35)
ICI						-0.063
						(-0.78)
Size						-0.002**
						(-1.94)
Illiq. ratio × 10^3						0.071
						(0.15)
# of fund years	15,268	15,526	13,785	12,392	11,878	7,691
R^2	0.00	0.00	0.00	0.01	0.00	0.01

Table 2.6: The change in mutual characteristics over time.

This table shows the development of average characteristics of the 1,374 U.S. equity mutual funds in our sample. Total net asset value (TNA) is in million dollars as of year-end. Fund flows are computed monthly as a percentage of total net assets (TNA) and the cells in the table contain the average value over the given year across all funds. ICI is the industry concentration index as defined by Kacperczyk et al. (2005), size the average size quantile rankings of all stock positions (from 1 for micro-cap to 20 for giant-cap), and the illiquidity ratio is defined as in Amihud (2002).

Fund Characteristics	1991	1995	2000	2005
TNA	91.2	129.2	210.2	267.9
Fund flows (as % of TNA)	0.14	0.47	-0.11	-0.74
Fees (%)	1.15	1.15	1.15	1.19
Turnover (%)	58.0	64.0	69.0	54.0
Number of stocks	62.0	77.0	81.2	82.0
ICI	0.16	0.15	0.15	0.14
Size	10.6	10.8	16.8	16.4
Illiquidity ratio*10^3	0.272	0.086	0.001	0.004
Number of funds	568	992	1345	1211

Table 2.7: Persistence in fund characteristics over time and differences in fund characteristics between fund starts and existing funds.

The first two rows show the differences in means between the initial 36 months period minus the subsequent 36 months period after inception. The last two rows describe the differences in means between fund starts minus existing funds over the first 36 months after inception. TNA is total net assets and fund flows are measured as a percentage of TNA. For each fund portfolio we compute the number of different stock positions, the industry concentration index (ICI) of Kacperczyk et al. (2005), the average size quantile rankings of all stock positions (from 1 for micro-cap to 20 for giant-cap), and a value-weighted average Amihud's (2002) illiquidity ratio. The values in brackets show the t-statistic for a two-sided t-test on the equality of the means. ***, ** and * indicates significance at the 1%, 5% and 10% level respectively.

Difference	TNA	Flows (%)	Fees (% of TNA)	Turnover (%)	# stocks	ICI	Size	Illiquidity ratio $\times 10^3$
First vs. second 36 mths	-138.26***	0.04***	0.00**	-0.00	-10.05	-0.00	-2.69***	-0.001
	(-5.75)	(15.03)	(2.61)	(-0.39)	(-0.99)	(-0.57)	(-3.84)	(-0.73)
New vs. old funds, 36 mths	-770.52***	0.05***	0.00**	0.18**	0.85	0.00	-1.02**	0.001
	(-53.57)	(10.81)	(3.26)	(2.11)	(0.10)	(-0.29)	(-2.35)	(1.22)

Table 2.8: Frequency table for the rankings of fund starts among the deciles formed by existing funds based on fund characteristics.

After the inception of a new fund all existing U.S. equity mutual funds are sorted into decile portfolios based on fund characteristics over the first 36 months. The new fund is then attributed to one of the deciles. The table reports the frequency of fund starts among the deciles of existing funds for total net assets (TNA), fund flows as a percentage of TNA, management fees, annual turnover, number of stock positions in the portfolio, industry concentration index (ICI) of Kacperczyk et al. (2005), average size quantile rankings of all stock positions (from 1 for micro-cap to 20 for giant-cap), and the value-weighted average Amihud's (2002) illiquidity ratio. Decile 1 contains the funds with the lowest values for the specific characteristic and decile 10 the funds with the highest values. The last two rows report the $\varkappa^2$-statistic along with the p-values for testing the null hypothesis that the frequencies across all deciles are equal. The sample includes returns from 1,374 funds (828 fund starts) over the period 1991-2005.

Decile	TNA	Flows (%)	Fees (% of TNA)	Turnover (%)	# of stocks	ICI	Size	Illiqui. ratio
1	170	13	86	76	107	90	111	73
2	146	9	72	66	103	81	84	67
3	123	13	52	74	109	77	72	74
4	99	23	74	84	88	76	55	74
5	104	32	72	90	78	76	87	70
6	78	45	74	89	58	86	87	72
7	53	97	77	85	72	69	77	72
8	37	143	104	71	65	90	78	80
9	15	210	108	95	52	95	75	98
10	3	243	109	95	91	77	60	106
$\varkappa^2 - Stat.$	109.71	883.30	232.36	95.38	19.03	29.38	38.58	54.48
$p - value$	0.00	0.00	0.00	0.00	0.002	0.00	0.00	0.00

Chapter 3

Performance Analysis of New Mutual Funds: a Bayesian Approach

3.1 Introduction

The number of mutual funds has dramatically increased over the last decade both in the U.S. and worldwide. A growing number of new mutual funds is started each year, which enlarges the possibilities of placement for investors. As the universe of choices is widening, selecting funds with significantly higher performance becomes a challenging task. A large span of the literature addresses the question of performance and persistence among mutual funds, however little has been done with new mutual fund performance. In this paper, we try to fill-in the gap by providing new performance measures that are more adequate for funds with short history.

The reduced ability of absolute returns to assess the fund performance raises the need to look for other measures. Using risk adjusted measures offers a better estimation of the performance and the managerial skill. The seminal work of Jensen (1968), for example, uses the single factor model to estimate the superior performance of funds over the market index. Fama-French (1993) adds two other factors: size and book-to-market. Carhart (1997) adds a momentum factor to capture investments made on past high performing stocks. The alpha computed from the four factor model of Carhart (1997), is now the standard approach used for the majority of mutual funds articles. Nonetheless, this approach raises some issues related to the number of factors used and their adequacy. Finding an optimal number of factors and appropriate benchmarks is one approach to sharpening performance measures. Another way to improve the precision of alpha is to use other assets with longer history. Incorporating additional information improves the estimation and the predictability of alphas. We propose to extract information from the fund family and use it in a Bayesian setting. In using the Bayesian approach we also expect significant consequences on the performance estimation and portfolios allocations.

The classical approach based on a multifactor model may be suitable to compare performance of funds of similar ages. However, differences arise when performance of new funds must be compared to that of seasoned ones. The main difference is that longer historical returns are available for seasoned funds. This fact may bias a performance evaluation based solely on OLS alpha, i.e. a multifactor model. One way to circumvent this problem is to use Bayesian estimates of factor model coefficients. Following this method, the estimation of coefficients is a balanced weight between the estimator obtained by OLS and prior information. We refer to a prior as any information that an investor may have and that could be used as an estimation of the potential performance of the fund. The combination of prior information and OLS estimation provides the posterior estimator. As an investor has larger prior information, his posterior estimation sharpens. The prior should be extracted from the real data to obtain logical results and should reflect any changes that could affect the returns.

The tremendous growth in the number of mutual funds in the U.S. market in the last 25 years has generated a large number of young funds available for investors. The number of young funds (i.e. < 3 years old) increased more than tenfold between 1980 and 2005, as mentioned in Table 1. Most of these funds are not well known to the public. The lack of information and the shortage of historical data increase the estimation risk for this type of funds. The issue of assessing new fund performance is more complex than for funds with longer historical data. First, there is a higher probability that fund managers use a temporary strategy in order to boost the fund. For instance, new funds may receive better manager teams or may be subsidized with a number of IPO allocations or successful incubated strategies already used in other funds within the family (Evans, 2004). New funds also exhibit a higher termination rate in comparison with seasoned funds (Wisen, 2002), which in turn puts more pressure on managers to achieve better performance. Second, the launch of the funds may also be wisely timed with the state of the market. In a bullish market, it is not clear whether the performance is due to an intrinsic value of the fund or to a timing strategy in some specific stocks. In addition, the smaller size of new funds increases the probability of higher performance. Third, for new funds, there are no ratings available (no Morningstar ratings available before three years of existence). Finally, any estimation of a performance measure would be biased due to the shortage of historical data. The characteristics of new funds, above mentioned, raise the need to look for adequate measures of performance. In this paper, we propose two measures of performance for funds with short historical data, the combined-sample and empirical Bayesian estimators. These measures enlarge the information used to estimate the performance of newly launched funds.

In more recent years, some authors have used the Bayesian method to tackle certain issues related to mutual funds performance. Baks, Metrick and Wachter (2001) employ a Bayesian measure of performance that incorporates a flexible set of prior beliefs about managerial skill. They show that the decision of investing in an actively managed fund is not solely based on the existence of skill among managers. Investors will still invest in actively managed funds even though they have a strong belief that managers do not exhibit any skill.

Pastor and Stambaugh (2002 a) support that using information from passive non-benchmark assets increases the precision of alpha estimations and Sharpe ratios. Significant differences are also observed in comparison with standard measures of performance. Pastor and Stambaugh (2002 b) use Bayesian alphas to construct optimal allocations by maximizing the Sharpe ratio. This approach disentangles market model mispricing from managerial skill. They show that using further information from non-benchmark assets is useful even for an investor who believes entirely in a pricing model.

Jones and Shanken (2005) show how returns from other funds are useful to estimate the performance of a specific fund. Dependence between funds is referred to as "learning across funds," and can be exploited in order to enlarge the information available about the performance of a fund. By estimating the statistical parameters of the performance of the entire sample of funds, an investor can improve his optimal allocations weights.

Busse and Irvine (2006) compare the performance predictability of Bayesian estimates of mutual fund performance with standard frequentist measures using daily returns. They highlight the usefulness of the use of other non-benchmark assets in order to improve the predictability of alphas. Huij and Verbeek (2007) use the information on the entire sample of mutual funds as a prior to estimate the performance of the fund. They use an empirical Bayes approach to study the short-run persistence among equity mutual funds over the period 1984-2003. Their results exhibit the superiority of the Bayesian estimator over the OLS one in measuring the performance persistence.

All of the articles mentioned above advocate the use of the Bayesian approach in order to increase performance precision. The Bayesian approach allows incorporating prior beliefs and takes advantage of further information from other assets. In our work, we use two methodologies: a combined-sample approach and an empirical Bayes approach. The first approach relies on the works of Little and Rubins (1987), while the second, relies on those of Koop (2003). We use these methodologies in the particular context of new mutual funds and contrast the results with those found with a classical approach. The remainder of the paper is organized as follows. Section 2 describes our sample and highlights the relationship between the family and the new fund performance. In Section 3, we provide a new measure of standard deviation that incorporates cross-sectional information from the fund family, fund style and mutual fund industry. In Section 4 and Section 5, we use a combined-sample and empirical Bayesian approach to estimate alphas of new funds. These estimations have many implications in persistence and performance rankings.

3.2 Data

We use the CRSP Survivor-Bias Free Mutual Fund Database to get monthly returns and monthly total net assets (TNA). The sample extends from January 1962 to December 2005. Daily returns are not used because they are only available from January 2002 onwards, and would therefore leave us with a small number of new fund starts. In order to highlight the dependency between the fund and its family, we chose to work solely on equity funds. Similarity in portfolio allocation as well as team management is responsible for relationship between the fund and its corresponding family performance. Furthermore, we select funds based on the information provided on CRSP classifications: Wiesenberger, Micropal/Investment Company Data, Inc., Strategic Insight, and the funds themselves. We use the same procedure as in Pastor and Stambaugh (2002b) to select equity funds. They illustrate seven categories of fund styles: Small Company Growth, Other Aggressive Growth, Growth, Income, Growth and Income, Maximum Capital Gains, and Sector Funds. Moreover, we eliminate funds that have less than 12 monthly returns observations or five quarterly observations and fund families that have only one fund. Finally, we eliminate duplicated funds (i.e. share classes) using a name matching procedure. The selection process for the sample ends with a number of funds equal to 3,707 funds. All returns are net of fees and we subtract the 1-month Treasury bill rate as a proxy for the risk-free rate to compute excess returns. To assess the risk-adjusted performance we estimate the intercept (alpha) of the 4-factor model introduced by Carhart (1997). The returns on these four factors were downloaded from Kenneth French's website[1]. We classify the 3,707 funds by their family name obtaining a sample of 406 families.

Table 1, Panel A, shows the evolution of the number of funds for each style. The sample is dominated by a Small Company Growth style. All styles registered a growth in the number of funds. Panel B presents the evolution of the number of old vs. young funds. The number of the latter having multiplied by more than ten in the last twenty years. The mutual fund industry reached its top activity at the end of the nineties when almost one out of every three funds was a young one.

[Table 1]

Table 2 is split into two panels. Panel A shows the style classification of sample firms. For each style classification we tabulate number of funds, percentage of funds,

[1]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french; Section "Data Library", "U.S. Research Returns Data". The website also details the portfolio formation methodology to construct these factor returns.

and market capitalization at the beginning and end of the sample period. When funds are sorted by these self-reported investment styles, it is evident that growth funds constitute more than one fifth of the sample (23.63%). Panel B summarizes the size of the fund families in our sample. We count a total of 406 fund family affiliations. Most families count of 2 to 5 funds. Only 6 families are represented with more than 51 equity funds. However, the sum of the total net asset (TNA) of the six largest families is equal to 937 812.4 (M $) and the sum of the TNA of the smallest families (232) is 241 267.9 (M $) in 2005, which underlines the domination of the mutual fund industry by large fund families.

[Table 2]

Figure 1 displays further descriptive highlights of the sample. Figure 1a shows the number of funds in activity each year between 1962 and 2005 in the chosen sample. There is a remarkable increase in the number of funds, especially from the 1990s onward. Figure 1b confirms this fact by exhibiting the number of new funds started each year. Since we have a large number of new funds, it is important to have an adequate performance measure that takes into account the specific characteristics of these funds. Figure 1c and Figure 1d display an upward trend for the number of families and the number of funds per family. A high development of the mutual funds industry and a tendency for a higher number of funds per family can be observed from the 1990s onward. Higher competition, need for scale economies and better portfolio diversification may be responsible for the increase in the average number of funds per family. Finally, Figure 1e shows the evolution of the median age of funds in activity each year. We notice a general decrease in the median age from one year to another. The mutual fund industry is at a growing stage and is incorporating a higher number of new funds each year, which makes fund performance a challenge to evaluate.

[Figure 1]

Beginning with the 1990s, families started creating more funds which allow them to enjoy scale economies and substantial diversification. Determining an optimal number of funds within the family is a key element for maximizing the overall total net assets of the family. In general terms, we support the existence of a relationship between the fund performance and its family performance. Present literature advocates the fact that managers favour some funds within the family as mentioned in Gaspar, Massa and Matos (2007). In particular, these authors find that fund families enhance not only the performance of high performing funds at the expense of low performing funds, but also young funds at the expense of old funds. Our hypothesis is also in accordance with Nanda, Wang and Zheng (2004) who advance that fund families are pursuing strategies toward creating star funds. Nanda et al.(2005) show that families with higher variation in investment have a higher probability in starting a star fund. Furthermore, Elton, Gruber and Green (2005) find that the correlation among funds within the family is higher than that outside of the family. This correlation is typically due to common stock holdings as well as similar exposures to economic sectors or industries. Finally, within a sample of institutional money managers, Berzins (2006) shows that new funds have a higher probability of falling within the same quartile as the family for the last period.

The above mentioned articles advocate interaction across funds within the family. As family performance may be informative for an investor, we chose it as prior for the estimation of the performance of newly launched funds. For instance, an investor interested in a particular fund will look at the historical fund performance. In case this information is not available, the investor will look at the family performance information. Our work, as a result, is in line with the literature that defends the existence of connection and strategic management within families of funds.

We verify whether past family performance offers insight into the future performance of the new fund. We estimate the performance of fund family for an interval window before the start of new funds [-36, 0] months. We also measure the performance of new funds 12 months since their inception. Is there a "continuity" phenomenon in the sense that the performance of the family will be transmitted to the new fund? We rank all funds of the family within the funds universe for a [-36, 0] months and for a [0, 12] months period for the new fund. We obtain the median rank decile of funds of the family and the rank decile of the fund. Can a similarity be established?

Fund managers may be in charge of numerous funds. As a consequence, a new fund may not necessarily coincide with a new management team. Part of the performance transmission may also be explained by the involvement of the same team within the family. To verify this hypothesis, we check two subsamples. The first one contains single manager funds, while the second one contains team manager funds. An imbedded hypothesis would be that a team manager funds would be more correlated to the family performance than a single manager funds. Funds managed by teams also have less extreme positions and as a result have a higher similarity with the overall performance distribution of the family (Baer, Kempf and Ruenzi, 2005).

Two main highlights can be drawn from analysing empirical results in Table 3 and Figure 2 within a transitional probabilities matrix. First, past successful fund families are more likely to launch new funds. 49.8 % of fund starts were created by fund families that belong to the tenth decile (i.e. most highly performing decile). Second, we find evidence of persistence among top deciles and a lower persistence among weak deciles. Fund families that are among top performers (losers) have a higher chance to launch a new fund among top performers (losers). In 19.6% of the cases, we see that top funds families (deciles 9 or 10) launch funds in top deciles (deciles 9 or 10). For bottom deciles, the number of starts is, by definition, low and we could not really make any concrete conclusions, except that the relative frequency of badly performing deciles of new funds is decreasing as we move from top family deciles to bottom ones. It is also evident that badly performing families will not launch as many funds or at least will delay their decision until their performance improves. Furthermore, we do not find substantial differences in results between single- and team-manager funds as presented in Panel B and Panel C of Table 2. For an investor, this information is sufficient, because he is primarily interested in top funds to invest in and badly performing ones to avoid. The use of family returns is without a doubt informative for an investor. Our findings are in line with Khorana and Servaes (1999), who advocate that the probability of launching a new fund is positively related to family past performance and with Karoui and Meier (2008), who suggest that new funds belong to extreme deciles rather than to middle ones.

[Figure 2]

[Table 3]

3.3 An adjusted standard deviation of new funds returns

Standard deviation is still a widely used risk measure. Despite its limits, most investors still rely on it to approximate the risk of their assets. Estimating standard deviation for particular time windows may be misleading. This problem worsens when we have fewer data. Estimating new fund risk based solely on standard deviation could give erroneous results. We propose to incorporate cross-sectional information extracted from funds within the same family, the same style or simply from the entire sample of funds. This methodology offers two advantages. First, incorporating information from funds which have a longer history better reflects the true values of the fund performance. Second, the methodology also takes into account the risk from deviation of the fund toward funds with family, the same style or toward the overall equity funds industry.

We propose an adjusted standard deviation that has two characteristics. First, it uses the information provided in the family, style and industry returns. As it is always higher than the original standard deviation, it will reflect part of the estimation risk due to the lack of data. Second, this standard deviation exhibits the degree to which the fund is different from the average family, style or industry returns. The higher the difference is the riskier the fund will be[2] .

3.3.1 Family returns as a prior

We give below the new measure of standard deviation which uses the mean of returns of the fund family (which typically has a longer historical data). We use fund i and family j. We propose an adjusted standard deviation $\tilde{\sigma}_i^2$ to measure the risk of new funds. In computing this statistic, we use the mean of the fund family μ_j in stead of the mean of the fund μ_i as specified in equation 3.1. The adjusted standard deviation $\tilde{\sigma}_i^2$ has two components: the original standard deviation of the fund σ_i^2 and the square of the difference in mean returns between the new fund and its family $\left(\mu_i - \mu_j\right)^2$ as mentioned in equation 3.2. The higher is this difference the riskier the new fund would

[2]If we use the mean of the fund returns, we will obtain the efficient estimator of the standard deviation. The first moment is the optimal value to have the minimum second moment. If we use any other value in stead of the first moment, we obtain a higher measure of the standard deviation. This difference in risk may be composed of two components: fund specific risk and family risk.

be compared to the family it belongs to. We refer σ_i^2 as fund specific risk and $\left(\mu_i - \mu_j\right)^2$ as family risk i.e. the risk to use a strategy that differs from the average family. We use fund i and family j.

$$\tilde{\sigma}_i^2 = \frac{1}{(T-T_1)} \sum_{t=T_1+1}^{T} \left(r_{ijt} - \mu_j\right)^2 \tag{3.1}$$

$$\tilde{\sigma}_i^2 = \frac{1}{(T-T_1)} \sum_{t=T_1+1}^{T} \left(r_{ijt} - \mu_i\right)^2 + \left(\mu_i - \mu_j\right)^2 \tag{3.2}$$

With $T_1 < T$

$$\tilde{\sigma}_i^2 = \underbrace{\sigma_i^2}_{Fund\ specific\ risk} + \underbrace{\left(\mu_i - \mu_j\right)^2}_{Family\ risk}$$

$\tilde{\sigma}_i^2$: adjusted standard deviation of returns for fund i

$\tilde{\sigma}_i^2$: standard deviation of returns for fund i

r_{ijt}: return of the fund i belonging to the family j at time t

r_{jt}: return of the family j at time t

μ_i: mean return of the fund i

μ_j: mean return of the family j

such that:

$$\mu_i = \frac{1}{T-T_1} \sum_{t=T_1+1}^{T} r_{it} \tag{3.3}$$

$$\mu_j = \frac{1}{T} \sum_{t=1}^{T} r_{jt} \tag{3.4}$$

This new measure of standard deviation is analogous to the cross-funds standard deviation used in Nanda, Wang and Zheng (2004). Their measure is intended to estimate the heterogeneity of funds belonging to the same family. In contrast, our measure is designated to estimate the deviation of each fund with respect to its family.

3.3.2 Style returns as a prior

We choose the average funds returns with the same style as a prior.

$$\tilde{\sigma}_i^2 = \frac{1}{(T - T_1)} \sum_{t=T_1+1}^{T} (r_{ijt} - \mu_S)^2 \tag{3.5}$$

$$\tilde{\sigma}_i^2 = \underbrace{\sigma_i^2}_{Fund\ specific\ risk} + \underbrace{(\mu_i - \mu_S)^2}_{Style\ risk} \tag{3.6}$$

μ_S: mean return of the style S

3.3.3 Industry returns as a prior

We choose the entire funds returns as a prior

$$\tilde{\sigma}_i^2 = \frac{1}{(T - T_1)} \sum_{t=T_1+1}^{T} (r_{ijt} - \mu_I)^2 \tag{3.7}$$

$$\tilde{\sigma}_i^2 = \underbrace{\sigma_i^2}_{Fund\ specific\ risk} + \underbrace{(\mu_i - \mu_I)^2}_{Industry\ risk} \tag{3.8}$$

μ_I: mean return of all mutual fund returns in the sample

For each fund introduction, we compute the standard deviation and the adjusted standard deviation using family, style and industry prior after 24 months from their start. We also compute family, style and industry risk measures. We compute these measures for this specific time window for existing funds. Moreover, we rank new fund measures among old ones. Figure 3 reports these rankings. Figures 3a-3d show that a majority of new funds belong to higher deciles, thereby confirming that they are high risk takers. These results are in accordance with Karoui and Meier (2008), who specify that new funds exhibit higher performance, but also adopt riskier strategies. Furthermore, new funds are not only riskier but also have higher family, style and industry risk, which confirms the fact that they are adopting strategies with higher idiosyncratic risk, as mentioned in Figures 3e-3f. However, some of these funds seem to have low family, style and industry deciles as shown by the U-shape of the histograms in Figures 3e-3f.

[Figure 3]

We find positive and significant correlations between the different measures of risk. Table 4 exhibits the correlation matrix between various risk measures. Funds that have high standard deviation are also those which exhibit high family and industry risk and to some extent style risk as well. Using family, style and industry risk is useful as it highlights part of the uncertainty in future returns of the new fund.

[Table 4]

Panel A in Table 5 compares the average risk measures for different subsamples based on the number of funds in the family. We verify the existence of any size effect in risk measures. For example, the [2,10] measures the standard deviation of funds belonging to families that have between 2 and 10 funds. The results are quite mixed and we cannot draw a clear conclusion concerning the impact of the size on various risk measures.

In Panel B of Table 5, we compare the average risk measures for different time windows since the inception of the fund. For example, the [0,12 months] measures the standard deviation for the first 12 months of existence for each fund. The results specify that as the time window of estimation is enlarged all risk measures decrease, implying that seasoned funds are less risky than new funds.

We have therefore shown that the use of family, style and industry returns improves the risk and performance assessment for new funds.

[Table 5]

3.4 Combined-sample estimator

3.4.1 Theoretical framework

As developed in the previous section, it is difficult to compare performance of funds with different ages. Standard performance measures provide biased conclusions. Morey (2002) found, for example, a significant relationship between age and Morningstar rating. The latter would favour aged funds. Adkisson and Fraser (2003) outlined what they call the "age bias" and advocate the use of new measures so as to take into account the difference of information available in evaluating fund performance.

Let us examine a simple example of a portfolio allocation problem to illustrate the estimation risk. An investor has a choice between two funds: the first fund has one year of records and a correspondent performance of 7%; whereas, the second fund has three years of records and has 4%, 5% and 4% as performance. If we suppose that the standard deviation for both funds and for each year is equal to 10%, what is the optimal choice? How do you choose between fund 1 and fund 2 if you only want to invest in one fund? Fund 1 has a higher performance, however, it has less historical data available. Fund 1 therefore has an additional estimation risk when compared to fund 2. One way to reduce this uncertainty is to shrink this performance toward another value, thereby reducing the estimation error.

We use the same methodology as in Stambaugh (1997) to determine first and second moments of new funds. Stambaugh's study shows to what extent historical returns from developed countries can be useful for making inferences about returns for emerging countries. Although this method has been used to estimate stock index returns, we use it for mutual funds. We think that extracting information from seasoned funds is useful for new funds. Furthermore, we extend the relationship from a mean estimation to a pricing model estimation. For conveniences we use the same notation as in Stambaugh (1997). [3]. We define an S*N matrix

$$Y_S = [Y_{1,S} Y_{2,S}] = \begin{bmatrix} R_{1,S} & R_{2,S} \\ R_{1,S+1} & R_{2,t+1} \\ .. & .. \\ R_{1,T} & R_{2,T} \end{bmatrix} \tag{3.9}$$

and $T * 2$ matrix:

$$Y_{1,T} = \begin{bmatrix} R_{1,1} \\ R_{1,2} \\ . \\ R_{1,T} \end{bmatrix} \tag{3.10}$$

$Y_{1,S}$ and $Y_{2,S}$ are the returns of two groups of stocks or funds that do not have the same historical data length. For simplicity, we take the case of only one fund for each group, and ultimately, we consider that this fund will represent a group of funds. Below is the joint distribution of returns under multivariate normal distribution assumption:

[3]Interested readers should refer to Little and Rubin (1987) for further details on missing data literature.

$$p(Y_{1,T}, Y_{2,S}/E, V, s) = \prod_{t=1}^{s-1} \left(\frac{1}{2\pi^{\frac{N_1}{2}}} |V_{11}|^{-\frac{1}{2}} \exp\left\{ -\frac{1}{2} (R_{1,t} - E_1)' V_{11}^{-1} (R_{1,t} - E_1) \right\} \right) * \prod_{t=s}^{T} \left(\frac{1}{2\pi^{\frac{N}{2}}} |V|^{-\frac{1}{2}} \exp\left\{ -\frac{1}{2} (R_t - E)' V^{-1} (R_t - E) \right\} \right) \quad (3.11)$$

The formulas of the first and second moments are based on a truncated sample:

The mean of the returns is:

$$\widehat{E}_s = \begin{bmatrix} \widehat{E}_{1,s} \\ \widehat{E}_{2,s} \end{bmatrix} = \frac{1}{S} Y_s \iota_s \quad (3.12)$$

The covariance matrix of the returns is:

$$\widehat{V}_s = \begin{bmatrix} \widehat{V}_{11,S} & \widehat{V}_{12,S} \\ \widehat{V}_{21,S} & \widehat{V}_{22,S} \end{bmatrix} = \frac{1}{S} \left(Y_S - \iota_s \widehat{E}'_S \right) \left(Y_S - \iota_s \widehat{E}' \right) \quad (3.13)$$

With $\iota_s$is an S vector of ones. We have also that:

$$C = \begin{bmatrix} \widehat{\alpha}' \\ \widehat{\beta}'_{corr} \end{bmatrix} = (X'X)^{-1} (X'Y_{2,S})$$

and

$$X = [\iota_s Y_{1,S}] \quad (3.14)$$

$$\Sigma = \frac{1}{S} \left[Y_{2,S} - X\widehat{C} \right]' \left[Y_{2,S} - X\widehat{C} \right] \quad (3.15)$$

$$\widehat{E} = \begin{bmatrix} \widehat{E}_1 \\ \widehat{E}_2 \end{bmatrix} \tag{3.16}$$

$$\widehat{V} = \begin{bmatrix} \widehat{V}_{11} & \widehat{V}_{12} \\ \widehat{V}_{21} & \widehat{V}_{22} \end{bmatrix} \tag{3.17}$$

Estimation of the mean:

$$\widehat{E}_1 = \frac{1}{T} \sum_{t=1}^{T} R_{1,t} \tag{3.18}$$

$$\widehat{E}_2 = \widehat{E}_{2,S} - \widehat{\beta}_{corr} \left(\widehat{E}_{1,S} - \widehat{E}_1 \right) \tag{3.19}$$

$\widehat{\beta}_{corr}$ is the factor loadings of a regression between

In our case, we have:

$$\widehat{E}_{New\ Fund,\ CS} = \widehat{E}_{New\ Fund,S} - \widehat{\beta}_{corr} \left(\widehat{E}_{Family,S} - \widehat{E}_{Family} \right) \tag{3.20}$$

Estimation of the variance:

$$\widehat{V}_{22} = \widehat{V}_{22,S} - \widehat{\beta}_{corr} \left(\widehat{V}_{11,S} - \widehat{V}_{11} \right) \widehat{\beta}'_{corr} \tag{3.21}$$

$$\widehat{V}_{21} = \widehat{V}_{21,S} - \widehat{\beta}_{corr}\left(\widehat{V}_{11,S} - \widehat{V}_{11}\right) \tag{3.22}$$

We get a new Sharpe ratio:

$$\frac{\widehat{E}_2}{\widehat{V}_{22}} = \frac{\widehat{E}_{2,S} - \widehat{\beta}_{corr}\left(\widehat{E}_{1,S} - \widehat{E}_1\right)}{\widehat{V}_{22,S} - \widehat{\beta}_{corr}\left(\widehat{V}_{11,S} - \widehat{V}_{11}\right)\widehat{\beta}'_{corr}} \tag{3.23}$$

Using an approximation from the equation (3.20)[4], we derive a formula for a combined-sample estimator of alphas:

$$\widehat{\alpha}_{2,CS} = \widehat{\alpha}_{2,S} - \widehat{\beta}_{corr}\left(\widehat{\alpha}_{1,S} - \widehat{\alpha}_1\right) \tag{3.24}$$

$$\widehat{\alpha}_{New\ Fund,\ CS} = \widehat{\alpha}_{New\ Fund,S} - \widehat{\beta}_{corr}\left(\widehat{\alpha}_{Family,S} - \widehat{\alpha}_{Family}\right) \tag{3.25}$$

$\widehat{\alpha}_{New\ fund,\ CS}$: combined-sample alpha

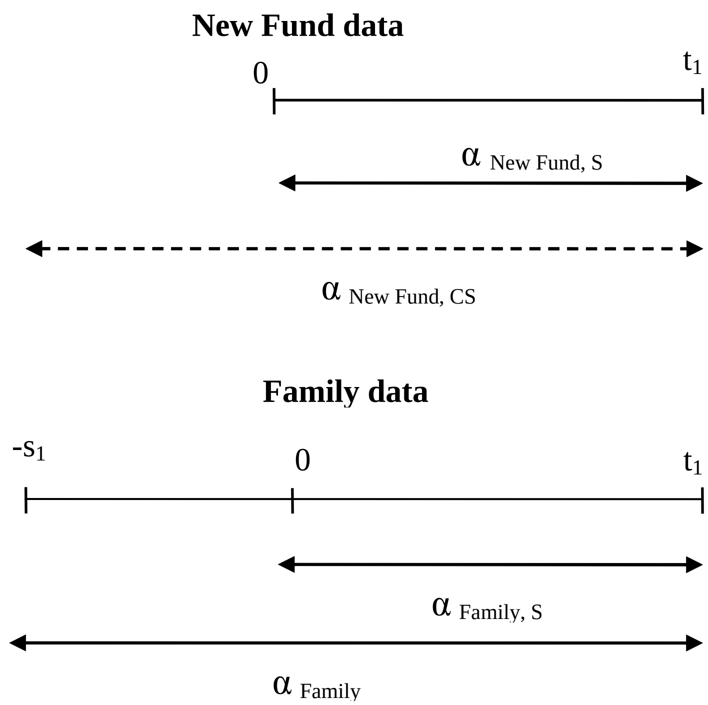
$\widehat{\alpha}_{New\ fund,S}$ and $\widehat{\alpha}_{Family,S}$ are alphas of the new fund and alpha of the family for the short sample

$\widehat{\alpha}_{Family}$: alpha of the family for the entire sample

The derivation of the equation (3.25) is subject to two hypothesis. First, factors must have a perfect pricing of stock (mutual fund) returns. Second, factors must follow a multivariate Normal distribution. We estimate this new alpha and we rank funds based on this measure. This adjusted alpha should be used in addition to the original

[4]See Appendix A for a derivation of the formula of the equation (3.25).

alphas and not apart from them. The graph below explains the periods of estimations used to compute $\widehat{\alpha}_{New\ fund,\ CS}$.



The $\widehat{\alpha}_{New\ fund,\ CS}$ will shrink (amplify) depending on whether the fund family $\widehat{\alpha}_{Family,S}$ achieves low (high) past performance. Supposing that the new fund has realized a higher (smaller) abnormal return, and at the same time the performance of the family has increased (decreased) i.e. $\widehat{\alpha}_{Family,S} - \widehat{\alpha}_{Family} > 0$ ($\widehat{\alpha}_{Family,S} - \widehat{\alpha}_{Family} < 0$)., the $\widehat{\alpha}_{New\ fund,\ CS}$ will decrease (increase) to take into account the bad (good) performance of the family made in past periods. In both cases, we suppose that fund family and new fund returns are commoving in the same way (i.e. $\widehat{\beta}_{corr} > 0$).

3.4.2 Empirical estimation

We rank alphas of the new funds among the seasoned funds for the t_1 first months of activity $[0, t_1]$ using OLS alphas and Combined-sample alphas. We choose one example with t_1=36 months [5]. For each new fund, we estimate the alpha of the new fund and the alphas of seasoned funds for this specific time window. We divide the alphas of seasoned funds into deciles and we range the alpha of the new fund among one of these deciles. We obtain the rank (i.e. the decile to which it belongs to) of each new fund for the $[0, t_1]$ interval. Figure 4 shows a histogram of the ranks of new funds using OLS vs. combined sample estimators, which clearly shows that ranking based on OLS alphas vs. combined-sample alphas leads to different results. Using classical alphas, we find that most of the new funds belong to the tenth decile (highest performing). However, when we use Combined-sample alphas we find that a large part of funds belong either to the first or to the tenth decile.

[Figure 4]

In testing the difference between average alphas using short and long sample, we find a mean difference of 2.98 basis points and a $t-Stat$ of 1.47 that is not statistically significant. Estimating performance using combined samples does not suffer from a systematic bias that may under- or overestimate the performance. Moreover, we find a mean difference between mean returns using short and long samples of 6.49 basis points with a $t-Stat$ equal to 1.44, which also is not statistically significant. Using combined-sample alphas does not automatically generate neither upward nor downward bias. To further illustrate this, Figure 5a and Figure 5b show that the kernel density

[5] Results are also available for different time windows of 12 and 36 months. Results are quite similar.

of the difference in means and alphas using OLS vs. combined-samples methods is symmetric.

This difference in results is explained by higher combined-sample alphas among new funds compared to OLS alphas. Fund families have lower performance after starting new funds than before. This means that the performance of fund families for windows corresponding to the start of funds is worse than before. Families are not timing the start of new funds in a beneficial way (timing ability) and seem to suffer from the costs resulting from the starts of new funds. Figure 5c and Figure 5d show a slight decline in the performance of the family after starting new funds. This result supports the argument that opening new funds may be a costly strategy that gives benefits only in the long run.

[Figure 5]

3.4.3 Efficiency of the estimator: estimation error of combined-sample alpha

In this paper, we advocate the use of the combined-sample alpha as an additional measure of adjusted risk performance. In this section, we evaluate the predictability power of the OLS and of the combined-sample alpha as well. To begin, we compute an estimation error measuring the difference between the combined-sample alpha and the real alpha, and then we compute the difference between short sample alpha and real alpha. We explain the methodology followed in a few steps. If we suppose that that we have s months of data available for the new fund, we can compute the alpha for the last (s-s_1) months and we call this alpha ($\widehat{\alpha}_{New\ Fund,S}$). Then, we compute the alpha for the s months ($\widehat{\alpha}_{\mathrm{real}}$) and we compute the alpha combined-estimator $\widehat{\alpha}_{New\ Fund,CS}$.

Moreover, we compute the estimation error for alpha short sample: $\widehat{\alpha}_{New\ Fund,S} - \widehat{\alpha}_{\text{real}}$ and for combined-sample alpha $\widehat{\alpha}_{New\ Fund,CS} - \widehat{\alpha}_{\text{real}}$. We compare these two errors of estimation in term of absolute medians (AME), standard deviation (STD)and also RMSE.

$$AME_S = Median(|\alpha_{S,i} - \alpha_{\text{real},i}|) \tag{3.26}$$

$$AME_{CS} = Median(|\alpha_{CS,i} - \alpha_{\text{real},i}|) \tag{3.27}$$

$$STD_S = \frac{1}{N}\sum_{i=1}^{N}\left[(\alpha_{S,i} - \alpha_{\text{real},i}) - (\overline{\alpha_{S,i} - \alpha_{\text{real},i}})\right]^2 \tag{3.28}$$

$$STD_{CS} = \frac{1}{N}\sum_{i=1}^{N}\left[(\alpha_{CS,i} - \alpha_{\text{real},i}) - (\overline{\alpha_{CS,i} - \alpha_{\text{real},i}})\right]^2 \tag{3.29}$$

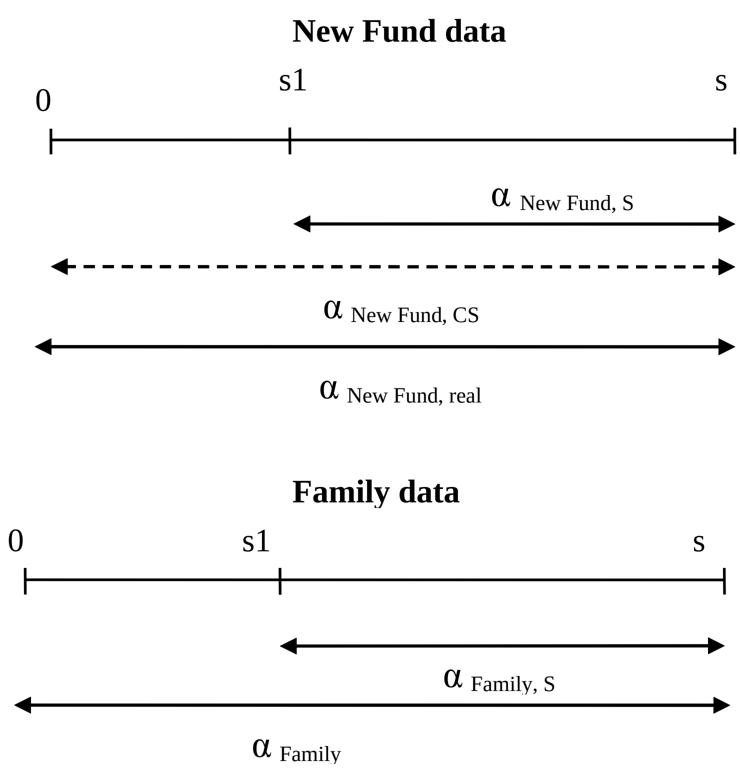
$$RMSE_S = \frac{1}{N}\sum_{i=1}^{N}(\alpha_{S,i} - \alpha_{\text{real},i})^2 \tag{3.30}$$

$$RMSE_{CS} = \frac{1}{N}\sum_{i=1}^{N}(\alpha_{CS,i} - \alpha_{\text{real},i})^2 \tag{3.31}$$

To show the robustness of this analysis, we perform two sensitivity analyses: first, we vary the size s of the data available. Second, we vary the fraction of missing values s_1 for a given value of the data available s.

For the first step, we choose different values of s in {12, 24, 36, 48, and 60 months} and we fix the fraction of missing values to 25%, i.e. s_1=.25(s-s_1). If we had more data, we would expect to obtain a smaller estimation error. Results related to this analysis are displayed in Panel A of Table 6. The second step consists in varying the length of s_1 while keeping the length of the data available unchanged (we choose s=36 months). We take different values of s_1 equal to {1, 3, 6, 12 and 18 months} as mentioned in Panel B of Table 6. As we enlarge the value of s_1, we have a higher percentage of missing data. We also expect the advantage of the combined-sample estimator to decrease because of a larger percentage of missing historical records. The graph below further explains our choice of the sample used to test the efficiency of the estimator.

$$\widehat{\alpha}_{New\ Fund,CS} = \widehat{\alpha}_{New\ Fund,S} - \widehat{\beta}\left(\widehat{\alpha}_{Family,S} - \widehat{\alpha}_{Family}\right) \tag{3.32}$$



Panel A of Table 6 analyses the sensitivity of the estimation error with respect to the size of the estimation window. Results show that as the number of data increase, mean and standard deviation of the estimation error decrease for both the combined-sample and OLS estimators. The RMSE also confirm these results. Furthermore, regardless of the amount of data available, the combined-sample still achieves higher efficiency (i.e. smaller error) when compared to the OLS estimator. Panel B of Table 6 displays the absolute mean and the standard deviation of the estimation error using both OLS and combined-sample estimators. Based on these estimates, we notice that the combined-sample has a smaller error regardless of the percentage of missing data. Conclusions based on RMSE clearly corroborate these results[6].

Figure 6

[Table 6]

The method described above would also be useful for comparing performance of funds of different ages. For instance, in order to compare a fund of only 3 years of activity to another set of funds which is 5 years old, we have three choices. First, we can use the five years of data for the old funds and the three years of data of the new fund to estimate alphas. [The worst solution]. Second, we can use only three years to estimate alphas of funds [Medium solution]. Our last solution would be to use the whole dataset and to estimate alphas for five years using real alphas for old funds and modified alphas for new funds [Better solution]. The results of this section highlight the importance of the use of a specific performance measure. Using a combined-sample alpha is better, because it includes more information extracted from the family performance. This information is particularly useful for funds with short records. Furthermore, the combined-sample alpha has better prediction power than the classical alpha. Finally, the use of another performance measure has significant consequences in ranking funds.

[6] For brevity we have displayed only results using a window length s equal to 36 months. Results for 12 and 24 months are also available, and they are qualitatively the same.

3.5 Estimation of alphas using an empirical Bayes approach

3.5.1 Theoretical framework

In this part, we propose to measure the performance of funds based on a Bayesian measure. The first step is to estimate the performance based on a factor model with an OLS regression. We use the four factor model as specified in Carhart (1997).

$$R_{it} = \alpha_i + \beta_{1i} RMT_t + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} MOM_t + \xi_{it} \tag{3.33}$$

For each new fund, we estimate the adjusted return and factor loadings with OLS estimation. The Bayesian approach estimator is a combination of a prior and OLS estimation. We use the new fund family performance as a prior, because it is more likely to reflect an investor's beliefs. For instance, an investor interested in a particular fund will look at the historical fund performance. If this information is not available, he will look at the family performance information. We showed in a previous section the existence of a connection between a fund's performance and its family. We prefer to use as priors the cross-sectional moments of the family to which the new fund belongs to. In contrast, Huij and Verbeek (2007) use the entire sample to get the cross-sectional mean and variance. Another possibility would be to take only funds with the same style as prior group parameters. We obtain $\underline{\beta}$ as the cross-sectional mean and $\underline{V}$ as the cross-sectional covariance of betas of funds belonging to the same family. Then, we estimate the posterior α_i based on the following formula:

$$\overline{\beta} = \overline{V} \left(\underline{V}^{-1} \underline{\beta} + \frac{1}{\sigma_i^2} X' X \hat{\beta} \right) \tag{3.34}$$

$$\overline{V} = \left(\underline{V}^{-1} + \frac{1}{\sigma_i^2} X'X\right)^{-1} \tag{3.35}$$

$$E(\beta/y) = \overline{\beta} \tag{3.36}$$

$$\beta/y \longrightarrow N(\overline{\beta}, \overline{V}) \tag{3.37}$$

$$Var(\beta/y) = \overline{V} \tag{3.38}$$

$\overline{\beta}$: Posterior beta

$\underline{\beta}$: Prior beta i.e. the mean of the factor loadings of equation (3.33) for different funds within the family

$\underline{V}$: Cross-sectional variance of factor loadings of funds within the family

$X'X$: Factors matrix

σ_i^2 : Variance of ξ_{it}

3.5.2 Empirical results

We estimate the performance of the new fund using OLS alphas and Bayesian alphas. We provide the kernel distribution of cross-sectional prior (family), likelihood and Bayesian alphas in Figure 6. Interestingly, we observe that new funds underperform their respective family performance. The Bayesian alpha distribution is an average between new fund performance and OLS estimation. To have a higher Bayesian alpha, a new fund must have a high OLS performance and must belong to a high-performing family conditional on positive covariance.

[Figure 6]

In a second step, we take an example of one fund and we compute the OLS alpha, the prior and the Bayesian alpha. Because the statistical distribution of these estimators is known, a graph of their distribution can be drawn. We use the "Hotchkis and Wiley Large Cap Value Fund" as an example. We show how the Bayesian alpha is a mix of the prior of the fund and the real performance as measured by the OLS alpha. Furthermore, we show the precision of Bayesian alphas by drawing a graph of the PDF distribution of the prior, posterior and likelihood for only one fund since the distribution density is known. We study two cases: the first one of an informative prior whereas the second is of a non-informative prior. As expected, using an informative prior gives a more precise Bayesian estimator, thereby demonstrating the usefulness of extracting information from the family results (Figure 7).

[Figure 7]

Using Bayesian alphas in stead of OLS alphas may lead to significant differences in terms of ranking of funds. We want to compare the performance of new funds to existent ones. To do so, we estimate Bayesian alphas of new funds and seasoned funds, and we rank new funds among existent funds. We compare the histogram of the ranks using Bayesian vs. OLS performance estimation. To study the performance persistence, we compute OLS alphas and Bayesian alphas for two consecutive sub-periods. It is interesting to show that funds that exhibit high persistence with Bayesian funds may have more stable results because they also belong to high-performing families. It can be assumed that families support their newly launched funds in order to avoid unsatisfactory results and thereby decrease the risk of this category of funds. It is crucial to have information about the family because managers inside the family may transfer performance across funds (Gaspar, Massa and Matos, 2006).

We rank alphas of the new funds among the seasoned funds for the t1 first months of activity [0, t_1] using OLS and Bayesian alphas. We choose an example with t_1=36 months. For each new fund, we estimate the alpha of the new fund and the alphas of seasoned funds for this specific time window. We divide the alphas of seasoned funds into deciles and we range the alpha of the new fund among one of these deciles. We obtain the rank (i.e. the decile to which it belongs to) of each new fund using the OLS and Bayesian computation method. Figure 8 shows the histogram of the rank of new funds among old funds based on the alpha. It confirms that based on Bayesian measures, a higher proportion of new funds rank among top deciles and a lower proportion among bottom deciles. We conclude that new funds are generally launched by good families, i.e. new funds are supported by their family for their first months of activity. These families also have higher expectations on the performance of new funds, which explains to some extent the higher risk among some of the new funds. Ranking based on Bayesian measures gives further information about the performance of the family, which is useful to improve the performance estimation of the fund.

[Figure 8]

We rank alphas of new funds among seasoned ones for the t_1 first months of activity [0 t_1] and for the subsequent time window [t_1 t_2]. We choose one example with t_1=36 months. Figure 9a and Figure 9b show the persistence among new funds using OLS estimates and Bayesian estimates. Both figures give the same results concerning persistence among top deciles. Using Bayesian estimates gives higher rates of persistence among top funds suggesting that top funds belong to top families. Moreover, a small persistence among poorly performing funds is found using either Bayesian or OLS estimation. Analyzing Figure 9b shows that a very small number of funds migrate from top deciles to bottom ones, further indicating that high-performing families have a higher probability of opening new funds that will be high-performing.

Figure 9c gives the migration in the performance ranking of new funds for two subsequent time windows. However, the ranking in the first period is based on Bayesian alphas measures whereas for the second period it is based on OLS measures. In this graph we show how successful the Bayesian alpha is in predicting the OLS alpha. We find higher persistence using this ranking methodology, thereby underlining the usefulness of ranking based on Bayesian methodology. We also observe a high persistence among top deciles and bottom deciles. In addition, we notice a smaller tournament effect using this methodology, i.e. funds ranked on top (bottom) deciles have a smaller chance of ending up among bottom (top) deciles in the subsequent period. These two results support the use of the Bayesian estimator with respect to the likelihood one.

[Figure 9]

3.5.3 Efficiency of the estimators

We use the same methodology as in Huij and Verbeek (2007) to test the variability of the Bayesian estimator [7]. We estimate the equation (3.33) and we get factor loadings. We obtain the mean values of the coefficients and the factors. We generate samples from a multivariate normal distribution for factor loadings as well as factors. Simulated samples of funds are generated for measurement horizons with a length of 12, 24, 36 and 60 months. The number of funds in the cross-section is set to 1,000. As a measure of accuracy we consider the cross-sectional average of the root mean squared error (RMSE) of both estimators. Table 7 displays the results of the estimation.

[7] Interested reader should refer to Huij and Verbeek (2007) for Monte-Carlo procedure details.

Confirming the results of Huij and Verbeek (2007), we also find that the Bayesian has a smaller RMSE than the OLS for the different time window lengths considered. This clearly confirms the initial presumption that Bayesian estimation is more suitable for estimation of young and new fund performance. As we enlarge the data available the difference in RMSE between the Bayesian and OLS estimators decreases. The difference remains positive even for horizons of 60 months.

[Table 7]

3.6 Concluding comments

Investors may be interested in investing in both young and seasoned funds. To reduce the difference in the information available between these two types of funds, we propose new adjusted measures of risk and performance. Using a sample of 3,307 U.S. domestic equity mutual funds over the period from 1962 to 2005, we extract further information from family, style and industry returns. First, we provide an adjusted measure of return standard deviation for young funds. This measure decomposes the fund risk into two components: fund specific risk, and family, style or industry risk. Furthermore, we find positive and significant relationship between the various risk measures. Second, we enlarge the existent literature on the estimation of the performance of funds. In particular, we improve the precision of beta and alpha estimation using two methods: a combined-sample and an empirical Bayesian estimator. These methods correct the bias resulting from the data shortage of new funds and take into account information available in family returns. Our predictability tests confirm the superiority of the combined-sample estimators over the OLS, especially when dealing with a small percentage of missing data (i.e. short horizon prediction). Our efficiency tests based on the RMSE confirm the superiority of the Bayesian estimator. Moreover, we study the issue of performance persistence. Using Bayesian alphas confirms persistence among top-performing new funds and to a lesser extent among poorly performing funds. Also, Bayesian performance measures have better predictability of future performance than OLS.

We offer a simple, yet useful method to evaluate the performance of young funds. Possible extensions may include finding further passive assets that present higher correlation with fund returns. We may also use the results presented in this paper to tackle questions related to portfolio allocations.

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Appendix A

Proof: We use Fama-French (1993) model and a momentum factor (MOM) to estimate the adjusted performance. Our proof is subject to two hypotheses:

Hypothesis 1: The factor model has a perfect pricing of returns, i.e. a high explanatory power.

For the longer historical returns asset and for the entire period:

$R_{1,t} = \alpha_1 + \beta_1 X_t + \xi_t$ This gives: $\widehat{E}_1 = \overline{R}_1 = \widehat{\alpha}_1 + \widehat{\beta}_1 \overline{X}$ (1)

For the last time window:

$R_{11,t} = \alpha_{11} + \beta_{11} X_{1t} + \xi_t$ This gives: $\widehat{E}_{11} = \overline{R}_{11} = \widehat{\alpha}_{11} + \widehat{\beta}_{11} \overline{X}_1$ (2)

For the shorter historical returns:

$R_{21,t} = \alpha_{21} + \beta_{21} X_{1t} + \xi_t$ This gives: $\widehat{E}_{21} = \overline{R}_{21} = \widehat{\alpha}_{21} + \widehat{\beta}_{21} \overline{X}_1$ (3)

Following Little and Rubin (1987), we have that:

$\widehat{E}_2 = \widehat{E}_{2,s} - \widehat{\beta}_{corr} \left(\widehat{E}_{1,s} - \widehat{E}_1 \right)$ (4)

We replace (1), (2) and (3) in (4):

$$\widehat{E}_2 = \widehat{\alpha}_{21} + \widehat{\beta}_{21} \overline{X}_1 \text{-} \widehat{\beta}_{corr} \left(\widehat{\alpha}_{11} + \widehat{\beta}_{11} \overline{X}_1 - \widehat{\alpha}_1 + \widehat{\beta}_1 \overline{X} \right)$$

$$\widehat{E}_2 = \widehat{\alpha}_{21} - \widehat{\beta}_{corr} \left(\widehat{\alpha}_{11} - \widehat{\alpha}_1 \right) + \left(\widehat{\beta}_{21} - \widehat{\beta}_{corr} \widehat{\beta}_{11} \right) \overline{X}_1 + \widehat{\beta}_{corr} \widehat{\beta}_1 \overline{X}$$

Hypothesis 2: We suppose that X_1 and X, the factors for the last sub-sample and for the entire dataset, are following multivariate Normal distributions with different parameters.

We can generate factors using multivariate Normal distribution:

$$R_{2,t} = \widehat{\alpha}_{21} - \widehat{\beta}_{corr} \left(\widehat{\alpha}_{11} - \widehat{\alpha}_1 \right) + \left(\widehat{\beta}_{21} - \widehat{\beta}_{corr} \widehat{\beta}_{11} \right) X_{1,t} + \widehat{\beta}_{corr} \widehat{\beta}_1 X_t + \mu_t$$

With X_1 simulated factors based on parameters estimated for the first period and X simulated factors based on the entire dataset

The intercept of this equation is the combined-sample alpha: $\widehat{\alpha}_{21} - \widehat{\beta}_{corr} \left(\widehat{\alpha}_{11} - \widehat{\alpha}_1 \right)$

Appendix B

Figure 3-1: **Descriptive statistics of the sample of mutual funds**

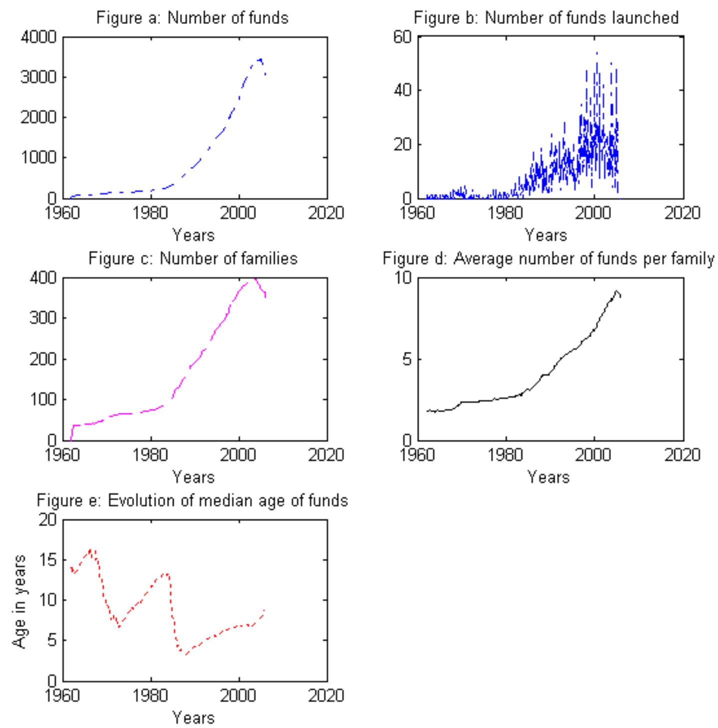
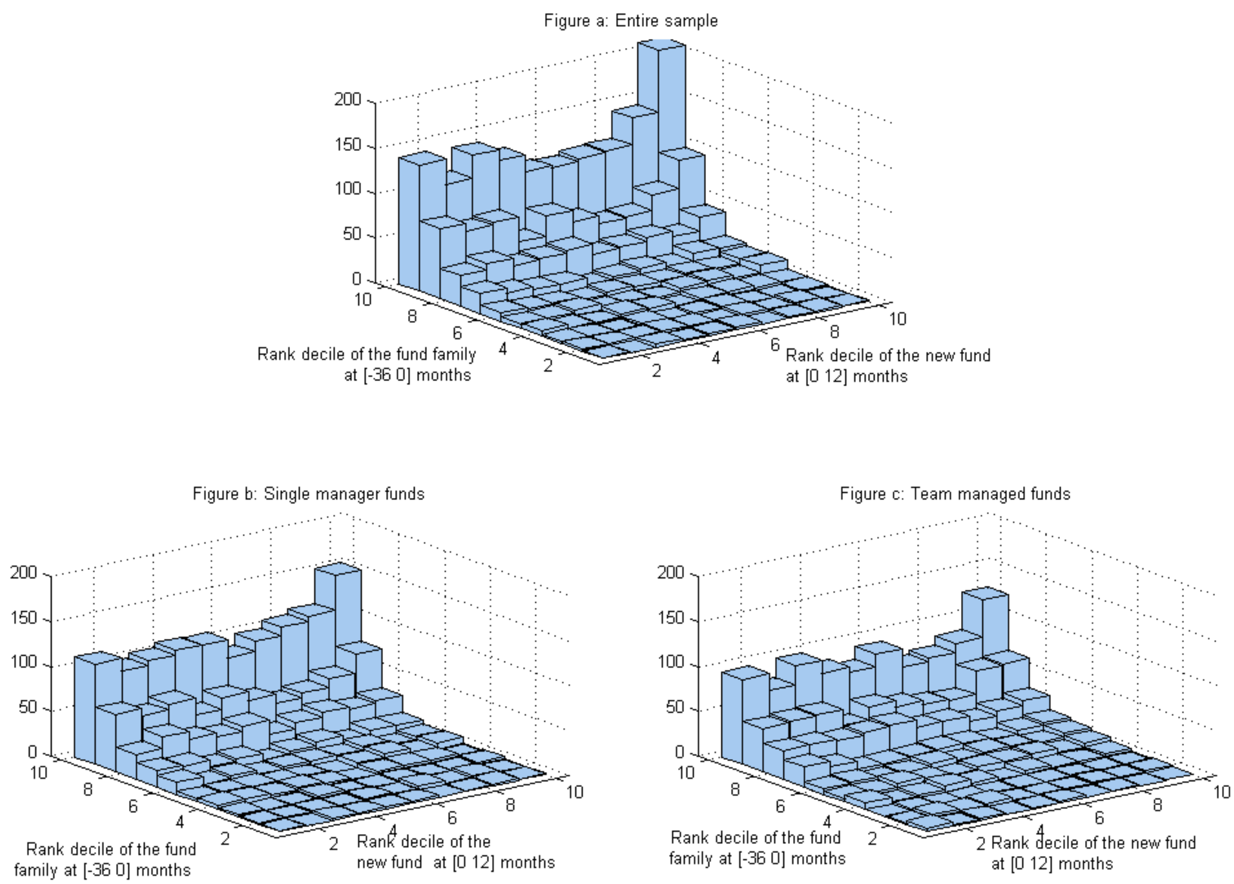


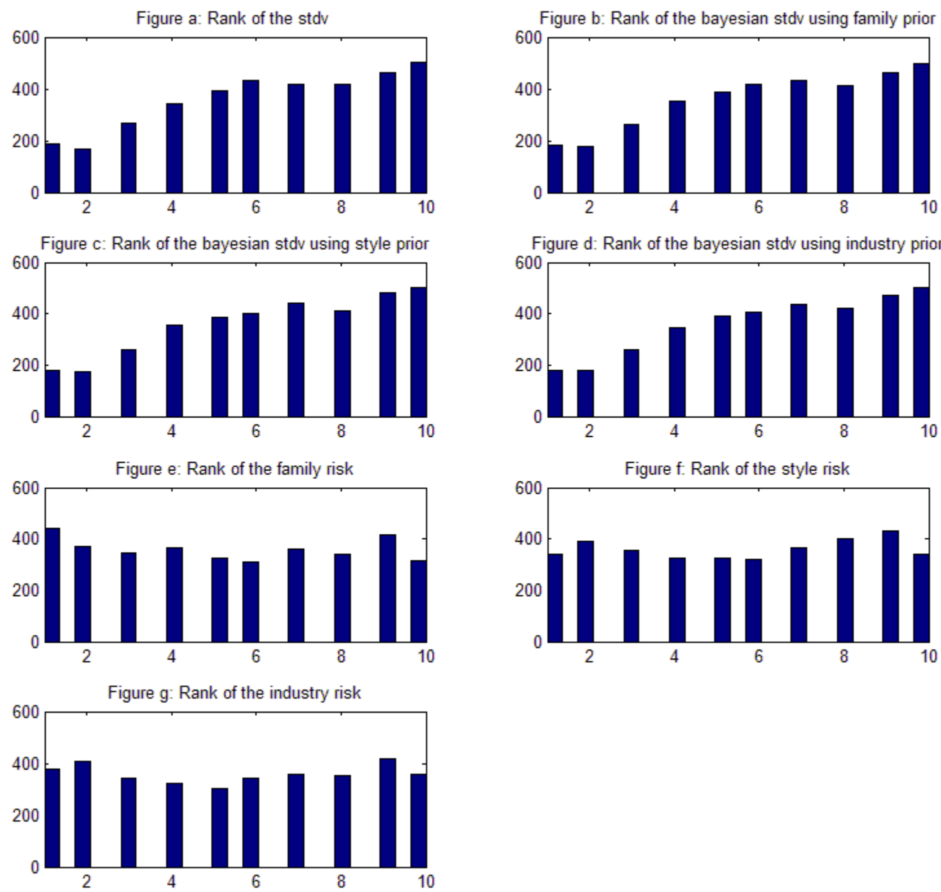
Figure 1a, Figure 1b and Figure 1c show the evolution of the number of funds, the number of launched funds and the number of families. Figure 1d shows the evolution of the average number of funds per family and Figure 1e shows the evolution of the median age of funds. There is a high development of the mutual funds industry and a tendency to have a higher number of funds per family starting with the nineties.

Figure 3-2: **Family-new fund transition probability matrix**



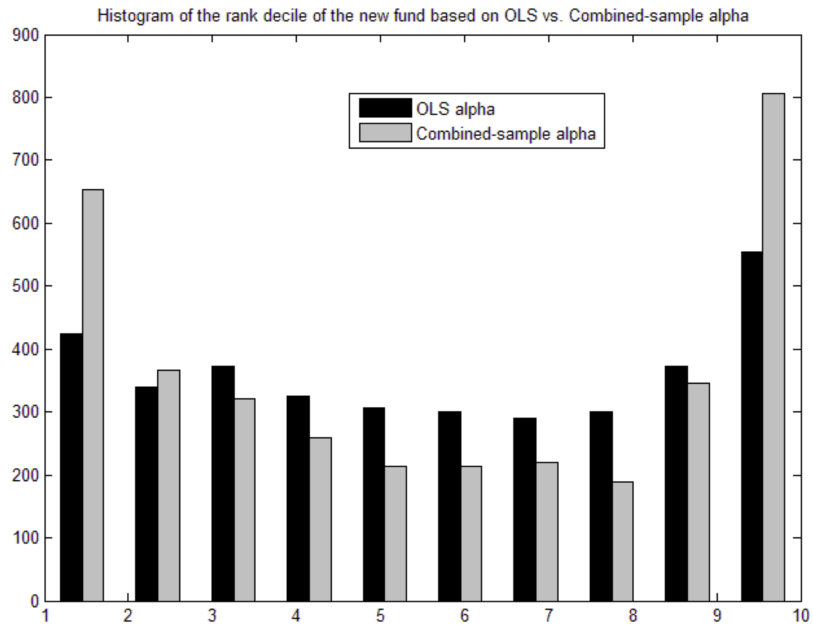
We estimate the performance of the family for [-36 0] months interval and we rank it into one of the ten deciles. We do the same for the new fund opened for the subsequent [0 12] months period. We obtain a matrix that gives the proportion of funds in a specific rank that are launched by a specific rank of families. Figure a diplays results related to the entire sample, Figure b is for funds that have a single manager while Figure c for those that are team managed.

Figure 3-3: **Risk measures of new funds**



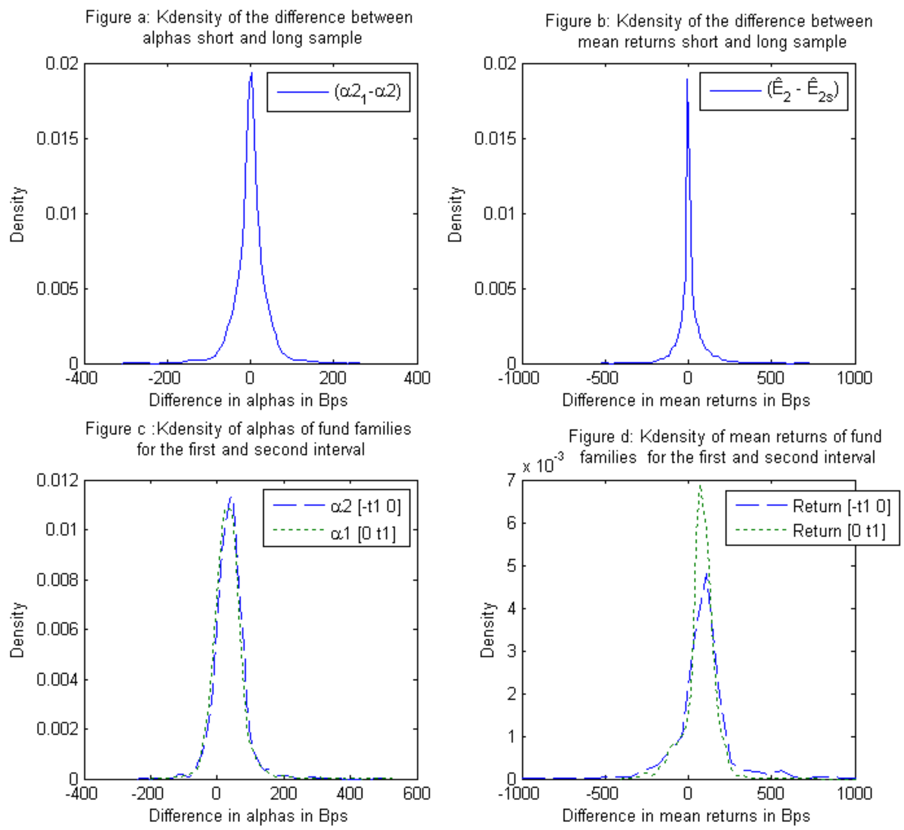
For each fund introduction, we compute the standard deviation, the adjusted standard deviation using family, style and industry prior after 24 months of their starts. We also compute family, style and industry risk measures. We compute these measures for this specific time window for existing funds. Moreover, we rank new funds measures among old ones.

Figure 3-4: **Performance ranking of new funds using OLS vs. Combined-sample alphas**



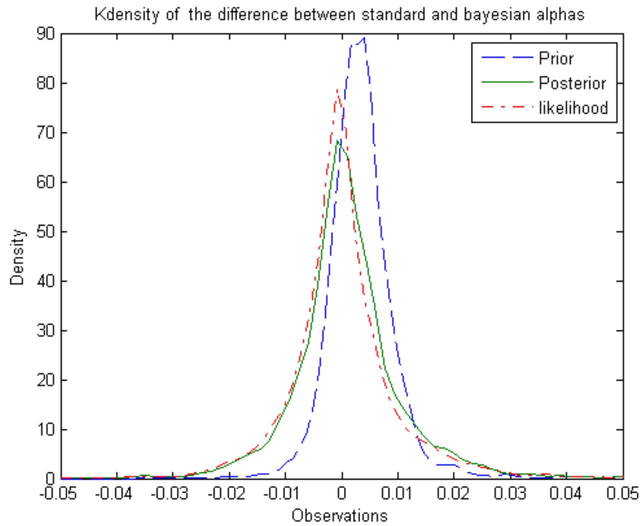
In this figure we rank new funds among existing funds for [0 24] months after the new fund start. It clearly shows that ranking based on classical alphas vs. on combined-sample alphas leads to similar results at one notable exception that the CS estimator increases the focus on top and bottom performing funds.

Figure 3-5: **OLS and Combined-sample estimator for mean returns and alphas**



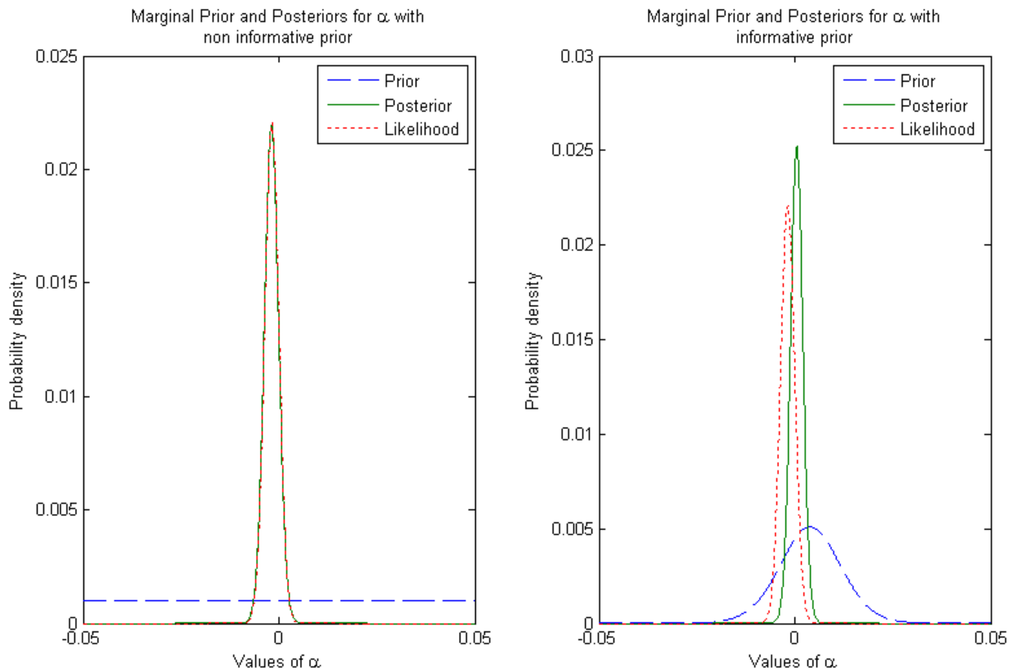
In testing the difference between means using short and long sample, we find an average difference equal to 2.98 basis points and a t-Stat equal to 1.47. The difference is not statistically significant. Moreover, we find an average difference between mean returns using short and long sample equal to 6.49 basis points and a t-stat equal to 1.44. The difference is also not statistically significant. Using combined-sample alphas will not automatically generate neither an upward no a downward bias.

Figure 3-6: **Kdensity of the difference between OLS and bayesian alphas**



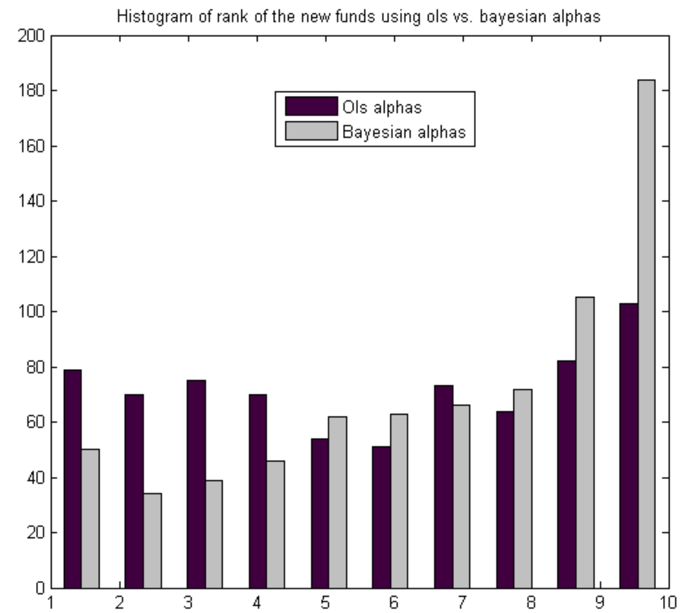
We provide the kernel density of OLS alphas of new funds, alphas family to which they belong to and the posterior alphas of new funds.The x-axis shows alphas values and the y-axis the kernel density estimate.

Figure 3-7: **Empirical bayesian distribution using non-informative and informative prior**



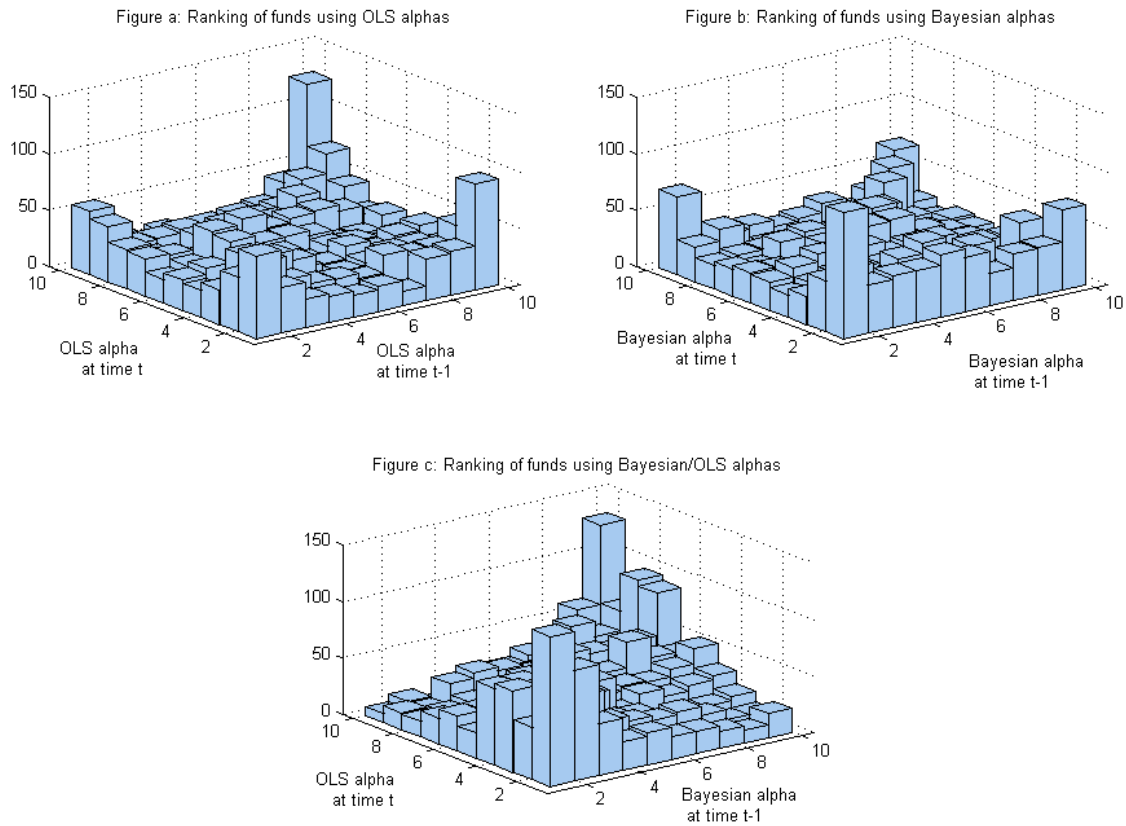
We show how the Bayesian alpha is a mix between the prior of the fund and its real performance as measured by the standard alpha. Furthermore we show the precision of Bayesian alphas by drawing a graph of the PDF distribution of the prior, posterior and likelihood for only one fund since we know the distribution density. The x-axis shows alphas values and the y-axis the kernel density estimate.

Figure 3-8: **Performance ranking of new funds using OLS vs. Bayesian alphas**



Using Bayesian alphas in stead of OLS alphas may lead to significant differences in terms of ranking of funds. We estimate Bayesian alphas of new funds and seasoned funds, and we rank new funds among existent funds. We compare after the histogram of ranking using Bayesian versus OLS performance estimation.

Figure 3-9: **Performance persistence among new funds using OLS alphas vs. Bayesian alphas**



We compute standard alphas and Bayesian alphas for two consecutive sub-periods. We want to compare the persistence of performance among new funds using different measures. It is interesting to show that funds that exhibit high persistence with Bayesian funds may have more stable results because they are also belonging to high performing families.

Table 3.1: The proportion of young funds in the sample used

Panel A reports the number of funds of the 3,307 U.S. equity mutual funds in our sample for different years and for different styles. The number of funds is increasing from a decade to another. Panel B reports the number of funds divided into two categories old (i.e. >3 years) and young funds.

Panel A: # of funds by Style

	1970	1980	1990	2000	2005
Small company growth	4	5	45	369	477
Other aggressive growth	17	18	55	326	403
Growth	52	69	141	612	700
Income	12	23	56	101	108
Growth and income	44	52	126	415	454
Maximum capital gains	2	2	2	2	1
Sector funds	6	8	65	275	331
Not specified	3	21	425	678	556
Total number of funds	140	198	915	2,778	3,030

Panel B: # of funds by Age

	1970	1980	1990	2000	2005
Number of young funds	55	25	296	779	398
Number of old funds	85	173	619	1,999	2,632
Total number of funds	140	198	915	2,778	3,030
# of young funds /Total # of funds	39.29%	12.63%	32.35%	28.04%	13.14%

Table 3.2: Descriptive statistics of the sample of mutual funds used

Panel A reports the number of funds, the percentage of funds, and total net assets under management (TNA) of the 3,307 U.S. equity mutual funds in our sample over the period 1962-2005. These funds are members of a total of 406 different fund families. Panel B reports the number of fund families for each category of family size (number of portfolios) and the TNA at the beginning and end of the sample period.

Panel A: Style classifications

Type of the fund	Number of funds	% of funds	TNA(in millions of US$) 1970	1980	1990	2005
Small Company Growth	558	15.0%	269.9	724.6	3 994.1	223 354.3
Other Agressive Growth	494	13.3%	2 292.9	1 752.5	6 633.5	186 969.9
Growth	876	23.6%	7 334.4	6 795.0	59 750.1	630 710.7
Income	131	3.5%	4 178.7	4 524.9	61 851.3	202 825.2
Growth and Income	568	15.3%	9 110.0	8 921.3	34 851.3	484 408.4
Maximum Capital Gains	2	0.0%	161.6	64.2	614.1	99.0
Sector Funds	399	10.7%	1 156.2	938.3	6 056.6	132 488.8
Not Specified	679	18.3%	29.9	3 538.4	89 399.1	552 664.9
Total	3 707	100.0%	24 533.5	27 259.2	263 150.1	2 413 521.1

Panel B: Fund family characteristics

# of portfolios	# of families	1970	1980	1990	2005
1	0	0	0	0	0
2-5	232	1,086.68	1,452.59	21,536.60	241,267.94
6-10	74	3,990.06	2,925.98	19,003.16	21, 241.15
11-50	94	16,852.24	20,215.29	146,468.77	1,017,199.62
>51	6	2,604.54	2,665.31	76,141.54	937,812.40
Total	406	24,533.51	27,259.17	263,150.06	2,413,521.11

Table 3.3: Transition probabilities matrix

We want to see whether past family performance gives an idea about the future performance of the new fund. We estimate the performance of the family for 36 months before new fund start and we rank it into one of the ten deciles. We do the same for the new fund opened for a subsequent 12 months period following its inception. We obtain a matrix that gives the proportion of funds (in %), in a specific rank that were launched by a specific rank of families.

Panel A Entire sample

Family performance at time t-1

Fund performance at time t

Deciles	1	2	3	4	5	6	7	8	9	10
1	0.04	0.08	0.08	0.23	0.19	0.34	0.84	1.29	2.97	5.36
2	0.00	0.08	0.08	0.11	0.19	0.27	0.65	1.56	2.62	4.30
3	0.11	0.08	0.04	0.08	0.30	0.27	0.53	1.22	2.74	5.29
4	0.04	0.11	0.11	0.23	0.08	0.15	0.53	1.29	1.67	4.83
5	0.08	0.08	0.00	0.19	0.11	0.27	0.19	1.41	2.55	4.11
6	0.11	0.00	0.08	0.00	0.08	0.23	0.34	0.99	2.05	4.03
7	0.00	0.11	0.11	0.15	0.27	0.23	0.46	1.06	1.71	4.18
8	0.08	0.04	0.04	0.19	0.34	0.30	0.30	1.22	1.79	4.26
9	0.08	0.11	0.00	0.11	0.19	0.27	0.61	0.99	2.47	5.40
10	0.04	0.04	0.08	0.11	0.49	0.46	0.57	1.60	3.69	8.02
Marg. Dist.	0.57	0.72	0.61	1.41	2.24	2.78	5.02	12.62	24.26	49.77
$Chi-2$	0.07	0.47	0.00	1.32	18.12	5.49	16.48	8.66	39.71	68.61
p-value	0.80	0.49	1.00	0.25	0.03	0.79	0.06	0.47	0.00	0.00

Panel B **Single manager funds**

Family performance at time t-1

Fund performance at time t

Deciles	1	2	3	4	5	6	7	8	9	10
1	0.05	0.05	0.09	0.23	0.14	0.59	0.81	1.27	2.89	5.07
2	0.00	0.05	0.00	0.23	0.18	0.23	0.77	1.85	2.53	4.43
3	0.09	0.09	0.05	0.14	0.18	0.36	0.45	1.45	2.85	4.66
4	0.09	0.05	0.18	0.23	0.09	0.14	0.54	1.27	1.99	4.88
5	0.09	0.14	0.05	0.14	0.09	0.23	0.14	1.54	2.58	4.84
6	0.09	0.05	0.05	0.00	0.00	0.23	0.36	0.81	2.17	3.93
7	0.00	0.18	0.09	0.18	0.23	0.18	0.54	1.13	1.72	4.48
8	0.05	0.00	0.05	0.18	0.41	0.36	0.23	1.36	1.94	4.88
9	0.09	0.14	0.05	0.18	0.18	0.14	0.54	1.22	2.40	5.16
10	0.05	0.05	0.14	0.05	0.36	0.27	0.50	1.36	3.35	6.92
Marg. Dist.	0.59	0.77	0.72	1.54	1.85	2.71	4.88	13.25	24.42	49.25
$Chi-2$	0.07	0.47	0.00	1.32	18.12	5.49	16.48	8.66	39.71	68.61
p-value	0.80	0.49	1.00	0.25	0.03	0.79	0.06	0.47	0.00	0.00

Panel C **Team managed funds**

Family performance at time t-1

Fund performance at time t

Deciles	1	2	3	4	5	6	7	8	9	10
1	0.21	0.05	0.00	0.36	0.21	0.31	1.14	1.65	2.48	4.90
2	0.05	0.21	0.10	0.05	0.21	0.36	0.83	1.65	2.58	3.92
3	0.10	0.10	0.00	0.15	0.41	0.15	0.36	1.55	2.63	5.01
4	0.00	0.21	0.00	0.36	0.26	0.26	0.36	1.70	1.65	4.28
5	0.05	0.05	0.00	0.21	0.15	0.46	0.41	1.81	2.43	3.97
6	0.10	0.00	0.05	0.00	0.36	0.26	0.52	1.34	2.12	4.70
7	0.00	0.05	0.05	0.26	0.36	0.46	0.52	1.34	1.91	3.61
8	0.05	0.10	0.05	0.10	0.46	0.41	0.36	1.03	1.81	3.82
9	0.00	0.05	0.00	0.10	0.21	0.31	0.62	1.29	3.15	4.33
10	0.00	0.10	0.05	0.21	0.41	0.57	0.72	1.55	3.25	6.50
Marg. Dist.	0.57	0.93	0.31	1.81	3.04	3.56	5.83	14.91	23.99	45.05
$Chi-2$	0.07	0.47	0.00	1.32	18.12	5.49	16.48	8.66	39.71	68.61
p-value	0.80	0.49	1.00	0.25	0.03	0.79	0.06	0.47	0.00	0.00

Table 3.4: Risk measures correlation matrix

In this table, we measure the correlation between different risk measures: specific standard deviation, sigma adjusted with family, sigma adjusted with style, sigma adjusted with the fund industry, family risk, style risk, industry risk. We give the Spearman's rank correlation coefficients (in %), and t-test values are between parentheses.

	σ Specific	$\widetilde{\sigma}$ Family	$\widetilde{\sigma}$ Style	$\widetilde{\sigma}$ Indus.	Family risk	Style risk	Indus. risk
σ Specific	100.0						
	(N/A)						
$\widetilde{\sigma}$ Family	94.8	100.0					
	(181.03)	(N/A)					
$\widetilde{\sigma}$ Style	99.7	95.1	100.0				
	(847.79)	(187.86)	(N/A)				
$\widetilde{\sigma}$ indus.	99.7	95.1	100.0	100.0			
	(845.10)	(187.56)	(2228.63)	(N/A)			
Family risk	35.8	44.4	36.7	37.2	100.0		
	(23.34))	(30.19)	(24.04)	(24.37)	(N/A)		
Style risk	46.6	46.7	48.5	48.4	44.9	100.0	
	(32.05)	(32.11)	(33.77)	(33.64)	(30.56)	(N/A)	
Indus. risk	38.2	38.1	39.7	40.6	57.4	64.5	100.0
	(25.17)	(25.06)	(26.33)	(27.06)	(42.72)	(51.40)	(N/A)

Table 3.5: Average risk measures

We measure the average values for various risk measures. Panel A shows the evolution of those measures as we vary the number of portfolios in the family (i.e. size of the family). Panel B shows the evolution of those measures as we vary the length of the time window estimation.

Panel A: Average risk measures and size of families

# of portfolios	σ Family	$\widetilde{\sigma}$ Family	$\widetilde{\sigma}$ Style	$\widetilde{\sigma}$ Indus.	Family risk	Style risk	Indus. risk
2-10	4.676%	4.734%	0.313%	0.315%	0.003%	0.007%	0.008%
11-50	4.499%	4.548%	0.298%	0.299%	0.005%	0.005%	0.007%
>51	4.410%	4.504%	0.275%	0.276%	0.005%	0.004%	0.005%

Panel B: Average risk measures for different time windows

T	σ Family	$\widetilde{\sigma}$ Family	$\widetilde{\sigma}$ Style	$\widetilde{\sigma}$ Indus.	Family risk	Style risk	Indus. risk
12 months	4.585%	4.705%	0.332%	0.335%	0.014%	0.015%	0.019%
24 months	4.550%	4.607%	0.300%	0.302%	0.004%	0.005%	0.007%
36 months	4.495%	4.468%	0.281%	0.282%	0.002%	0.003%	0.004%

Table 3.6: Efficiency of the Combined-Sample (C-S) estimator

Panel A exhibit error measures for different time horizons. We fix the fraction of the missing data to 25% of the data available (s-s_1). As we have more data, the error of estimation is decreasing even though we keep the same proportion of missing values. In Panel B, we choose a value of s equal to 36 months and we vary the length of s_1. We take different values of s_1 equal to 1, 3, 6, 12 and 18 months as mentioned in table. As we enlarge the value of s_1 we have a smaller percentage of missing data. Moreover, we would expect that combined -sample (C-S) estimator would perform worse as we have a larger percentage of missing historical records.

Panel A Sensitivity to the time window length

Total data available s	12	24	36	48	60
Median error OLS (bps)	17.89	13.95	11.59	11.41	10.73
Median error C-S (bps)	14.60	11.04	9.80	9.19	8.62
(OLS)- (C-S) (bps)	3.29	2.91	1.79	2.22	2.11
Stdv error OLS .10ˆ3	0.0122	0.0069	0.0058	0.0056	0.0059
Stdv error C-S.10ˆ3	0.0094	0.0057	0.0048	0.0044	0.0044
(OLS)- (C-S) .10ˆ3	0.0028	0.0012	0.0010	0.0013	0.0015
RMSE OLS .10ˆ3	0.0745	0.0553	0.0490	0.0468	0.0465
RMSE C-S .10ˆ3	0.0644	0.0490	0.0435	0.0405	0.0394
RMSE OLS-RMSE C-S .10ˆ3	0.0101	0.0063	0.0055	0.0063	0.0070

Panel B Sensitivity to the fraction of missing data

Fraction of Missing data s_1/s	1/36	3/36	6/36	12/36	18/36
Median error OLS (bps)	2.68	5.66	8.57	11.68	14.99
Median error C-S (bps)	2.14	4.61	7.39	10.08	12.56
(OLS)- (C-S) (bps)	0.54	1.04	1.17	1.603	2.42
Stdv error OLS .10ˆ3	0.0008	0.0020	0.0033	0.0063	0.0086
Stdv error C-S.10ˆ3	0.0006	0.0014	0.0025	0.0054	0.0065
(OLS)- (C-S) .10ˆ3	0.0002	0.0006	0.0008	0.0009	0.0021
RMSE OLS .10ˆ3	0.0168	0.0283	0.0371	0.0507	0.0595
RMSE C-S .10ˆ3	0.014	0.0238	0.0322	0.0462	0.0513
RMSE OLS-RMSE C-S .10ˆ3	0.0028	0.0045	0.0049	0.0045	0.0085

Table 3.7: Efficiency of the empirical Bayes estimator

We find that the Bayesian estimator has a smaller RMSE than the Ols for different time window lengths considered. This clearly confirms the initial intuition that bayesian estimation is more suitable for estimation of young and new funds performance. As we enlarge the data available the difference in RMSE between the Bayesian and OLS estimator decreases. The difference remains positive even for horizons of 60 months.

Time Horizon Measurement	RMSE OLS	RMSE bayes	RMSE OLS-RMSE bayes
12 months	.55%	.49%	.06%
24 months	.39%	.34%	.05%
36 months	.32%	.29%	.03%
48 months	.27%	.25%	.02%
60 months	.24%	.22%	.02%

Chapter 4

Mutual Fund Tournaments

4.1 Introduction

In this paper, we tackle the question of risk tournament among 1,233 actively managed U.S. mutual funds. The alteration of portfolio risk as a response to past performance may generate a particular risk pattern where fund that perform poorly (highly) in the first half of the year increase (decrease) their risk in the second half. This pattern provides further information as to competition across portfolio managers and mutual fund firms. Our contributions are summarized in three different sections.

First, we propose a study of the tournament hypothesis through a comparison between index and non-index funds. As the first group holds a passive strategy, it should not exhibit a risk tournament pattern. Our results show no noticeable differences between the two groups of funds, thereby rejecting the hypothesis of actively risk change.

Second, we analyze a sorting bias related to the tournament pattern and underscore its importance. Indeed, the typical approach when studying risk tournament is to sort funds based on their first half year performance and their risk-adjusted ratio (RAR), i.e. the ratio of the second half year standard deviation over that of the first half year. However, the drawback of this method is that the two criteria are not necessarily independent. We advocate the use of an orthogonalization method, meaning that we only study the effect of performance liberated of any risk factor. We show that once we apply the orthogonalization method, some of the previous conclusions on the existence of tournament and inverse tournament no longer hold true. The sorting bias is important enough to qualitatively change the results of the study: four years of the fifteen considered. For the other years, the magnitude of the change in risk varies greatly. More generally, we find that about 10% of additional correlation between risk and returns artificially adds 1% in tournament frequencies. We also show that tournament factor loadings cease to exist when we use an orthogonalization methodology.

Third, to the best of our knowledge, we are the first to look at stock/bond allocations as a response to past performance. The null hypothesis requires that winner funds decrease their allocation in stocks in the second half year to reduce the market exposure. However, we found no evidence of flight to quality among winner funds.

The risk-return relationship and risk aversion are important concepts in modern finance theory. Parameterizing these variables allows one to set up models that reflect different economic schemes. We consider two hypotheses of which the first is ceteris paribus; if one is taking more risk, he should be rewarded by additional income (Markowitz, 1952). Secondly, the more one possesses, the fewer incentives he has to increase his wealth (increasing absolute risk aversion). By combining these two statements, we could argue that a fund manager who has registered a poor performance will take higher risks to improve his final rank. This statement summarizes the tournament model hypotheses. For instance, Goriaev, Palomino and Prat (2000) show that interim losers increase their risk proportionally to the degree of underperformance. Acker and

Duck (2001) argue that poorly performing managers adopt extreme portfolios for the second half of the year. The same conclusion is drawn by Li and Tiwari (2006) who show that it is optimal for loser funds to increase their idiosyncratic risk. Contrasting with this first group of articles, another branch of literature defends the idea of zero tournament, i.e. strategic behavior among managers. Taylor (2003) points out that in the presence of active mutual fund players, the winning manager is more likely to gamble. Moreover, Makarov (2008) demonstrates that interim winners optimally choose higher portfolio volatility compared to interim losers.

A median contingency table is a straightforward way to disclose the tournament effect. Funds are sorted by a specific criterion in the first half of the year and are then ranked with respect to their risk-adjusted ratio (RAR), i.e. the ratio of the second period standard deviation divided by that of the first period. A test of equality of frequencies across the different subgroups is then performed. Armed with this approach, Brown, Harlow and Starks (1996) find that losers of the first half year increase their risk in the second half year while winners lock in their positions. However, Busse (2001) finds no evidence of fund tournament using daily returns on 230 funds over the period 1985-1995. Moreover, he argues that the auto-correlation bias present in monthly returns drives the tournament effect. Once this bias in monthly standard deviation is corrected, evidence of tournament no longer exists. Providing a closed formula, Goriaev, Nijman and Wercker (2005) advocate the robustness of monthly returns over daily returns. They find slight evidence of tournament among U.S. equity funds for the period 1976-2001. Ammann and Verhofen (2009) use daily data to examine the question of tournament among mutual funds. They verify whether past performance causes tournament factor loadings in the subsequent half year. In contradiction with the tournament hypothesis, they find that winner funds exhibit an increase in betas and total return volatility in the second half of the year. Working on a larger data-set using a contingency methodology similar to BHS (1996), Qiu (2003) finds slight evidence of tournament for the period of 1992-1999. Moreover, he makes a distinction between two groups of funds: single- vs. team-managed funds. He shows that single manager funds are more likely to alter their risk for the second half year. Elton et al (2006) do not find results in favor of tournament behavior using both monthly returns and fund holdings. In our paper, we also obtain mixed results related to the existence of tournament phenomenon: loser (winner) funds do not systematically increase (de-crease) their risk in the second half of the year. Furthermore, most of the previous articles find a strong negative relationship between shifts in risk and the level of risk of the first half of the year. The inclusion of the first half year standard deviation aims to capture the mean reversion effect of volatility. Nonetheless, it is not sure whether this relationship is exempt from any estimation bias. For example, Schwartz (2008) points out that sorting funds based on returns may bias the results of the risk ratio in the second half of the year. The author shows weak evidence of tournament behavior using both monthly returns and holdings. He suggests a holding based analysis to control this bias. We confirm some of his results and prove that the sorting process may inflate the tournament and inverse tournament effects. We show that sorting on cumulative returns suffers from an upward (downward) tournament bias and downward (upward) inverse tournament bias if the correlation between risk and return is positive (negative). Moreover, when we sort funds on an orthogonalized measure of cumulative returns, we find that the results change both qualitatively and quantitatively. We conclude that the sort bias is important enough to alter the tournament conclusion.

One can also demonstrate the tournament effect using a linear regression frame-work that explains the risk-adjusted ratio with past performance. The tournament hypothesis stipulates a negative relationship between the risk-adjusted ratio and past performance. For instance, Koski and Pontiff (1999) compare the risk of funds that use derivatives to those that do not. They did not find significant differences between the characteristics of the two groups of funds. However, other authors argue that change in risk is negatively related to past performance and past risk. Using a cross-sectional regression, Busse (2001) also reaches the same results for the period 1985-1996 and Qiu (2003) tests the influence of the fund's standard deviation, age and size on the shift in risk. Past standard deviation has a negative impact while age has a positive impact on the change in risk. The size of the fund is not significant. Kempf and Ruenzi (2008) analyze the tournament at a family level using a panel regression. They link the change in risk of mutual funds to the rank reached within the family in the first half year. Substantial differences between small and large families are disclosed. The latter group exhibits less strategic behavior. A convex and positive relationship between past returns and flows is an incentive for fund managers to increase their level of risk. As the sensitivity of flows to past performance asymmetrically increases, managers are encouraged to assume a higher level of risk for the last part of the year. Chevalier and Ellison (1997) find that the degree of convexity of the relationship between flows and performance creates an incentive for the manager to alter the underlying risk. A flat relationship in the negative part incites managers to take higher risks. Pagani (2006) presents the relationship between the convexity of the flow-performance relationship and the degree to which risk changes. He explains changes in risk using a number of explanatory variables such as managerial ability, marketing efforts, and size of the fund family. Using squared returns in addition to convexity flows-performance variables, he finds that an increase in the convexity of the flow-performance relationship leads to an increase in the convexity of U-shaped tournament behavior. In current works, within a panel regression, we find that the RAR is higher for funds that exhibit weak flow-performance dependence, high mean returns, low total risk and high inflows. Age and TNA are also negatively related to the RAR.

Analyzing specific fund patterns based solely on fund returns may lead to non-robust conclusions. To further support any hypothesis, the use of fund holdings is definitely a suitable approach. Following on from Schwartz (2008) and Elton et al (2006), we also analyze whether loser funds increase their allocation in riskier stocks. We found no evidence that loser (winner) funds systematically increase (decrease) their allocation in riskier stocks for the second half year. Moreover, we analyze changes in stock/bonds allocations as a response to past performance. The null hypothesis is that loser funds increase their allocation in stocks in order to increase their active management and thereby their risk. Nevertheless, the results related to this hypothesis were of little significance.

Studying risk tournament among non-U.S. funds, or among hedge funds, is an interesting addition to the original work of BHS (1996). Studies related to the tournament effect in the U.K. for example include Taylor (2003), Jans and Otten (2005), and Acker and Duck (2006). Even though the U.K. mutual fund industry may present specific characteristics, one should be able to draw some comparisons with results found in the U.S. Jans and Otten (2005) use a sample of 422 U.K. mutual funds and found no evidence of tournament for the entire period of 1989-2003, while Taylor (2003) finds evidence of strategic behavior within a dataset of 660 funds (weekly returns) for the period of 1984-1996. Acker and Duck (2006), within a sample for the period of 1997-2001, show evidence that managers of loser funds adopt extreme market positions for the second half year. Hedge fund managers may also have incentives to change their risk level during the year. Kazemi and Li (2007) study shifts in risk among hedge funds. They found evidence of risk adjustment in response to relative performance. Their results are in line with those previously found by Brown et al (2001). Risk tournament during the year is a particular case of a shift in risk. Given that fund managers can take profit on various opportunities, they may be tempted to shift their risk from one year to another. Huang, Sialm and Zhang (2008) link change in risk from one year to another with past performance. Finally, we also come across the tournament theory in the different works of Bronars (1987), Knoeber and Thurman (1994), Chiang (1999) and Melton (2000). These articles highlight the fact that in the presence of high incentives, competitors are encouraged to take higher risks.

As the previously mentioned articles did not use the same sample, it is difficult to affirm in a binary question whether or not the tournament phenomenon exists. Contradictory results may be due to sample or/and methodology differences. Furthermore, few articles have attempted to explain the heterogeneity of results from one year to another: why is tournament favored in certain years more than others? One notable exception is no doubt the work of Olivier and Tay (2008). They link tournament to economic activity and show that poor mid-year performers only increase portfolio risk when economic activity is strong.

The remainder of the paper is organized as follows. Section 2 describes the sample. Section 3 proposes a comparison between index and non-index funds and offers a contingency approach to the study of tournament. Section 4 demonstrates the interaction between risk and return and explains the orthogonalization methodology. In Section 5, we link the change in risk to fund characteristics. Section 6 analyzes the holdings of funds. Concluding comments are provided in Section 7.

4.2 Data

We use three main sources of data: the CRSP Survivor Bias-Free Mutual Funds Database (MFDB), the Morningstar fund database, and the CRSP stock database. Data on portfolio holdings and general industry classification (GIC) for each stock in the portfolio are provided by Morningstar for the period starting January 1991 and ending December 2005. Monthly fund returns, monthly total net assets under management (TNA), annual fees and turnover are taken from the CRSP Survivor Bias-Free Mutual Fund Database. We select U.S. domestic equity funds based on criteria provided by Pastor and Stambaugh (2002b). These style criteria stem from four different sources: Wiesenberger, Micropal/Investment company data, strategic insight, and the funds themselves. Furthermore, we make a distinction for index funds as we do not expect to find any tournament effect for passively managed funds. We match the two databases and for each fund portfolio, we retain the return series of the oldest share class. The final sample comprises 1,233 U.S. domestic equity mutual funds and 140 index funds.

We use the 1-month Treasury bill rate as the risk-free rate to compute excess returns. The intercept (alpha) of the Carhart (1997) four-factor model is used to assess risk-adjusted performance. The four factor-mimicking portfolios are downloaded from Kenneth French's website[1]. As measures of liquidity we use the size quintile rankings of stocks and the Amihud (2002) liquidity ratios from Joel Hasbrouck's website[2]. For each fund portfolio we compute value weighted measures of the industry concentration index of Kacperczyk et al. (2005), the market capitalization rankings of stock holdings, and the illiquidity measure of Amihud (2002).

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french; Section "Data Library", "U.S. Research Returns Data". The website also provides details of the portfolio formation methodology to construct these factor returns.

[2] http://pages.stern.nyu.edu/~jhasbrou; Section "Research and Working Papers".

Table 1 displays the descriptive statistics of our sample. For each style classification we include the number of funds, the percentage of funds, and the market capitalization for different points in time. We notice that growth, and growth and income funds constitute almost one half of the sample (51.4%).

[Table 1]

4.3 Fund tournament using returns

4.3.1 Non-Index Funds vs. index funds: active vs. passive management

The first approach we use to uncover tournament behavior among U.S. equity funds is a comparison between actively managed funds and passively managed index funds. Tournament behavior suggests that fund managers actively vary their risk in the second part of the year in order to enhance performance. The null hypothesis is that index funds will exhibit zero tournament.

Each year we sort funds over the first and second half of the year into deciles based on risk and return characteristics. To measure returns we use mean returns and alphas from Carhart (1997) four-factor regressions. The three risk measures are standard deviation (total risk), market beta (systematic risk), and the R^2 (unsystematic risk). Decile 1 comprises those funds with the lowest values and decile 10 those with the highest values. Figure 1 illustrates the transition frequencies f(l,m) that a fund has a rank m during the second six months of the year conditional on the initial rank l over the first six months. The null hypothesis implies that funds maintain the same rank. Among the different measures, standard deviation is the one that exhibits the largest persistence in ranks. This result is in contradiction with the hypothesis that funds alter their risk in the second half of the year. Figure 2 shows the histogram of differences between the initial decile rank l and the subsequent decile rank m for the same return and risk measures as in Figure 1. Again, standard deviation is the measure that exhibits the smallest dispersion in ranks between the first and second half of the year.

Additionally, we study the risk-adjusted ratio (RAR) introduced by Brown, Harlow, and Starks (1996). If funds engage in a tournament over the calendar year then we would expect that funds with a mediocre performance during the first half of the year would take more risk over the second in an attempt to improve their annual return. RAR expresses the change in risk by dividing the standard deviation of fund i over the second half of the year, $\sigma_{i,2}$, by the standard deviation over the first six months, $\sigma_{i,1}$

$$RAR_i = \frac{\sigma_{i,2}}{\sigma_{i,1}} \tag{4.1}$$

Over the first six months of each year we sort all non-index funds into deciles based on the same five characteristics as in Figures 1 and 2: mean return, risk-adjusted alphas from the Carhart four-factor model, standard deviation, market beta, and the R^2 from the four-factor model estimation. Then, we compute for each fund the RAR between months [7,12] and months [1,6] and assign a decile rank. Figure 3 shows the frequencies that a fund ranks in one of the RAR deciles given its decile ranking over the first six months of the year based on one of the five characteristic. As before, for the characteristics decile 1 comprises those funds with the lowest values and decile 10 those with the highest values. The plot for standard deviation indicates negative relationship between the RAR and σ_1. On one hand, funds with a high standard deviation over the first six months, in particular those ranked in deciles 10 and 9, are more frequently ranked in decile 1 for RAR, which indicates that their standard deviation is relatively low for the second six months of the year when compared to the standard deviation over the first six months. On the other hand, funds with a low standard deviation over the period [1,6] are more likely to rank in the deciles with the highest values of RAR. Thus, it appears that the level of the standard deviation of fund returns is correlated with RAR rankings. Moreover, funds with very low R^2 for the four-factor model tend to exhibit a high RAR. For all other graphs, no clear conclusion can be drawn.

[Figure 1]

[Figure 2]

[Figure 3]

Next, we repeat the same computations but for a sample of 140 index funds. Index funds are not actively managed and, therefore, should not exhibit a tournament effect. Figure 4, Figure 5 and Figure 6 display results related to index funds. By summarizing results based on a comparison between index funds and non-index funds we do not find any notable differences in the shape of the histograms. Standard deviation is the measure with the highest degree of persistence (Figures 1 and 4) or, stated in other words, the measure with the smallest dispersion in the difference in rankings between the first and second half of the year (Figures 2 and 5). These findings are an argument against the existence of a tournament effect among actively managed funds. As Figure 6 illustrates, the negative relation between standard deviation decile rankings and the RAR that divides the standard deviation over months [7,12] by the standard deviation over the months [1,6] disappears for index funds. This is explained by the fact that standard deviations of returns on index funds are more homogeneous and the levels are relatively low.

[Figure 4]

[Figure 5]

[Figure 6]

4.3.2 Contingency approach to tournament

Sorting on cumulative returns

In this section, we use contingency tables to analyze tournament among mutual funds. As in Brown, Harlow, and Starks (1996, BHS hereafter), this allows us to formally test whether funds change their risk behavior conditional on their realized performance over the beginning of the year. Each year, we rank funds based on their performance, i.e. cumulative excess returns for the first six months of the year [3]. We classify funds into two groups: above median "winners" and below median "losers". Secondly, we compute the risk-adjusted ratio (4.1) for winner and loser funds as the risk for the second part of the year divided by the risk for the first part. We use the χ^2-test of BHS to test the null hypothesis that winner and loser funds are equally distributed into low and high RAR funds. We do not find a systematic pattern in risk behavior across funds: for certain years we do observe a tournament effect, where funds with low (high) returns have more likely above (below) median RARs, and for others, we observe an inverse tournament effect (interpreted by Taylor, 2003 as strategic behavior), where funds with low (high) returns tend to have low (high) RARs. Our results are in contradiction with BHS (1996) who find considerable support for tournament behavior of funds. Panel A of Table 2 shows that only years 1991 and 1996 exhibit a significant tournament effect, while inverse tournament is significant for 1993, 1997, 1998, 2000, 2001, 2002, and

[3] We did the computations for different intervals: [4, 8], [5, 7], [7, 5]. Furthermore, we recomputed the given results by excluding December or/and January returns. All in all, results are quite similar. Most significant results are obtained using a [6, 6] window. Entire results are available upon request.

2003. For the other years we cannot reject the null hypothesis of an equal distribution. We have yet to discover why we observe tournament for those specific years and not the others.[4].

[Table 2]

Sorting on prior risk

Our finding of a negative relation between the level of standard deviation and RAR in the previous section raises some concerns about the methodology used by BHS (1996). Comparing RAR may not truly reflect the pattern in the risk taking behavior across fund managers.

Rather than ranking funds based on cumulative excess returns, we rank then based on risk (measured by total return standard deviation). The null hypothesis is that funds tend to revert to the average risk for the second part of the year. Funds that have taken large (small) risks in the first half year will increase (decrease) the risk of their positions in the second half.

We rank funds based on return standard deviation for the first six months of the year and split them into two groups: above and below median risk funds. We then compute the risk adjustment ratio (RAR) for winner and loser funds as the standard deviation for the second part of the year divided by the standard deviation for the first part. Based on this classification, results displayed in Panel B of Table 2 show more inverse tournament. However, one caveat of this classification is that the information

[4] We also tried a tournament style analysis. We computed a contingency table for each CRSP Style group, and Morningstar's style box. Results are qualitatively the same, and we can not draw a clear a conclusion of the existence of systematic tournament. Finally, for each Morningstar style box, we have regressed fund returns on the corresponding Russell style index (ex: Russell Growth and Small cap for the corresponding style box) and we computed the residual risk. We did not find a significant tournament phenomenon.

contained on the classification criterion is also part of the RAR measure. Hence, this ranking methodology is biased.

Sorting on prior flows

The third test consists of ranking funds based on flows received in the first six months of the year. Instead of estimating the success of a fund by its risk-adjusted return we directly use fund inflows as an indicator. We expect funds that received less flows during the first part of the year to increase their risk in the second part. We measure monthly fund flow as a percentage of fund size, where TNA is the total net asset under management at time t and R_t is the fund return from month $t-1$ to t.

$$Flows_t = \frac{TNA_t - TNA_{t-1}(1+R_t)}{TNA_{t-1}} \tag{4.2}$$

Panel C of Table 2 shows that ranking based on flows exhibits fewer significant results.

Middle vs. extreme quartiles

In this section, we corroborate our findings by focusing on the funds in the tails of the distribution of realized returns. We test the following tournament hypothesis: successful funds and poorly performing funds will decrease their risk as they are highly exposed. On the hand, middle-class funds will attempt to differentiate by taking higher risks. In our opinion, funds that belong to extreme deciles are more likely to decrease their risk. Low-performing funds will try to avoid an exit, and high-performing funds will look to maintain good and stable results.

For the first period, we classify funds based on their cumulative returns, return standard deviations or flows into different quartiles. We define quartiles 1 and 4 as extreme quartiles, and quartiles 2 and 3 as middle quartiles. Panel A of Table 3 sorts funds based on their cumulative return for the first part of the year, Panel B of Table 3 uses risk as a sorting criterion, and Panel C uses flows. Results seem consistent with the idea that extreme-performing funds will decrease their risk while middle-quartile funds will increase theirs. However, they are significant enough as only 7 of the 15 years considered show a statistically significant χ^2. Results from risk and flow classifications are mixed and hardly interpretable.

[Table 3]

4.4 Controlling for risk: orthogonalization approach

4.4.1 Combining risk and returns

In the previous section, the contingency tables were based solely on one criterion, thereby obtaining a 2×2 contingency table. This enabled us to document a negative relation between standard deviation over the first six months of the year and RAR between the first and second six months period. Given that mean returns are correlated with standard deviation, sorting funds in the first period on mean returns and then evaluate RAR over the second period is problematic. Therefore, in this section, we expand the contingency table approach to account for two criteria: cumulative excess returns and risk. We obtain a 4×2 contingency table where the null hypothesis implies that all frequencies equal 1/8. We take two examples from Table 4 to distinguish which of the cumulative excess returns or risk has a higher impact on the risk-adjusted ratio.

First, in order to assess the impact of risk, we compare the frequencies of funds with the same level of returns and RAR (risk-adjusted ratio). For example, we examine the proportion of funds that have a low RAR and low returns. If σ_1 plays no role in tournament in terms of the RAR, we should have equal frequencies. However, we find that the average frequency of low-risk funds is 7.9% while that of high-risk funds is 18.9%. The difference between the two groups is noteworthy.

Second, to assess the impact of returns, we compare the frequencies of funds with the same level of risk and RAR. The average frequency of funds with low returns is 7.9% while that of funds with high returns is 6.2%. The difference is less than that observed based on risk as a discrimination factor. We conclude that the effect of sorting on cumulative excess returns is less significant than that obtained when sorting on standard deviation.

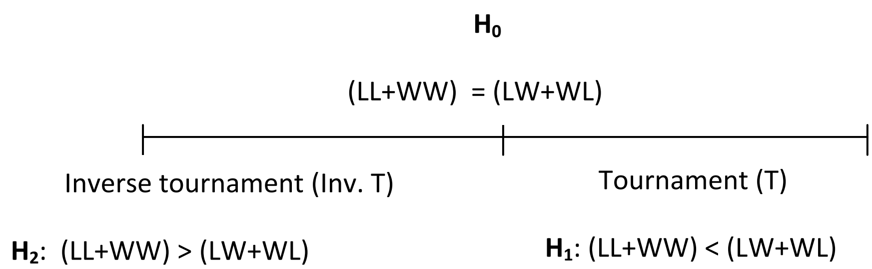
[Table 4]

Figure 7 confirms this intuition. It displays the average risk-adjusted ratio (RAR) for each pair of quintiles in cumulative return and standard deviation for the first part of the year. We complete this classification for each year and provide the average value. It is evident that prior risk drives the RAR, while less evidence is seen for cumulative returns. Low standard deviation is associated with a higher RAR.

[Figure 7]

Figure 8 highlights the dependence between return and standard deviation through a frequency matrix plot. Funds are ranked into deciles based on their cumulative return and standard deviation. Panel A depicts results for the first six months of the year, while panel B displays results for the second half year dependence. The hypothesis of no correlation implies no statistical differences across quintile frequencies. Figure 8 rejects this hypothesis.

[Figure 8]



4.4.2 Orthogonalization

In the previous section, we highlighted the importance of the risk sort over the return sort. In this section, we aim to obtain new contingency tables based on the measure of performance liberated from the risk effect. The impact of the sort bias on the contingency frequencies can be observed by comparing contingency tables based on a non-orthogonalized and an orthogonalized measure of performance. The null hypothesis implies no significant differences between the two rankings. As sorting based on mean returns is biased by risk, we propose the orthogonalization of cross-sectional mean returns on risk. For each year, we compute each fund's mean returns and standard deviation and regress mean returns on standard deviation. We then use the residuals of this regression for the ranking of the contingency tables. This residual is, by definition, orthogonal to standard deviation [5].

$$p\,\mathrm{erf}_i = a_0 + a_1\sigma_{i,[0,6]} + p\,\mathrm{erf}\_orth_{i,[0,6]} \tag{4.3}$$

The small graph below summarizes the hypothesis to test. It specifies a null hypothesis, a hypothesis 1 of tournament as defined by BHS (1996) and a hypothesis 2 of an inverse tournament effect.

[5] For further details on orthogonal regression refer to Green, p.228 for example.

The tables below explain the direction of the bias implied by the correlation between returns and standard deviation for the first part of the year. Sorting on non orthogonalized returns suffers from a bias in favor of (against) tournament and a bias against (in favor of) finding an inverse tournament effect if the correlation between risk and return is positive (negative). We provide a table to compare the χ^2 of the non-orthogonalized sort with that of the orthogonalized sort. We define the notation {i,j} where i and j stand for the state observed using, respectively, a non-orthogonalized and an orthogonalized sort. For example, {Inv.T, T} means that we have obtained an inverse tournament effect using mean return sorting and tournament using orthogonalized mean return sorting.

The sign of the difference in χ^2 using non-orthogonalized vs. orthogonalized mean returns is conditional on the sign of the relationship between the mean and sigmas for the first half year. In tables a and b below, we provide the sign of the difference in χ^2 for a positive and a negative relationship between mean and returns.

Table a: the sign of the cross-sectional correlation of $\{\mu, \sigma_1\}$ for the first half year [1, 6 months] is positive: upward tournament bias (downward inverse tournament bias)

Non orth sort\Ortho sort	T	Inv. T
T	+	never
Inv. T	unknown	-

Table b: the sign of the cross-sectional correlation of $\{\mu, \sigma_1\}$ for the first half year [1, 6 months] is negative: downward tournament bias (upward inverse tournament bias)

Non orth sort\Ortho sort	T	Inv. T
T	-	unknown
Inv. T	never	+

Table 5 shows the results of sorting based on the orthogonalized measure of cumulative return. We must compare the results obtained here with those obtained using the returns sort (Table 2, panel A). In Table 6, we report the difference in frequencies using a returns sort and an orthogonalized returns sort. Provided that mean returns and standard deviation are not independent, any sorting based on cumulative returns will partially induce a sort based on risk. If this effect dominates, we observe the 'tournament phenomenon'. We report the correlation between cumulative returns and return standard deviation for the first half year. First of all, the difference in frequencies confirms our explanation. We find that the correlation between the difference in frequencies and the correlation coefficient risk-return is 90%. Secondly, we find that sorting on orthogonalized returns reduces the observed tournament or inverse tournament, i.e. we tend toward the null hypothesis. The average χ^2 for cumulative returns sorting is 52.4 while that of the orthogonalized sort is 27.0. Thirdly, this bias is significant enough to qualitatively change the results, i.e. instead of finding tournament we observe inverse tournament, and vice-versa. For example, for the years 1995, 1996, 2002 and 2005, we obtain conflicting results depending on the sort measure used. Moreover, each additional correlation of 10% between mean returns and standard deviation adds almost 1% in the frequency of tournament subgroups (WL or LW). We obtain this result by simply regressing the correlations observed across the years and the frequency tournament differences (i.e. column 1 and column 4 of Table 6). The results of this regression are shown in Figure 9.

[Table 5]

[Table 6]

[Figure 9]

4.4.3 Numerical example

To numerically highlight the impact of the correlation between risk and return on tournament magnitude, we conduct a simple simulation procedure: we first obtain σ_1 and σ_2 as given in each year. Then, for each year, we generate cross-sectional cumulative returns for the first half year:

$$\widetilde{\mu}_{1,i} = \mu_{1,i} + \upsilon_i \tag{4.4}$$

where υ_i is a white noise. We modify the variance of $\upsilon_i$to change the level of the correlation between μ_1 and σ_1. For each level of noise, we draw 1,000 samples of $\widetilde{\mu}_1$.We arbitrarily choose an example of one specific year; the methodology however applies to all years. Panel A of Table 7 presents the true results extracted from the contingency Table 2 (Panel A). Panel B in Table 7 provides the ratio of the standard deviation of real mean returns over the standard deviation of the noise, the level of correlation between the generated variable and the original σ_1, the different sample frequencies, the χ^2 statistic and the p-value.

Interpretation of the results is quite straightforward: as the variance of the noise increases, the correlation between $\widetilde{\mu}_1$and σ_1 decreases. The χ^2 statistic that initially favored the hypothesis of tournament decreases to reach an insignificant level in the presence of high noise. The significance of tournament was also partly linked to the correlation between μ_1 and σ_1. As this relationship weakens, so does the tournament.

Panel C of Table 7 repeats the same simulation as above with one exception; we start with the original sigma and add noise so that:

$$\widetilde{\sigma}_{1,i} = \sigma_{1,i} + \upsilon_i \tag{4.5}$$

[Table 7]

The χ^2 statistic that initially favored the hypothesis of tournament decreases to reach an insignificant level in the presence of high noise. The significance of tournament is also partly linked to the correlation between μ_1 and σ_1. As this relationship weakens, so does the likelihood of detecting tournament behavior. However, our methodology suffers from one caveat: as we add noise, the correlation between μ_1 and σ_1 decreases, but the structure of the obtained differs from the original μ_1. Our aim however is simply to illustrate the impact of the correlation between mean returns and risk on the identification of tournament effects.

4.4.4 Factor loadings and alpha: is there a tournament effect?

In this section we verify the existence of tournament in factor loadings using the Carhart (1997) model. For each year, we sort funds based on alpha and compute the difference in factor loadings between the first and second half of the year for each group of funds ("winner" and "loser" funds in terms of alphas). Is there a significant change?

$$R_{it} = \alpha_i + \beta_{1i}RMT_t + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}MOM_t + \xi_{it} \tag{4.6}$$

In this section we analyze the existence of tournament in factor loadings using the Carhart (1997) model. For each year, we sort funds based on alpha and compute the difference in factor loadings between the first and second half of the year for each group of funds ("winner" and "loser" funds in terms of alphas). Is there a significant change?

Panel A of Table 8 reports the results of these computations. We notice that four-factor R^2 decreases in the second part of the year, which implies an increase in idiosyncratic risk. Furthermore, we find an interesting pattern concerning market betas and momentum exposure. The difference between the second and the first period of market betas equals 0.05 ($t-stat =$ - 0.25). When we split the sample in two subgroups, we find that "winners" decrease their market beta by 0.04 ($t - stat =$ - 3.33) whereas "losers" increase their market betas by 0.13 ($t - stat = 2.89$). The same comments also hold true for HML factor loadings. Winners increase their HML values whereas losers decrease their values. These results are in contradiction with the tournament hypothesis.

Nonetheless, one can argue that the results presented above are biased by the cross-sectional correlation between alphas and factor loadings for the first half year. To control this bias, we orthogonalize alphas over factor loadings. Panel B of Table 8 reports the results. Once we orthogonalize, the pattern related to the inversion in sign of market betas and HML factor no longer exist.

[Table 8]

Table 9 reports the contingency table results. Panel A and Panel B report, respectively, the results of the sort based on alphas and orthogonalized alphas. We find no evidence of tournament. For brevity purposes, we simply report the mean frequency rather than the year-by-year results[6].

[Table 9]

The results of this section highlight the importance of the sorting process in operating the contingency tables. The sorting process must be exogenous to the risk observed in the first period.

[6] Year-by-year results and results for different intervals are available upon request

4.5 Fund characteristics and change in risk

4.5.1 Variable Definitions and Hypotheses

The explained variable in this section is the risk-adjusted ratio (RAR). We use cumulative excess returns and adjusted performance measured by the four-factor model as explanatory variables. The tournament theory supposes that funds that perform better in the first part will lock in their risk position. A negative relationship between past performance and risk ratio is expected. The same sign for the relationship stands also for the 'orthogonalized' cumulative returns.

Moreover we examine portfolio characteristics funds: Total net asset (TNA) values, fund flows, performance-flows sensitivity, management fees, turnover, number of stocks in reported portfolios, industry concentration index (ICI), and illiquidity ratio. We measure monthly fund flow as a percentage of fund size, where TNA is total net asset under management at time t and Rt the fund return from month t − 1 to t. We already introduced this variable in a previous section. Chevalier and Elisson (1997), and Pagani 2006 link the level of tournament to the convexity of the relationship between flow and performance. Chevalier and Elisson (1997) find a positive relationship between risk incentives and shifts in risk. Here however, we attempt to directly link flow-performance sensitivity to shifts in fund risk. Our hypothesis is that funds with substantial flow sensitivity to past performance increase the portfolio risk to attract additional inflows. On the other hand, inelastic flow funds will have no incentive to increase their risk as doing so will not necessarily increase their inflow. In this model, we do not account for asymmetry, i.e. the reaction with respect to positive vs. negative returns. As we only have 12 observations for each year, this distinction would hardly provide consistent results. We use the slope of a linear time-series regression between performance and subsequent flows. We regress flows over lagged raw excess returns using monthly returns for each fund and for each year. The slope of this regression is our measure of flows-performance sensitivity as given by λ_2 in the equation (4.7)

$$Flows_{i,t} = \lambda_{1,i} + \lambda_{2,i} Performance_{i,t-1} + \lambda_{3,i} Flows_{i,t-1} + \xi_{i,t} \tag{4.7}$$

We expect a positive relationship between flow-performance sensitivity ($\lambda_{2,i}$) and the risk-adjusted ratio (RAR). The opposite hypothesis may also state that funds with high performance-flow sensitivity do not alter their risk to avoid any outflow.

We use the industry concentration index provided of Kacperczyk et al. (2005) to measure portfolio diversification. A perfect diversification implies equal weights among different industries and an ICI equal to 0.1. The higher the ICI, the less diversified the portfolio. We also consider the number of stocks held in each portfolio as an indicator of diversification. Funds with a high level of diversification should exhibit less tournament of their portfolio risk.

$$ICI_{i,t} = \sum_{j=1}^{10} \omega_{j,t}^2 \tag{4.8}$$

$\omega_{j,t}$: weight of the reported mutual fund holdings in industry j at time t.

The market capitalization of stocks could also explain risk tournament. For instance, we expect micro-cap stocks to exhibit higher volatility and thereby higher tournament. To assess the market size of stocks, we rely on the Hasbrouck (2006) stocks classification (where micro-cap stocks are ranked in the 1^{st} quintile and the largest firms in the 20th quintile). Finally, we compute the value-weighted illiquidity of all stock positions in the reported portfolio using the Amihud (2002) measure. The latter measures the impact of dollar volume on returns. On average, we succeed in matching 94.1% of the holdings.

By construction, ICI varies between 0.1 (perfect diversification) and 1.0 (the portfolio is fully invested in one industry). Thus, higher values of ICI indicate a lower degree of diversification. Another proxy for portfolio diversification is the number of different stock positions. Hasbrouck (2006) sorts all stocks in CRSP into 20 quantiles (where the stocks in quantile 1 are micro-cap and in quantile 20 stocks issued by the largest firms), we call this variable Size. Furthermore, we assess the value-weighted average liquidity of all stock positions in the reported portfolio. On average, we succeed to match 94.1% of the holdings. The Amihud ratio measures the impact of dollar volume on returns.

$$IR_t = \frac{|R_{i,t}|}{T_{i,t}P_{i,t}} \tag{4.9}$$

where $R_{i,t}$ is the daily return on stock i from t − 1 to t, $T_{i,t}$the number of stocks traded over the same day, and $P_{i,t}$ the stock price at the end of the day.

4.5.2 Linear approach: annual regressions

We run a cross-sectional regression for each year that links the risk-adjusted ratio of the fund to its characteristics. Koski and Pontiff (1999), Busse (2001) and Qiu (2003) explain change in risk using certain explanatory variables.

$$\begin{aligned} \Delta risk_i &= a_1 + a_2(flows/performance\_sensitivity) \quad (4.10) \\ +a_3\_performance\_measures_i + & \quad a_4 TNA_i + a_5 flows_i \\ +a_6 fees_i + a_7 age_i + a_8 turnover_i & \quad +a_9 nber\_of\_stocks_i \\ & \quad +a_{10} ICI_i + a_{11} Size + a_{12} Illiquidity_i + \xi_{i,t} \end{aligned}$$

Panel A of Table 10 shows that risk tournament is only affected by the lagged standard deviation and residual risk. Cumulative returns have an average t-statistic equal to 1.58 whereas orthogonalized cumulative returns have an average t-statistic equal to 3.53. However, 5 years have the same sign for cumulative returns compared to 10 years for orthogonalized cumulative returns (we considered 12 years in all). In both cases, the positive relationship is in contradiction with the risk tournament hypothesis. Among fund characteristics, only size seems to have an impact on changes in fund risk. Panel B relates the risk ratio of funds to factor loadings of the four-factor model. Once again confirming our initial idea, risk tournament is linked to past risk measures and is negatively related to market betas, and the SMB factor. Also, funds that have a lower four-factor R^2 (higher unsystematic risk) will exhibit higher risk ratio tournament.

[Table 10]

4.5.3 Panel regression

We follow Busse (2001), and Kempf and Ruenzi (2008) in choosing a time fixed-effect regression to study the determinants of risk tournament among mutual funds. We explain the risk-adjusted ratio (RAR) using several explanatory variables. For Panel A, our variables belong to four groups: flow, performance, market state and control variables that reflect core mutual funds characteristics. In Panel B, we regress the RAR over the four-factor model loadings.

[Table 11]

The first hypothesis we test is whether funds for which flows are sensitive to performance exhibit higher tournament risk. We find a negative and significant relationship between flows-performance sensitivity and shifts in risk. Funds for which flows are independent of their performance will increase their risk. As their strategy will have only a limited impact on outflows, they have more freedom to alter their risk.

Moreover, we find that changes in risk are positively related to the percentage of flows obtained in the first half year. Funds that have attracted more inflows are more inclined to alter their risk. Unsurprisingly, the RAR is negatively related to fund risk and market risk. In addition, we find a strong positive relationship between the RAR of the fund and the RAR of the market index. This finding shows that fund tournament is, in part, simply driven by market movement. Interestingly enough, we find a positive impact of non-orthogonalized and orthogonalized returns on the RAR. This positive sign is clearly in contradiction with the tournament hypothesis. Finally, we used additional models to control for different fund characteristics. Our conclusions on flows-performance sensitivity, flows, mean return, and standard deviation remain qualitatively the same. We also found a negative relationship between the RAR and market betas, and the R^2 of the four-factor model.

4.5.4 Non linear approach: Portfolio Approach

As the regression approach may not perfectly highlight the relationship between fund characteristics and risk tournament, we choose to broaden the analysis using a portfolio approach. We use the same criteria as in the previous section to set up yearly rebalanced fund portfolios based on different quintiles. We verify whether a specific group of funds exhibits greater tournament behavior. For example, for the first criterion, i.e. performance, for each first part of the year, we rank funds by performance and split them in quintiles. We compute, for the second part of the year, the average risk ratio of each quintile. We do this for all the years in the sample and compute the average value. While appealing, the results of this approach are fairly mixed. To the exclusion of standard deviation, mean returns and flows, all other portfolio characteristics seem unevenly related to the risk-adjusted ratio. They present either U-shape results or simply scrambled results. Analyzing Panel B of Table 13, it seems evident that tournament is negatively related to market betas and SMB, although not perfectly for the latter. Also, funds that belong to lower quintiles of R^2 (higher unsystematic risk) exhibit a higher tournament risk ratio.

[Table 12]

Linear and non-linear approaches provide almost the same results: tournament risk is mainly driven by the risk level recorded for the first period of the year.

4.6 Fund tournament using holdings

4.6.1 Stock risk and tournament

In this section, we attempt to disclose tournament patterns using holdings. This methodology provides more information because we can verify whether managers are really changing their portfolio allocation for the second part of the year. When analyzing holdings, we focus solely on stocks held by at least 500 funds in the sample. We reduce the universe of stocks studied to 2,557 stocks. For many funds, certain year or semester data are missing. We prefer to eliminate funds for which we do not have continuous data. After eliminating inconsistencies in data holdings, we are left with information on only 471 funds.

One way to measure a portfolio's increase in risk is to check the variation in positions for the riskiest and the least risky assets. Typically, a manager seeking to augment portfolio risk will increase allocations in stocks with a high first-half-year risk. For each year, we compute $\Delta\omega_{i,t} = \omega_{i,2} - \omega_{i,1}$and $\sigma_{i,1}$. We then compute the correlation between the two elements. We run 471 panel regressions at fund level and for each year, distinguish whether the fund is a winner or a loser (above or below median performance).

$$\Delta\omega_{i,j,t} = \delta_{1,i} + \delta_{2,i}\sigma_{i,j,t-1} + e_{i,j,t} \tag{4.11}$$

[Table 13]

The tournament hypothesis implies a negative coefficient δ_2 for winner funds and a positive sign for loser funds. Table 13 provides an average estimation of regression coefficients and statistics. We provide the estimation for winner and loser funds, as well as for the entire sample. For winner funds, δ_2 is not significant and positive. For loser funds however, δ_2 is significantly positive. We provide the results of the estimation using the entire sample as a robustness check, i.e. we verify whether the relationship is significant regardless of the fund's rank. We find no significant relationship between past risk and changes in stock weights for the entire sample of funds. Summarizing all of these findings, a clear conclusion can hardly be drawn, and the relation between changes in stock weights and past standard deviation appears to be relatively weak.

4.6.2 Stock/bonds allocation and tournament

We use a second approach based on holdings to highlight changes in risk among equity funds. We compute the proportion of stocks/bonds in the portfolio to underline the risk investment preferences of the fund managers[7] . Any increase in stock allocation is perceived as an increase in the risk taken by the portfolio. A manager seeking to decrease his risk may be tempted to augment the allocation in favor of bonds. The

[7] For this part we have information available for 1,374 funds.

hypothesis of tournament would typically impose an increase in the stock allocation for loser funds, while winner funds will operate a flight to safety by increasing bond allocations. To test this proposition, we use a contingency table in which we rank funds based on their cumulative returns for the first part of the year and $\frac{\%stocks_2}{\%stocks_1}$ for the second part. $\%stocks_1$ is the proportion of the portfolio invested in stocks for the first half year and $\%stocks_2$ is that of the second half year. We also use our orthogonalization methodology to check the robustness of the results even though we do not expect a high correlation between portfolio returns and the percentage of allocation in stocks. Table 14 shows no evidence of a flight to quality for winner funds, nor does it show an increase in stock allocation for loser funds. We observe only a slight difference between the two ranking methodologies due to a low correlation between asset allocation and returns.

[Table 14]

4.7 Concluding comments

In this paper, we study the risk tournament effect among actively managed funds. Using different methods to disclose this phenomenon, we reach mixed results. We find no evidence that poorly performing funds increase their risk in the second part of the year. We show that sorting on cumulative returns is affected by risk and in such a case, we must control this bias. Using an orthogonalization method, we show that tournament effect behavior is dependent on the sign of the correlation between mean return and risk observed in the first half year. If this relationship is positive (negative), the results observed using the BHS (1996) method reveals an upper (lower) bias tournament. Once corrected of this bias, we observe less tournament and inverse tournament behavior as well. Furthermore, we link risk adjusted ratio (RAR) to fund characteristics. We find that RAR is higher for funds that exhibit weak flow-performance dependence, high mean returns, low total risk and high inflows. Market beta, R^2, age and TNA are negatively related to RAR. Finally, we analyze holdings of funds with no tangible success to highlight any tournament or inverse tournament pattern.

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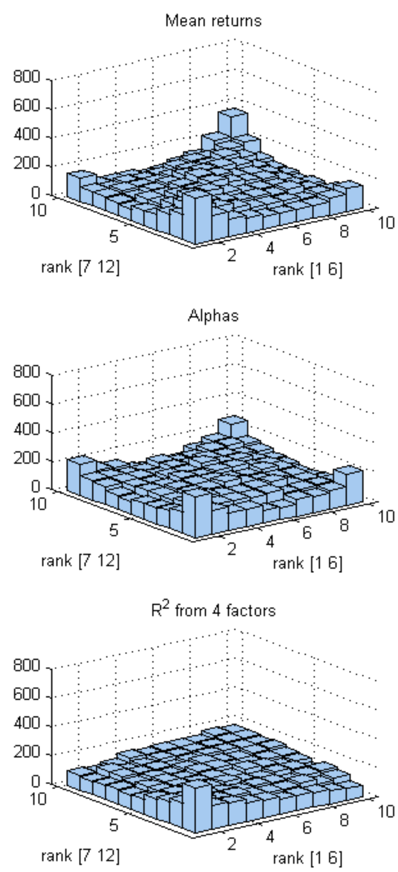
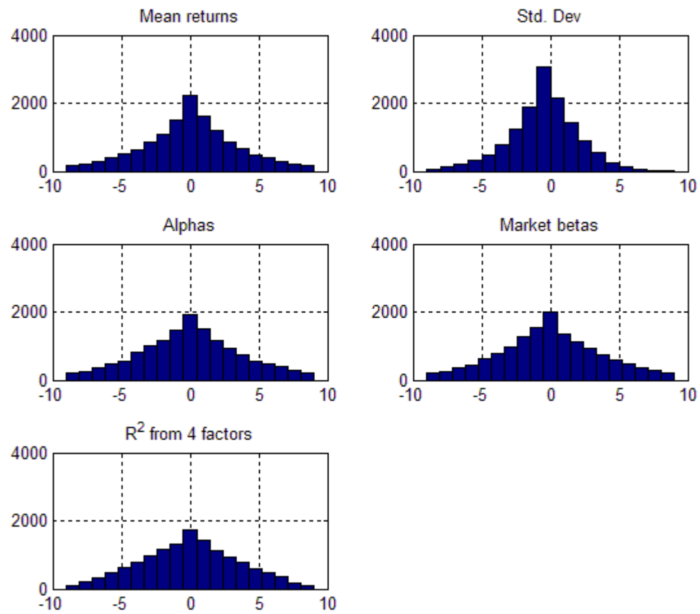
Appendix

Figure 4-1: **Rank for the first and second period for non-Index funds**



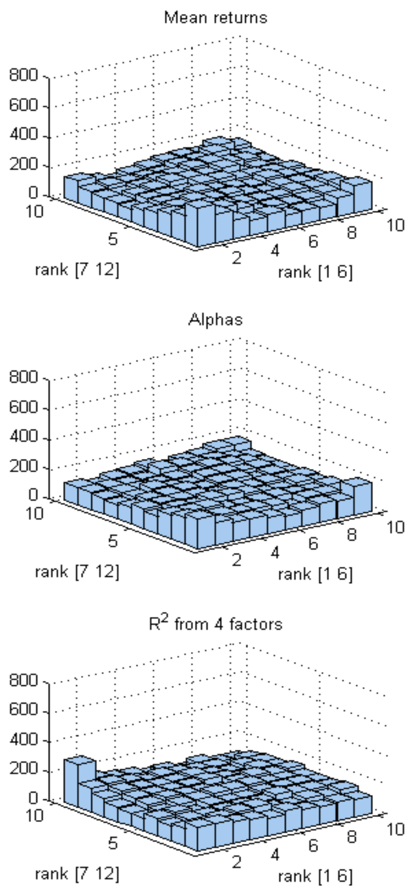
The bar chart plots the transition frequencies f(l,m) that a fund with an initial decile rank l over the first period [1, 6] months (initial rank) is sorted into decile m over the subsequent period [7, 12] months (subsequent ranking). We measure mean returns, standard deviation, alphas, market betas and R^2 from the four factor model. Decile 1 comprises those funds with the lowest values and decile 10, those with the highest values.

Figure 4-2: **Difference in rank between the first and second period for non-Index funds**



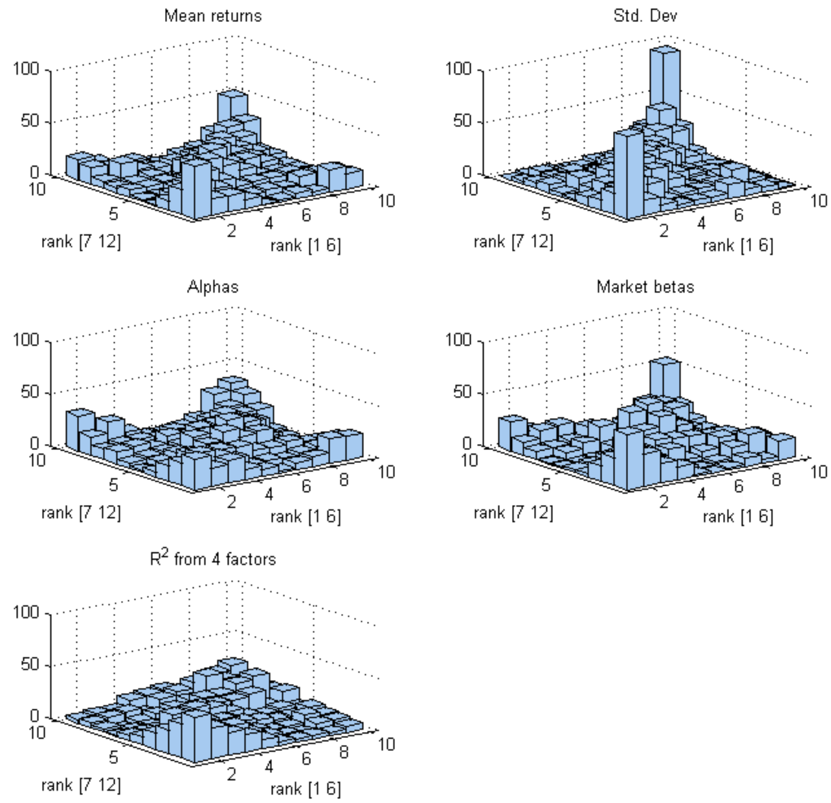
The bar chart plots the frequencies of the differences between initial decile rank l over the first period [1, 6] months and subsequent rank decile m over the second period [7, 12] months for different measures: mean returns, standard deviation, alphas, market betas and R^2 from the four factor model.

Figure 4-3: **Fund characteristics and RAR for non-Index funds**



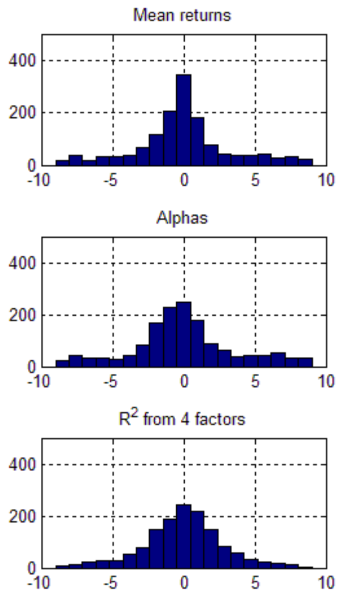
The bar chart plots the transition frequencies f(l, m) that a fund with an initial decile rank l over the first period [1, 6] months (initial rank based on specific measure: means returns, standard deviation, alphas, market betas and R^2) is sorted into decile m over the subsequent period [7, 12] months (subsequent ranking based on risk adjusted rank RAR) . We measure mean returns, standard deviation, alphas, market betas and R^2 from the four factor model. . Decile 1 comprises those funds with the lowest values and decile 10, those with the highest values.

Figure 4-4: **Fund ranks for the first and second period for Index funds**



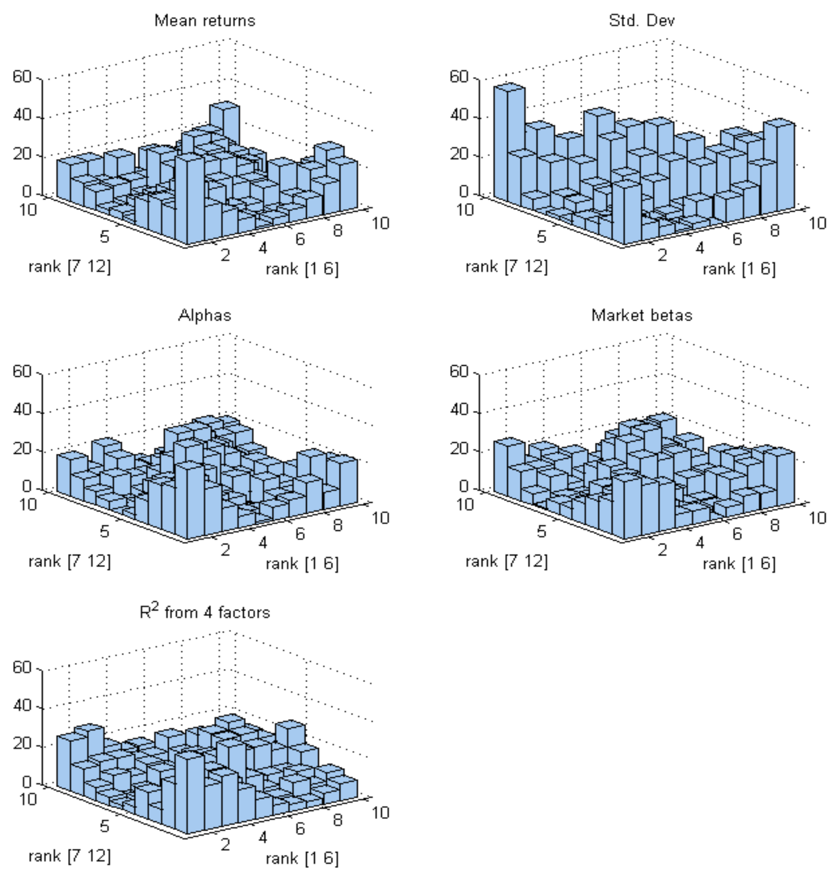
The bar chart plots the transition frequencies f(l,m) that a fund with an initial decile rank l over the first period [1, 6] months (initial rank) is sorted into decile m over the subsequent period [7, 12] months (subsequent ranking). We measure mean returns, standard deviation, alphas, market betas and R^2 from the four factor model. Decile 1 comprises those funds with the lowest values and decile 10, those with the highest values.

Figure 4-5: **Difference in rank between the first and second period for Index funds**



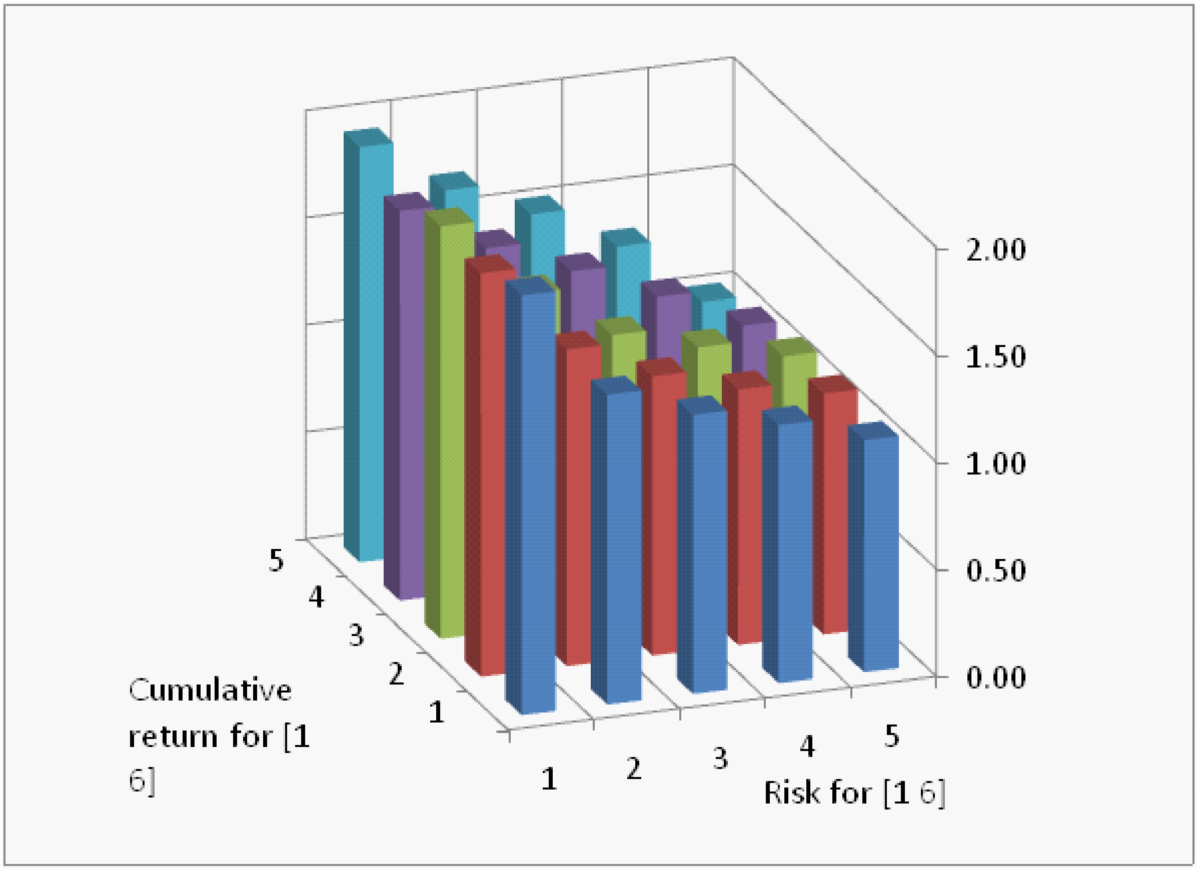
The bar chart plots the frequencies of the differences between initial decile rank l over the first period [1, 6] months and subsequent rank decile m over the second period [7, 12] months for different measures: mean returns, standard deviation, alphas, market betas and R^2 from the four factor model.

Figure 4-6: **Fund characteristics and RAR for Index funds**



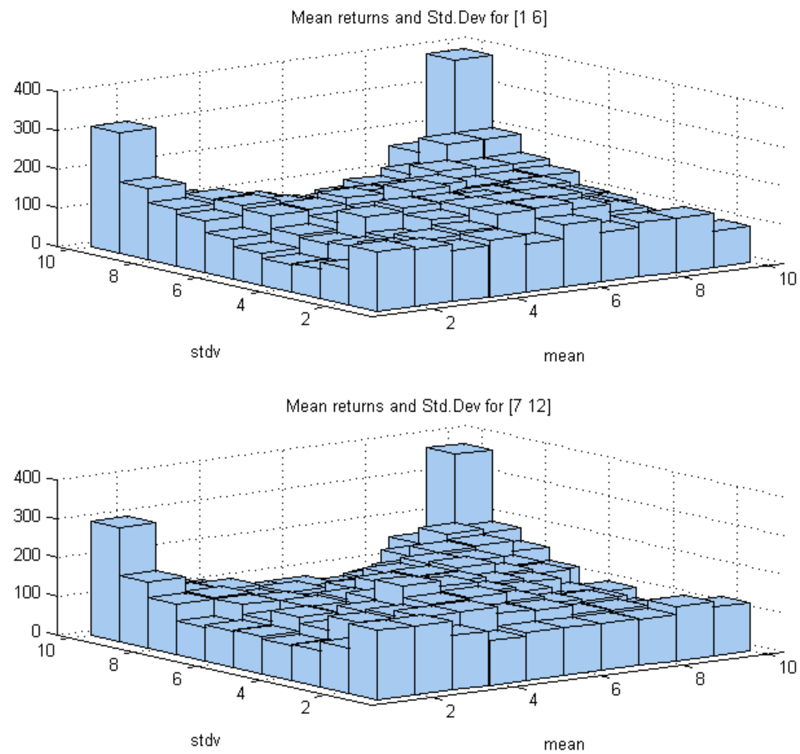
The bar chart plots the transition frequencies f(l, m) that a fund with an initial decile rank l over the first period [1, 6] months (initial rank based on specific measure: means returns, standard deviation, alphas, market betas and R^2) is sorted into decile m over the subsequent period [7, 12] months (subsequent ranking based on risk adjusted rank RAR) . We measure mean returns, standard deviation, alphas, market betas and R^2 from the four factor model. Decile 1 comprises the funds with the lowest values and decile 10 with the highest.

Figure 4-7: **RAR sorted on cumulative return and risk**



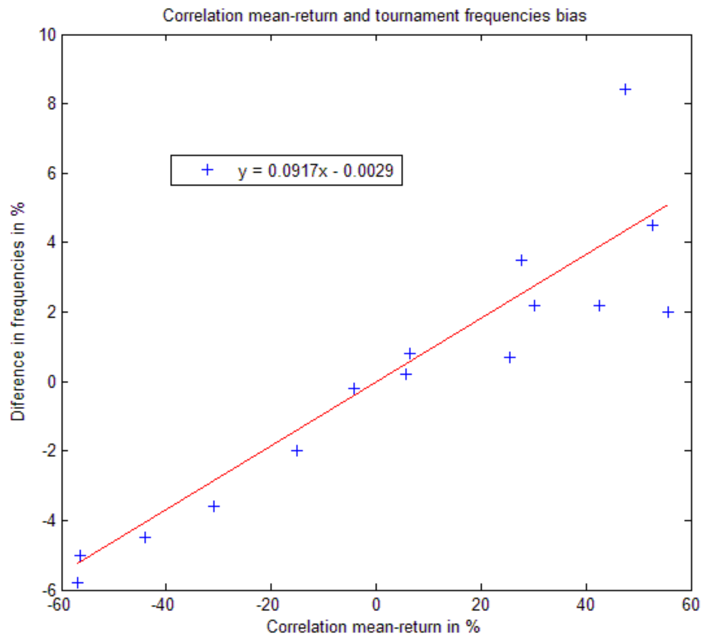
Each year funds are ranked into quintiles based on their cumulative return and standard deviation of the first half year. Figure 7 displays the average risk-adjusted ratio (RAR) for each pair of quintiles in cumulative return and standard deviation for the first part of the year. Higher risk quintiles are associated with higher RAR whereas less evidence is seen for cumulative return quintiles.

Figure 4-8: **Cumulative return and standard deviation relationship**



This figure highlights the dependence between return and standard deviation through a frequency matrix. Funds are ranked into deciles based on their cumulative return and standard deviation. Panel A depicts results for the first six months of the year, while panel B displays results for the second half year dependence. The hypothesis of no correlation implies no statistical differences across quintile frequencies.

Figure 4-9: **Correlation mean-returns and frequencies bias**



In this figure, we plot the correlation coefficient between mean and standard deviation returns, and the difference in frequencies between orthogonalized and non orthogonalized mean return sorts. Higher correlation implies an upward tournament frequencies' bias.

Table 4.1: Descriptive statistics

Table 1 reports the number of funds, the percentage of funds, and total net assets under management (TNA) sorted by self-declared investment style.

Type of the fund	Number of funds	Percentage	TNA(in millions of US$) 1970	1980	1990	2005
Small Company Growth	248	18.05%	354.9	810.1	6,530.3	214,772.0
Other Aggressive Growth	195	14.19%	1,964.3	1,757.9	11,974.1	153,412.3
Growth	424	30.86%	7,592.1	6,418.3	63,544.5	676,040.0
Income	48	3.49%	3,599.4	2,785.6	21,314.8	110,621.4
Growth and Income	284	20.67%	14,941.5	13,079.0	64,155.3	719,644.4
Sector Funds	170	12.37%	514.9	491.4	9,613.7	102 947.1
Not Specified	5	0.36%	0	0	1,269.4	134.2
Total	1,374	100.00%	28,967.3	25,342.6	178,402.3	1,977,571.4

Table 4.2: Contingency table in a year by year

This table presents a 2×2 classification table involving the rank-ordered variables: (i) the Risk Adjustment Ratio (RAR); and (ii) the total return (RTN) through the first six months of the year for Panel A, the total risk (RSK) through the first six months of the year for Panel B and Flows in percentage of TNA for Panel C. We divide the funds into four groups on a yearly basis according to whether RTN, RSK or Flows is below ("low" or "loser") or above ("high or "winner") the median and whether RAR is above ("high") or below ("low") the median.

Panel A: Funds sorted on cumulative excess returns

	Sample Frequency (% of Observations)						
	Low RTN ("Losers")		High RTN ("Winners")				
Year	"Low" RAR	"High" RAR	"Low" RAR	"High" RAR	χ^2	p-value	# obser
1991	15.3%	34.8%	34.8%	15.3%	81.0	0.000	529
1992	26.3%	23.7%	23.7%	26.3%	1.6	0.667	574
1993	31.1%	18.9%	18.9%	31.1%	38.8	0.000	660
1994	24.7%	25.3%	25.3%	24.7%	0.1	0.994	772
1995	23.9%	26.1%	26.1%	23.9%	1.6	0.649	878
1996	18.3%	31.7%	31.7%	18.3%	69.5	0.000	972
1997	31.4%	18.7%	18.7%	31.4%	65.6	0.000	1023
1998	29.2%	20.8%	20.8%	29.2%	31.8	0.000	1112
1999	26.0%	24.0%	24.0%	26.0%	1.8	0.609	1158
2000	29.6%	20.5%	20.5%	29.6%	39.3	0.000	1197
2001	39.5%	10.6%	10.6%	39.5%	407.1	0.000	1221
2002	29.4%	20.6%	20.6%	29.4%	37.4	0.000	1226
2003	27.3%	22.7%	22.7%	27.3%	10.3	0.016	1212
2004	25.4%	24.7%	24.7%	25.4%	0.2	0.978	1151
2005	24.8%	25.2%	25.2%	24.8%	0.1	0.996	1028

Panel B Sorting based on total risk (RSK)

	Sample Frequency (% of Observations)						
	Low RTN ("Losers")		High RTN ("Winners")				
Year	"Low" RAR	"High" RAR	"Low" RAR	"High" RAR	χ^2	p-value	# obser
1991	17.4%	32.7%	32.7%	17.2%	50.2	0.000	529
1992	13.4%	36.6%	36.6%	13.4%	123.3	0.000	574
1993	10.6%	39.4%	39.4%	10.6%	218.8	0.000	660
1994	15.7%	34.3%	34.3%	15.7%	107.4	0.000	772
1995	10.3%	39.7%	39.7%	10.3%	305.6	0.000	878
1996	5.5%	44.5%	44.5%	5.5%	594.2	0.000	972
1997	11.0%	39.0%	39.0%	10.9%	320.9	0.000	1023
1998	14.3%	35.7%	35.7%	14.3%	203.8	0.000	1112
1999	19.7%	30.3%	30.3%	19.7%	52.3	0.000	1158
2000	16.5%	33.5%	33.5%	16.5%	138.4	0.000	1197
2001	11.4%	38.7%	38.7%	11.3%	364.4	0.000	1221
2002	13.5%	36.5%	36.5%	13.5%	261.3	0.000	1226
2003	20.0%	30.0%	30.0%	20.0%	47.5	0.000	1212
2004	19.0%	31.0%	31.0%	18.9%	66.7	0.000	1151
2005	13.3%	36.7%	36.7%	13.3%	224.1	0.000	1028

Panel C Sorting based on flows

	Sample Frequency (% of Observations)						
	Low RTN ("Losers")		High RTN ("Winners")				
Year	"Low" RAR	"High" RAR	"Low" RAR	"High" RAR	χ^2	p-value	# obser
1991	22.9%	27.1%	27.5%	22.5%	4.2	0.239	529
1992	22.4%	27.6%	27.0%	23.0%	4.6	0.201	574
1993	25.9%	24.1%	24.1%	25.7%	0.6	0.887	660
1994	26.2%	23.9%	24.0%	25.9%	1.3	0.730	772
1995	24.6%	25.4%	25.9%	24.1%	0.7	0.877	878
1996	22.5%	27.5%	27.7%	22.3%	10.3	0.016	972
1997	26.7%	23.3%	23.1%	26.8%	5.0	0.169	1023
1998	26.5%	23.5%	23.6%	26.3%	3.6	0.308	1112
1999	27.3%	22.7%	22.7%	27.3%	9.7	0.021	1158
2000	26.1%	23.9%	23.8%	26.1%	2.4	0.503	1197
2001	28.9%	21.2%	21.3%	28.7%	27.7	0.000	1221
2002	27.4%	22.6%	22.5%	27.4%	11.6	0.009	1226
2003	23.6%	26.4%	26.4%	23.5%	3.9	0.267	1212
2004	24.3%	25.7%	25.9%	24.1%	1.1	0.767	1151
2005	27.3%	22.8%	22.8%	27.2%	8.1	0.044	1028

Table 4.3: Contingency table in a year by year

This table presents a 2×2 classification involving the rank-ordered variables: (i) the Risk Adjustment Ratio (RAR); and (ii) the total return (RTN) through the first six months of the year. We divide the funds into four groups on a yearly basis according to whether RTN is extreme quartile ("Extreme") or middle quartile ("Middle") and whether RAR is above ("high") or below ("low") the median. Panel A ranks fund by their total return, while Panel B ranks funds by their standard deviation through the first six months of the year and Panel C ranks funds by their flows through the first six months of the year.

Panel A: Funds sorted on cumulative excess returns

Sample Frequency (% of Observations)							
	Extreme RTN ("Losers")		Middle RTN ('Winners")				
Year	"Low" RAR	"High" RAR	"Low" RAR	"High" RAR	χ^2	p-value	# obser
1991	24.0%	26.1%	26.1%	23.8%	1.0	0.800	529
1992	24.0%	26.0%	26.0%	24.0%	0.8	0.839	574
1993	23.9%	26.1%	26.1%	23.9%	1.2	0.756	660
1994	24.4%	25.6%	25.6%	24.4%	0.5	0.915	772
1995	21.1%	28.9%	28.9%	21.1%	21.7	0.000	878
1996	17.4%	32.6%	32.6%	17.4%	90.1	0.000	972
1997	22.8%	27.2%	27.3%	22.8%	8.1	0.044	1023
1998	24.3%	25.7%	25.7%	24.3%	0.9	0.820	1112
1999	19.6%	30.4%	30.4%	19.6%	57.7	0.000	1158
2000	21.0%	29.1%	29.1%	20.9%	31.8	0.000	1197
2001	24.3%	25.7%	25.7%	24.2%	1.0	0.800	1221
2002	19.6%	30.4%	30.4%	19.6%	57.7	0.000	1226
2003	27.2%	22.8%	22.8%	27.2%	9.6	0.022	1212
2004	25.0%	24.9%	25.0%	25.0%	0.0	1.000	1151
2005	23.0%	27.0%	27.0%	23.0%	6.9	0.076	1028

Panel B: Sorting based on total risk (RSK)

	Sample Frequency (% of Observations)						
	Extreme RTN ("Losers")		Middle RTN ('Winners")				
Year	"Low" RAR	"High" RAR	"Low" RAR	"High" RAR	χ^2	p-value	# obser
1991	20.2%	29.9%	29.9%	20.0%	20.1	0.000	529
1992	23.5%	26.5%	26.5%	23.5%	2.0	0.570	574
1993	25.0%	25.0%	25.0%	25.0%	0.0	1.000	660
1994	24.5%	25.5%	25.5%	24.5%	0.3	0.954	772
1995	24.5%	25.5%	25.5%	24.5%	0.4	0.947	878
1996	24.6%	25.4%	25.4%	24.6%	0.3	0.967	972
1997	23.8%	26.2%	26.3%	23.8%	2.5	0.467	1023
1998	24.7%	25.3%	25.3%	24.7%	0.1	0.988	1112
1999	26.3%	23.7%	23.7%	26.3%	3.3	0.345	1158
2000	26.1%	23.9%	23.9%	26.1%	2.3	0.503	1197
2001	25.2%	24.8%	24.8%	25.1%	0.1	0.995	1221
2002	24.3%	25.7%	25.7%	24.3%	0.9	0.815	1226
2003	27.9%	22.1%	22.1%	27.9%	16.2	0.001	1212
2004	23.3%	26.7%	26.8%	23.3%	5.4	0.143	1151
2005	25.0%	25.0%	25.0%	25.0%	0.0	1.000	1028

Panel C Sorting based on flows

	Sample Frequency (% of Observations)						
	Extreme RTN ("Losers")		Middle RTN ('Winners")				
Year	"Low" RAR	"High" RAR	"Low" RAR	"High" RAR	χ^2	p-value	# obser
1991	24.9%	25.1%	25.5%	24.5%	0.1	0.992	529
1992	23.4%	26.6%	26.1%	23.9%	1.7	0.635	574
1993	24.9%	25.1%	25.2%	24.8%	0.0	0.999	660
1994	26.0%	24.0%	24.2%	25.8%	1.0	0.804	772
1995	23.8%	26.2%	26.8%	23.2%	3.0	0.386	878
1996	22.5%	27.4%	27.7%	22.4%	9.9	0.019	972
1997	24.7%	25.2%	25.1%	24.9%	0.1	0.996	1023
1998	24.6%	25.4%	25.5%	24.4%	0.4	0.939	1112
1999	22.6%	27.4%	27.4%	22.6%	10.5	0.015	1158
2000	21.7%	28.3%	28.3%	21.8%	20.6	0.000	1197
2001	27.3%	22.7%	22.8%	27.1%	9.5	0.024	1221
2002	24.8%	25.2%	25.1%	24.8%	0.1	0.995	1226
2003	25.6%	24.4%	24.4%	25.6%	0.7	0.874	1212
2004	24.2%	25.8%	26.0%	24.0%	1.4	0.704	1151
2005	22.2%	27.8%	27.9%	22.2%	12.9	0.005	1028

Table 4.4: Sorting on cumulative return and risk

This table presents a classification involving the rank-ordered variables: (i) the Risk Adjustment Ratio (RAR); and (ii) the total risk (RSK) through the first six months of the year and (iii) the total return (RTN) through the first six months of the year. We divide the funds into eight groups on a yearly basis according to whether RAR for Panel A (Flows for Panel B) is below ("low" or "loser") or above ("high or "winner") the median and whether RSK is above ("high") or below ("low") the median and whether RTN is above ("high") or below ("low") the median. The null hypothesis is that means and returns have no impact on RAR ranking i.e. all frequencies should be equal to 1/8. We reject this hypothesis for all years.

	Low RTN ("Losers")				High RTN ("Winners")						
Year	"Low" RAR	"High" RAR	"Low" RAR	"High" RAR	"Low" RAR	"High" RAR	"Low" RAR	"High" RAR	χ^2	p-value	# obser
1991	9.3%	27.8%	5.9%	7.0%	8.1%	4.7%	26.8%	10.4%	257.4	0.000	529
1992	4.9%	15.5%	21.4%	8.2%	8.5%	21.1%	15.2%	5.2%	144.5	0.000	574
1993	5.5%	14.7%	25.6%	4.2%	5.2%	24.7%	13.8%	6.4%	283.3	0.000	660
1994	5.3%	15.0%	19.4%	10.2%	10.4%	19.3%	14.9%	5.4%	134.4	0.000	772
1995	5.9%	20.5%	18.0%	5.6%	4.3%	19.2%	21.8%	4.7%	312.3	0.000	878
1996	4.0%	29.4%	14.3%	2.3%	1.4%	15.1%	30.2%	3.2%	775.5	0.000	972
1997	5.1%	14.7%	26.3%	3.9%	5.9%	24.3%	12.8%	7.0%	440.2	0.000	1023
1998	9.1%	13.8%	20.1%	6.9%	5.2%	21.9%	15.6%	7.4%	248.3	0.000	1112
1999	12.0%	16.8%	14.0%	7.3%	7.7%	13.6%	16.3%	12.4%	80.6	0.000	1158
2000	12.9%	15.9%	16.6%	4.5%	3.5%	17.6%	17.0%	11.9%	210.4	0.000	1197
2001	7.1%	5.5%	32.4%	5.0%	4.2%	33.2%	6.4%	6.3%	1075.1	0.000	1221
2002	3.6%	11.6%	25.8%	9.1%	9.9%	25.0%	10.8%	4.4%	489.5	0.000	1226
2003	15.1%	16.6%	12.2%	6.1%	5.0%	13.4%	17.7%	13.9%	147.1	0.000	1212
2004	12.5%	17.5%	12.9%	7.1%	6.4%	13.6%	18.2%	11.8%	115.2	0.000	1151
2005	6.2%	19.3%	18.6%	5.9%	7.1%	17.4%	18.1%	7.4%	226.8	0.000	1028
Average	7.9%	17.0%	18.9%	6.2%	6.2%	18.9%	17.0%	7.9%			

Table 4.5: Contingency table based on an orthogonalized cumulative excess returns

This table presents a 2×2 classification table involving the rank-ordered variables: (i) the Risk Adjustment Ratio (RAR); and (ii) orthogonalized cumulative excess returns (RTN) through the first six months of the year for. We divide the funds into four groups on a yearly basis according to whether orthogonalized RTN, below ("low" or "loser") or above ("high or "winner") the median and whether RAR is above ("high") or below ("low") the median.

	Sample Frequency (% of Observations)						
	Low RTN ("Losers")		High RTN ("Winners")				
Year	"Low" RAR	"High" RAR	"Low" RAR	"High" RAR	χ^2	p-value	# obser
1991	19.8%	30.2%	30.2%	19.8%	23.3	0.000	529
1992	27.0%	23.0%	23.0%	27.0%	3.7	0.297	574
1993	29.1%	20.9%	20.9%	29.1%	17.7	0.001	660
1994	21.1%	28.9%	28.9%	21.1%	18.7	0.000	772
1995	27.4%	22.6%	22.6%	27.4%	8.4	0.038	878
1996	26.7%	23.3%	23.3%	26.7%	4.8	0.190	972
1997	26.9%	23.2%	23.2%	26.8%	5.5	0.139	1023
1998	29.4%	20.6%	20.6%	29.4%	34.5	0.000	1112
1999	28.0%	22.0%	22.0%	28.0%	16.4	0.001	1158
2000	31.7%	18.3%	18.3%	31.7%	86.1	0.000	1197
2001	33.7%	16.4%	16.4%	33.6%	145.2	0.000	1221
2002	24.4%	25.6%	25.6%	24.4%	0.7	0.865	1226
2003	29.5%	20.5%	20.5%	29.5%	39.9	0.000	1212
2004	25.2%	24.8%	24.8%	25.1%	0.0	0.998	1151
2005	25.6%	24.4%	24.4%	25.6%	0.6	0.905	1028

Table 4.6: Comparison between sorting on cumulative returns and sorting on orthogonalized cumulative returns

This table simply reports the difference in frequencies observed using sorting on cumulative returns and sorting on orthogonalized cumulative returns. This is also the difference between the frequencies between Panel A and Panel B of table 2. We also report the correlation between cumulative excess returns and return standard deviation for the first half year. Sorting on returns suffers from an upward (downward) tournament bias and downward (upward) inverse tournament bias if the correlation between risk and return is positive (negative). Correlation between the difference in frequencies and the correlation coefficient risk-returns is 91.77%.

	Sample Frequency (% of Observations)							
	ρ (σ_i, R_i)	Differences in frequencies				Tournament or Inverse Tournament		
	$[0, 6 months]$	Low RTN ("Losers")		High RTN ("Winners")		Non Orthogonlized	Orthogonlized	$\chi^2_{non\_orth}$ $-\chi^2_{orth}$
Year		"Low" RAR	"High" RAR	"Low" RAR	"High" RAR			
1991	52.8%	-4.5%	4.5%	4.5%	-4.5%	T	T	57.7
1992	25.4%	-0.7%	0.7%	0.7%	-0.7%	Inv. T	Inv. T	-2.1
1993	-15.1%	2.0%	-2.0%	-2.0%	2.0%	Inv. T	Inv. T	21.1
1994	-30.9%	3.6%	-3.6%	-3.6%	3.6%	T	T	-18.6
1995	27.6%	-3.5%	3.5%	3.5%	-3.5%	T	Inv. T	-6.8
1996	47.4%	-8.4%	8.4%	8.4%	-8.4%	T	Inv. T	64.8
1997	-44.1%	4.5%	-4.5%	-4.5%	4.5%	Inv. T	Inv. T	60.1
1998	5.7%	-0.2%	0.2%	0.2%	-0.2%	Inv. T	Inv. T	-2.8
1999	55.6%	-2.0%	2.0%	2.0%	-2.0%	Inv. T	Inv. T	-14.6
2000	30.3%	-2.2%	2.2%	2.2%	-2.2%	Inv. T	Inv. T	-46.7
2001	-57.0%	5.8%	-5.8%	-5.8%	5.8%	Inv. T	Inv. T	261.9
2002	-56.5%	5.0%	-5.0%	-5.0%	5.0%	Inv. T	T	36.6
2003	42.5%	-2.2%	2.2%	2.2%	-2.2%	Inv. T	Inv. T	-29.6
2004	-4.1%	0.2%	-0.2%	-0.2%	0.2%	Inv. T	Inv. T	0.2
2005	6.4%	-0.8%	0.8%	0.8%	-0.8%	T	Inv. T	-0.5

Table 4.7: Simulation results

We choose year 1991 as an example to illustrate the impact of the sorting bias on the final ranking. Panel A displays the real frequencies observed in our tests. Panel B displays simulations results starting with mean returns. Panel C displays simulation results starting with standard deviation.

Panel A Real observed sample							
		Sample Frequency (% of Observations)					
$\sigma_{\xi}/\sigma_{returns}$	$\rho_{\ (\sigma i,Ri)}$ $_{[0,6months]}$	Low RTN ("Losers")		High RTN ("Winners")			
		"Low" RAR	"High" RAR	"Low" RAR	"High" RAR	χ^2	p-value
Sorting based on cumulative returns							
	52.8%	15.3%	34.8%	34.8%	15.1%	81.0	0.000
Sorting based on risk							
	52.8%	15.3%	34.8%	34.8%	15.1%	81.0	0.000
Panel B Simulated results: starting with cumulative returns and adding noise							
0	52.8%	15.3%	34.8%	34.8%	15.1%	81.0	0.000
.2	51.7%	15.8%	34.3%	34.3%	15.6%	73.5	0.000
.5	47.3%	17.2%	32.9%	32.9%	17.0%	52.8	0.000
1	37.3%	20.0%	30.1%	30.1%	19.8%	22.9	0.002
2	23.2%	22.1%	28.0%	28.0%	21.9%	8.0	0.134
5	10.0%	23.8%	26.2%	26.2%	23.7%	2.4	0.621
10	5.3%	24.5%	25.6%	25.6%	24.3%	1.4	0.758
Panel C Simulated results: starting with sigma and adding noise							
0	100.0%	17.4%	32.7%	32.7%	17.2%	50.2	0.000
.2	71.9%	19.4%	30.7%	30.7%	19.3%	27.9	0.002
.5	37.6%	22.0%	28.0%	28.0%	21.9%	8.6	0.135
1	20.3%	23.5%	26.6%	26.6%	23.3%	3.2	0.533
2	9.4%	24.4%	25.7%	25.7%	24.2%	1.6	0.708
5	4.2%	24.9%	25.2%	25.2%	24.7%	1.2	0.794
10	2.8%	24.9%	25.2%	25.2%	24.7%	1.1	0.799

Table 4.8: Sorting based on alphas and difference in subsequent factor loadings

In this table we test the tournament hypothesis using sorting based on alphas. In panel A, we sort funds on alpha measured for the first part of the year and we distinguish above median ("winners") and below median ("losers") groups in term of factor loadings. We compute the difference in the average factors loadings between the second half year and the first half year for different groups (winners and losers). Panel A sorts funds based on alphas while Panel B sorts alphas based on orthogonalized alphas. We also displya the t-statistic of the difference and the number of years for whcih we have the same sign.

Panel A: sorting on non orthogonalized alphas

Entire sample

	MKT	SMB	HML	PR1YR	R^2
difference	0.05	-0.18	-0.07	-0.03	-1.19%
t-statistic	-0.25	-3.65	-0.55	-1.66	-3.25
p_value	0.16	0.12	0.10	0.08	0.10
# of years	6	8	8	10	12

Winner funds

	MKT	SMB	HML	MOM	R^2
difference	-0.04	-0.16	0.03	-0.07	-1.62%
t-statistic	-3.33	-3.61	0.85	-2.50	-2.76
p_value	0.11	0.10	0.03	0.03	0.85
# of years	13	9	7	10	10

Loser funds

	MKT	SMB	HML	PR1YR	R^2
difference	0.13	-0.20	-0.17	-0.01	-0.76%
t-statistic	2.89	-1.48	-1.81	-0.24	-1.81
p_value	0.12	0.05	0.08	0.08	0.08
# of years	10	9	8	9	11

Panel B: sorting on orthogonalized alphas

Entire sample

	MKT	SMB	HML	PR1YR	R^2
difference	0.05	-0.18	-0.07	-0.03	-1.19%
t-statistic	-0.25	-3.65	-0.55	-1.66	-3.25
p_value	0.16	0.12	0.10	0.08	0.10
# of years	6	11	8	10	12

Winner funds

	MKT	SMB	HML	PR1YR	R^2
difference	0.05	-0.25	-0.08	-0.04	-1.10%
t-statistic	-0.15	-3.01	-0.87	-1.61	-2.30
p_value	0.15	0.17	0.04	0.01	0.14
# of years	7	12	10	10	9

Loser funds

	MKT	SMB	HML	PR1YR	R^2
difference	0.04	-0.11	-0.05	-0.02	-1.28%
t-statistic	-0.21	-2.08	-0.70	-0.70	-2.51
p_value	0.08	0.16	0.19	0.09	0.05
# of years	7	11	8	9	11

Table 4.9: Contingency table: sorting based on alphas, and risk adjusted ratio is measured by the ratio of betas of the second half year over the first one.

In this table we use the same contingency methodology as in BHS (1996), except that we are considering alphas in stead of cumulative excess returns, and factor loadings in stead of standard deviation.

$\sigma_\xi / \sigma_{returns}$	Sample Frequency (% of Observations)					
	Low RTN ("Losers")		High RTN ("Winners")			
	"Low" RAR	"High" RAR	"Low" RAR	"High" RAR	χ^2	p-value
Panel A: sorting on non-orthogonalized alphas						
MKT	26.7%	23.3%	23.3%	26.7%	21.6	0.274
SMB	24.9%	25.1%	24.9%	25.1%	12.0	0.425
HML	25.7%	24.3%	24.1%	25.9%	10.0	0.577
PR1YR	24.5%	25.5%	25.3%	24.7%	7.9	0.578
R^2	25.7%	24.3%	24.3%	25.7%	7.3	0.402
Panel B: sorting on orthogonalized alphas						
MKT	24.4%	25.6%	25.6%	24.4%	6.2	0.384
SMB	24.9%	25.1%	24.9%	25.1%	2.8	0.616
HML	25.6%	24.4%	24.2%	25.8%	5.3	0.693
PR1YR	25.1%	24.9%	24.7%	25.3%	2.6	0.585
R^2	24.6%	25.4%	25.4%	24.5%	3.6	0.574

Table 4.10: Risk adjusted ratio and fund characteristics: a cross-sectional regressionr

This table we provide an annual cross-sectional regression of risk adjusted ratio over different fund characteristics. Panel A distinguishes main fund characteristics while Panel B uses Carchart (1997) factor loadings. We provide also the number of years for which we observe the same sign in the coefficient regression.

Panel A Fund characteristics and risk ratio

	Flows-performance sensitivity	Flows	Flows volatility	Cumulative returns	alpha	Cumulative returns ortho	Std.dev	Resid std
difference	-0.002	0.00	0.04	-0.67	1.90	3.89	-10.90	-7.32
t-statistic	-0.19	-0.05	0.31	-0.60	1.58	3.53	-18.50	-3.77
p_value	0.2%	0.2%	0.1%	0.8%	0.5%	1.1%	24.6%	1.2%
# of years	8	7	6	6	7	10	12	11

	Age	TNA	Fees	Turnover	# of stocks	ICI	Size	Illiquidity
difference	0.001	-0.002	-2.02	-0.01	-0.02	0.07	0.00	-0.48
t-statistic	0.88	-0.66	-0.97	-1.39	-0.85	0.86	2.36	-1.04
p_value	0.3%	0.4%	0.7%	0.4%	0.2%	0.9%	1.2%	0.6%
# of years	8	7	9	7	8	9	8	7

Panel B Fund risk measures and risk ratio

	MKT	SMB	HML	PR1YR	R^2
difference	-0.09	-0.05	0.01	-0.03	-0.64
t-statistic	-3.99	-2.14	1.06	-1.64	-3.41
p_value	1.3%	3.8%	4.5%	1.7%	1.2%
# of years	11	9	7	6	11

Table 4.11: Fixed-effect regression of RAR and characteristics of funds

This table explains the risk adjusted ratio (RAR) using several explanatory variables and using a fixed effect panel regression methodology. For Panel A our variables are divided in four groups: flow variables, performance variable, market state variables and control variables that reflect mains mutual funds characteristics. In Panel B, we regress RAR over the four factor model loadings.

Panel A

	1	2	3	4	5	6	7	8	9
Flows variables									
Flows-Perf. sensitivity	-0.008 **		-0.007 *	-0.005 *	-0.007 *			-0.008 *	
	-(2.23)		-(1.88)	-(1.65)	-(1.66)			-(1.93)	
Flows	0.109 **					0.314**			
	(1.95)					(2.71)			
Performance variables									
alpha [0,6 mths]							0.714 **	-1.062	
							(2.16)	-(2.81)	
Mean returns [0,6]	2.578 ***	2.623 ***							
	(6.65)	(6.82)							
Mean returns [0,6] orth.									4.50 ***
									(6.78)
Risk [0,6]	-1.957 ***	-1.600 ***	-2.896 ***	-3.506 ***	-4.199 ***	-2.460 ***	-2.414 ***	-2.772***	-2.10 ***
	-(7.01)	-(5.82)	-(10.07)	-(17.60)	-(12.42)	-(8.10)	-(9.65)	-(-(9.05))	-(6.99)
Market state variables									
Market return [0,6]			6.333 ***						
			(13.27)						
Market volatility [0,6]					-12.139 ***		-14.682 ***		
					-(27.96)		-(36.66)		
Market risk ratio				0.595 ***					
				(99.75)					

Control variables									
Age					-0.016 ***				
					-(7.03)				
log(TNA)						-0.033***		-0.025***	
						-(3.91)		-(2.88)	
Fees					-12.073 **				0.537
					-(3.45)				-(0.15)
Turnover					0.001	-0.009		-0.009	-0.008 *
					(0.17)	-(1.67)		-(1.58)	-(1.47)
# of stocks						0.027		0.042	-0.006
						(1.16)		(1.74) *	-(0.26)
ICI					-0.577 ***	-0.401 *		-0.463**	-0.435 **
					-(3.39)	-(2.29)		-(2.60)	-(2.45)
MERankFF (SIZE)					-0.001	-0.006 ***		–0.006 ***	-0.006 ***
					-(0.90)	-(8.10)		-(8.41)	-(8.65)
Illiquidity					-2.927**	-.140		-0.127	-0.276
					-(2.00)	-(0.43)		-(0.38)	-(0.18)
# of fund years	13935	14241	13656	13656	9471	9932	14419	9557	9852
R^2	0.61%	0.50%	1.65%	44.59%	10.81%	1.53%	9.43%	1.80%	1.70%

Panel B

MKT	-0.081 ***
	-(8.92)
SMB	-0.015 *
	-(1.83)
HML	0.024 ***
	(3.74)
PR1YR	-0.009
	-(1.11)
R^2	-1.732 ***
	-(22.40)
# of fund years	14713
R^2	4.84%

Table 4.12: Portfolio approach for RAR and fund charcateristics

Each year we divide the universe of funds in five quintiles based on each characteristic. We form different quintile portfolios based on each characteristic. For example, quintile 1 for flows measures the RAR for a portfolio formed with the first quintile in terms of flows for each year. Panel A distinguishes main fund characteristics while Panel B uses Carchart (1997) factor loadings.

Panel A Sorting on non orthogonalized alphas

Quintiles	Flows-performance sensitivity	Flows	Flows volatility	alpha	Cumulative returns	Cumulative returns ortho	Std.dev	
1	1.11	1.04	1.16	1.07	1.03	1.16	1.07	
2	1.07	1.08	1.08	1.12	1.05	1.15	1.11	
3	1.08	1.10	1.05	1.13	1.11	1.11	1.15	
4	1.10	1.12	1.08	1.17	1.24	1.06	1.22	
5	1.12	1.21	1.11	1.08	1.25	1.09	1.26	
spread 1-5	0.00	-0.17	0.05	-0.01	-0.22	0.07	-0.19	
Quintiles	Age	TNA	Fees	Turnover	# of stocks	ICI	Size	Illiquidity
1	1.15	1.12	1.06	1.05	1.15	1.17	1.18	1.13
2	1.08	1.06	1.14	1.07	1.12	1.09	1.14	1.14
3	1.13	1.10	1.11	1.14	1.16	1.12	1.10	1.14
4	1.17	1.12	1.11	1.11	1.15	1.13	1.06	1.19
5	1.26	1.09	1.10	1.09	1.11	1.11	1.11	1.19
spread 1-5	-0.11	0.03	-0.04	-0.04	0.04	0.06	0.07	-0.05

Panel B Fund risk measures and risk ratio

Quintiles	alpha	MKT	SMB	HML	PR1YR	R^2
1	1.07	1.24	1.16	1.06	1.12	1.36
2	1.12	1.16	1.20	1.16	1.14	1.23
3	1.13	1.09	1.19	1.15	1.12	1.21
4	1.17	1.09	1.12	1.24	1.21	1.18
5	1.08	1.07	1.10	1.21	1.17	1.09
spread 1-5	-0.01	0.18	0.06	-0.15	-0.06	0.17

Table 4.13: Variation in holdings and first half year standard deviation of funds

For each fund, we use a panel regression to relate variation in asset positions and first half year standard deviation of stocks. We distinguish two groups of funds, winners vs. losers.

Entire sample			
	δ_0	δ_1	R^2
Coef.	0.0004	-0.00003	0.21%
t-statistic	1.43	-0.52	

Winner funds			
	δ_0	δ_1	R^2
Coef.	0.00016	-0.00005	0.67%
t-statistic	0.54	-1.11	

Loser funds			
	δ_0	δ_1	R^2
Coef.	-0.0005	0.0001	.85%
t-statistic	-1.36	2.40	

Table 4.14: Asset allocation as a response to first half performance.

We use the BHS (1996) contingency methodology. We rank funds based on their cumulative returns for the first half year, then we measure the ratio of the allocation made in stocks between the first and the second half year. We want to verify whether loser funds increase their allocation in stocks relatively to bonds for the second half year. Panel A displays results based on stock allocation ratio, while Panel B displays results based on orthogonalized stock allocation ratio with respect to first half year performance. For years 1991, 1992, 1993, 1994 we do not obtain symmetric frequencies because the median value of the stock allocation ratio is 1 and the number of funds having this value is relatively high.

Panel A

Sample Frequency (% of Observations)							
	Low RTN ("Losers")		High RTN ('Winners")				
Year	"Low" RAR	"High" RAR	"Low" RAR	"High" RAR	χ^2	p-value	# obser
1991	22.7%	27.2%	19.9%	30.3%	10.9	0.012	423
1992	20.5%	29.5%	19.9%	30.1%	17.4	0.001	468
1993	20.3%	29.6%	22.6%	27.5%	11.7	0.009	527
1994	19.5%	30.5%	20.5%	29.5%	23.8	0.000	590
1995	23.2%	26.7%	26.7%	23.3%	3.6	0.312	729
1996	23.4%	26.6%	26.6%	23.5%	3.4	0.341	839
1997	24.4%	25.6%	25.6%	24.5%	0.5	0.920	899
1998	25.3%	24.7%	24.7%	25.3%	0.1	0.986	1020
1999	26.9%	23.1%	23.1%	27.0%	5.4	0.142	927
2000	24.7%	25.2%	25.2%	24.8%	0.1	0.994	1003
2001	23.6%	26.4%	26.4%	23.6%	3.3	0.347	1053
2002	27.4%	22.6%	21.9%	28.1%	14.0	0.003	1137
2003	25.1%	24.9%	24.9%	25.2%	0.0	0.998	1175
2004	24.7%	25.3%	25.3%	24.7%	0.1	0.988	1116
2005	24.5%	25.5%	25.5%	24.5%	0.5	0.929	1062

Panel B

	Sample Frequency (% of Observations)						
	Extreme RTN ("Losers")		Middle RTN ('Winners")				
Year	"Low" RAR	"High" RAR	"Low" RAR	"High" RAR	χ^2	p-value	# obser
1991	22.9%	27.0%	19.6%	30.5%	11.4	0.010	423
1992	21.0%	28.9%	18.8%	31.3%	19.9	0.000	468
1993	20.7%	29.2%	22.1%	28.0%	10.8	0.013	527
1994	22.0%	28.0%	17.9%	32.1%	26.8	0.000	590
1995	22.9%	27.1%	27.1%	22.9%	4.9	0.181	729
1996	22.9%	27.1%	26.8%	23.2%	4.9	0.179	839
1997	24.6%	25.3%	25.4%	24.6%	0.2	0.978	899
1998	25.8%	24.2%	24.3%	25.7%	0.8	0.849	1020
1999	26.6%	23.3%	23.2%	26.8%	4.4	0.223	927
2000	25.0%	24.9%	25.1%	24.9%	0.0	1.000	1003
2001	23.1%	26.8%	26.7%	23.3%	5.0	0.171	1053
2002	27.3%	22.6%	22.5%	27.6%	10.3	0.016	1137
2003	24.6%	25.4%	25.9%	24.1%	0.8	0.839	1175
2004	24.6%	25.4%	25.2%	24.8%	0.2	0.979	1116
2005	24.2%	25.8%	24.4%	24.4%	0.8	0.860	1062

Chapter 5

Conclusion

La littérature sur les fonds communs de placement a connu un grand développement au cours des dernières années. Une plus grande disponibilité des données et une meilleure divulgation de l'information de la part des fonds mutuels a rendu un grand nombre d'études possibles. Les principales questions abordées dans la littérature des fonds mutuels portent sur la comparaison entre la gestion active et la gestion passive, la persistance de la performance, les déterminants de la performance des fonds, la relation entre les flux et la performance. Aussi quelques phénomènes particuliers ont retenu l'attention des académiciens: la prime ou l'escompte observée pour les fonds de placement à capital fixe, le changement de risque parmi les gestionnaires de fonds, la modification des positions en fin d'année ou en fin de mois, l'incubation, et le mimétisme des gestionnaires. La littérature des fonds communs de placement est assurément l'un des domaines de recherche les plus dynamiques de la finance.

Dans cette thèse nous avons essayé de contribuer avec trois idées différentes. La première partie se concentre sur les caractéristiques de nouveaux fonds communs de placement. Ce choix est une conséquence directe du développement de l'industrie des fonds communs de placement et de l'agrandissement des possibilités d'investissement. Nous démontrons que les nouveaux fonds présentent des caractéristiques spécifiques en termes de performance, de frais de gestion, de risque idiosyncratique et d'exposition aux facteurs de marché. Les fonds nouvellement lancés ont, en moyenne, des rendements absolus et des rendements anormaux plus élevés. Leur performance ajustée au risque est également supérieure à celle des fonds existants. En outre, nous fournissons l'évidence de la présence de persistance à court terme parmi les nouveaux fonds qui ont le mieux performé. Cependant, une fraction substantielle des fonds migre des déciles supérieurs aux déciles inférieurs pour les périodes suivantes. Analysant les caractéristiques de leurs portefeuilles, nous constatons que les rendements des nouveaux fonds montrent des rapports plus élevés de risque non systématique sur risque total. Les portefeuilles des nouveaux fonds sont en général moins diversifiés en termes de nombre de stocks et d'industries, et sont investis dans des titres moins liquides et à plus faible capitalisation. En résumé, nous prouvons que les nouveaux fonds ont des caractéristiques spécifiques et qu'il est intéressant d'entreprendre une étude sur cette classe particulière d'actifs.

L'idée de la deuxième partie est née de la conclusion de la première. Notant que les nouveaux fonds ont des caractéristiques spécifiques, nous concluons que les modèles de performance standards peuvent ne pas être totalement satisfaisants pour cette catégorie de fonds. Pour remédier à ce problème, nous proposons de nouvelles mesures de performance pour cette classe spécifique d'actifs. Ces mesures utilisent des informations supplémentaires de la famille, du style ou de l'industrie de fonds et montrent une plus petite erreur de prévision. Aussi, nous améliorons la précision des bêtas et alphas en recourant à deux méthodes: un estimateur à échantillons combinés et un estimateur bayésien empirique. En confirmation des travaux précédents, nous trouvons que l'approche bayésienne est tout à fait appropriée pour améliorer l'évaluation de la performance des fonds communs de placement.

Le troisième papier étudie le phénomène de changement de risque parmi les fonds communs de placement. Nous vérifions si les fonds qui sous performent au premier semestre, augmentent leur risque dans la deuxième partie de l'année. Malgré l'utilisation de différentes méthodologies, nous trouvons des résultats mitigés liés à l'existence de ce phénomène. Nous prouvons qu'une partie du changement de risque et de persistance est directement liée au signe de la corrélation entre la performance des fonds et l'écart type des rendements observé dans la première partie de l'année. Nous mettons de sérieuses interrogations quant à l'existence systématique du phénomène de tournament/persistance, mais nous laissons la porte ouverte à d'autres méthodologies pour découvrir le changement de risque.

Utilisant une quantité importante de données, nous avons proposé de nouvelles approches sur différent aspects de l'industrie de fonds mutuels et avons contribué de manière significative à la littérature de fonds mutuels. Nous avons proposé de nouvelles idées pour l'évaluation de la performance des fonds et du changement de risque. Les futures recherches devraient utiliser les résultats actuels dans un contexte d'un modèle d'allocation d'actifs: les nouveaux fonds attirent-ils d'une façon irrationnelle les flux des investisseurs? Nous pouvons également proposer une nouvelle mesure de flux des fonds pour les nouveaux fonds qui seraient plus réalistes au lieu de simplement considérer l'accroissement de la valeur nette des actifs sous gestion. En conclusion, la recherche d'une nouvelle approche pour mesurer le changement de risque des fonds est également un axe de recherche qui mérite une grande attention. Nous avons prouvé qu'en contrôlant la corrélation avec le risque observé en première période, le changement de risque offre des résultats moins stables. Néanmoins il serait toujours utile de trouver de nouvelles approches pour mettre en lumière le phénomène de changement de risque au sein des fonds mutuels.