# ESSAYS ON US MUTUAL FUND INDUSTRY

**Ines Gargouri**

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By: Inès Gargouri

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Signed by the final examining committee:

Pr. Kamal Arghayed, Concordia University — Chair

Dr. Louis Gagnon, Queen's University — External Examiner

Dr. Bryan Campbell, Concordia University — External to Program

Dr. Ian Rakita, Concordia University — Examiner

Dr. Simon Lalancette, HEC — Examiner

Dr. Lawrence Kryzanowski — Thesis Supervisor

Approved by

Chair of Department or Graduate Program Director

Dean of Faculty

**ABSTRACT**

Essays on us mutual fund industry

Ines Gargouri, Ph.D.

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The first of three essays assesses the performance of U.S. equity funds over 45 years using the stochastic discount factor (SDF) approach. We test the applicability of nine candidate models for describing the pricing kernel, and use these pricing kernels to test whether fund managers can earn abnormal risk-adjusted returns for their unitholders. The Carhart model yields the smallest pricing errors under the conditional setting and is the appropriate pricing kernel specification based on the Hansen-Jagannathan boundary test. The percentage of abnormal average alphas is very low overall and is the highest using the CAPM-based pricing kernel. Robustness tests confirm the superiority of the Carhart model and show that the ranking of the candidates depends on the choice of the investment opportunity set.

In the second essay, we study M&A activity in the US mutual fund industry over the period 1962-2009. Any improvement in abnormal performance around M&As accrues primarily to target unitholders. The risk level of acquirers increases around such transactions. An analysis of the risk-return trade-offs finds that low levels of risk do not yield greater mean-variance efficient portfolios after merger, but that higher levels of risk are associated with a loss in asset allocation efficiency for unit holders in the acquirer. The analysis of success determinants finds that the target's prior performance, bidder's

risk post-M&A and an indicator of market state are significant determinants of the potential success of such M&As.

The third and final essay examines the relation between net fund flows and performance around the two most recent U.S. economic recessions for U.S. equity funds. Post-recessionary period net fund flows are positively (negatively) correlated with absolute (peer-relative) performance for the Early 2000 recession, and with absolute and peer-relative performance for the Great Recession (the most recent one) according to non-parametric measures. Empirical copulas in the extreme left tails indicate a positive dependence for the Early 2000 Recession, and independence for the Great Recession between performance and net fund flows.

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# CHAPTER 1

# INTRODUCTION

According to the 2011 Investment Company Fact Book, the total net assets (TNA) of US mutual funds grew from about $17 billion in 1960 to about $12 trillion in 2010 and the respective number of funds grew from 161 to 7,581. Fund flows varied over time and ranged between aggregate net sales of $884 billion in 2007 and aggregate net redemptions of $282 billion in 2010. In 2010, the US mutual fund industry had a predominance of equity funds with $5.7 trillion of TNA, compared to $2.6 trillion for bond funds, $2.8 trillion for money market funds and $0.7 trillion for hybrid funds. Hence, the exponential growth of US mutual funds, and the substantial time-variation in net fund flows in the industry lead to three central questions: (1) Are there outperforming active fund managers in the US market? (2) Does consolidation in the mutual fund industry lead to better asset allocation in a mean-variance context? (3) Is there a consistent relationship between performance and fund flows around recessionary periods?

In chapter 2 (essay 1), we provide an answer to the first question by examining the performance of equity US mutual funds over a 45 year period using the stochastic discount factor approach (SDF thereafter). The technical advantages of the SDF framework consist in relaxing the assumption that the distribution of error terms is normal that is imposed in a multivariate linear regression, and the alleviation of the biases due to errors-in-variables stemming from double-stage estimations à la Fama-McBeth. The conceptual advantages of the SDF approach consist in bypassing the step of picking the "right" mean-variance efficient benchmark. According to Cochrane (2005), if the

SDF prices the investment opportunity set, then financial markets are efficient. Therefore, we use Hansen's (1982) generalized method of moments (GMM) in order to estimate the parameters of the evaluation model and the risk-adjusted returns for over 14,000 US equity funds for the period starting in 1962 and ending in 2006. We estimate the abnormal performance (SDF alpha) for nine benchmark models and test the weak and semi-strong forms of the US market efficiency hypothesis using both unconditional and conditional performance measures.

Our study extends the studies by Dahlquist and Söderlind (1999), Farnsworth *et al.* (2002), and others, by estimating SDF parameters in a mutual fund performance context over almost a half century of data. Furthermore, we examine the existence of abnormal returns from active management for nine different SDF candidates (Capital Asset Pricing Model or CAPM, 3-factor Fama-French, 4-factor Carhart or Momentum, Labor-CAPM, Arbitrage Price Theory or APT, Cubic, Quadratic, Labor-Cubic, Labor-Quadratic). Our work also extends that of Fletcher and Forbes (2004) by applying the benchmark models to U.S. equity and bond mutual funds (and not U.K. unit trusts) as well as allowing for time-variation of the SDF coefficients when measuring conditional risk-adjusted returns.

Thus, this first essay makes four contributions to the mutual fund literature. First, the three highest ranked models based on Hansen-Jagannathan (H-J) distances (first ranking criterion) in descending order of appropriateness are the Carhart model, the APT model and the Cubic, with the CAPM model in the ninth rank under both settings (conditional and unconditional). Second, the three highest ranked models based on the Hansen-Jagannathan (H-J) boundaries (second ranking criterion) in descending order of appropriateness are the four-factor Carhart model, the three-factor Fama-French (henceforth FF) model and the Labor-Cubic model, and ending with the APT under the unconditional setting. Conditioning results in minor changes in ranking. Third, the three highest ranked of the nine candidate models based on average absolute pricing errors (third ranking criterion) in descending order of appropriateness are the CAPM, the FF model and the Carhart model under both settings. Finally, the three highest ranked models based on the percentage of significant alphas (fourth ranking criterion) in descending order of appropriateness are the Carhart, Labor-Quadratic and Labor-Cubic models, with the Labor-CAPM and CAPM model in the eighth and ninth ranks for both settings.

To answer the second question, we study combinations between US mutual funds (equity, bond, money market, hybrid or asset allocation and convertibles) in chapter 3 (essay 2). This study provides insight about the Mergers & Acquisitions (M&A thereafter) activity in the US mutual fund industry over a 48-year period starting in 1962 and ending in 2009. We consider the two central variables inherent to an investment decision: performance and risk. The conditional abnormal returns using the four-factor Carhart (1997) model within the SDF framework for the target and the acquiring funds are used to proxy managerial performance around a M&A, and the semi-variance of fund returns is used as the proxy for a measure of downside risk.

This essay extends the Jayaraman *et al.* (2002) study by examining the determinants of mutual fund success in lieu of the forces driving their occurrence. The success odds are based on the outperformance of the funds post-M&A, and the explanatory variables considered in a logistic regression include the ages of the target and acquiring funds at transaction dates to proxy for their reputations, the sizes of the bidder and the target fund, the past performance of the target fund, the average MER of the bidder and the target, the average net asset flow for the target prior to the M&A, dummy bull/bear market indicators to proxy for the timing of the deal, the Investment Style (hereafter IS) of the target and merger type (within vs. across-IS and within vs. across-family).

We find that the abnormal performance improvement around the M&As primarily benefits target unitholders, but that the increase in risk post-M&A is incompatible with a significantly higher abnormal performance. Fund risk increases post-M&A for the unitholders of acquirers and is unchanged for unitholders of targets. The latter finding is consistent with the continuity or smooth transition hypothesis. The mean-variance efficiency of high-risk bidder funds deteriorates while that of low-risk bidder funds remains unchanged. Thus, M&As only affect unitholders of high-risk bidder funds adversely. The window of opportunity and smooth transition hypotheses are supported since the target's reputation (as proxied by its age), target's size and timing of the deal are significantly related to prospective post-M&A outperformance.

To answer the third question, we study the relationship between performance and net fund flows around recessions in chapter 4 (essay 3). The occurrence of downturns in the US economy has been more frequent since the beginning of the 21$^{st}$ century. This is a reason for focusing on recessionary periods when examining the dependence of post-recession fund flows to/from equity mutual funds and the during-recession performance of fund managers. We consider only the funds investing in equity assets because they are the major category in terms of assets under management (AUM) in the US market, and since they are considered as being more risky than bond or money market funds.

In this third essay, we examine the relationship between the two variables, net fund flows and performance, over their whole distributions, and over their lower and upper tails separately. For this purpose we examine correlations (parametric and non-parametric) and use the copulas method (Gaussian, Student t and empirical). We also estimate empirical survival copulas to cover the right tails of the distributions of the two variables.

The third essay contributes to the literature by examining the behavior of net fund flows and fund performances using the copulas method around two recent economic recessions in the U.S., namely the Early 2000 Recession (the Dotcom crisis) and the Great Recession (the Subprime crisis). Since the investment behavior of individual investors cannot be linked to any sophisticated risk-adjusted performance measure, we consider both absolute and objective-adjusted monthly returns and fund flows.

Our major findings in the third essay show significant differences between both recessionary periods and for both return and fund flows measures. First, the Early 2000 Recession yields a positive correlation between during-recessionary period absolute returns and post-recessionary period absolute fund flows and a negative linear dependence between their objective-adjusted counterparts. This suggests that higher performance during downturns is rewarded by subsequent higher money flows on an absolute basis, and that investors direct less net cash flow to outperformers on a peer-relative basis. On both an absolute and relative basis, performance positively impacts post-Great Recession fund flows according to the non-parametric measures. Second, the extreme left and right regions of the tails of the peer-relative distributions are associated with negative dependence for both recessionary periods. Median Gaussian, and Student t, copulas for the absolute variables show a positive (negative) dependence in the 1% left (right) tail for the Early 2000 Recession. The right and left 1% tail dependence for the Great Recession is positive. Empirical copulas in the extreme left tail exhibit a positive dependence for the Early 2000 Recession, and independence for the Great Recession, between performance and net cash flow. Third, survival copulas show an overall positive dependence on an absolute basis and a negative dependence on an objective-adjusted basis in the right region of the marginal distributions.

# CHAPTER 2

# PERFORMANCE OF U.S. EQUITY MUTUAL FUNDS USING THE STOCHASTIC DISCOUNT FACTOR APPROACH

## 2.1. INTRODUCTION

The performance of mutual funds remains an important research problem since the economic size of the industry has grown exponentially since the 1980s. About 90 million Americans own mutual funds and total mutual fund assets reached almost $13 trillion as of year-end 2010.[1] Moreover, mutual fund units are available for large-scale purchases or redemptions on a daily basis, with very negligible execution costs since they are marked-to-market at the close of each day and are traded at the NAVPS of the day.[2]

The theory of efficient markets states that even expert investors are not able to exploit mispricing or profit from free lunches. In such markets, portfolio managers should not be able to outperform relevant benchmarks to register abnormal returns for the funds they manage. This statement casts doubt on the raison-d'être of active management and the viability of non-indexed mutual funds. Since the middle of the last century, researchers have investigated the extent to which portfolio managers are able to take advantage of asset mispricings by constructing strategies that result in net positive abnormal performance. The issue is still unresolved although models have been further refined to delimit the possible risk sources that explain the cross-section of financial asset returns.

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[1] For more exhaustive information about the mutual fund industry, see the Investment Company Institute's Fact Book (51st edition).

[2] NAVPS is *Net Asset Value Per Share* or the weighted average of the market values of securities composing the portfolio at the close of the market minus any fund liabilities, divided by the number of fund shares.

Early studies evaluate performance using beta-pricing models. The well-known Jensen's alpha relies on the Sharpe-Lintner (1964-1965) CAPM as the "true" model specification for pricing assets. However, empirical implementations of the unconditional CAPM using a stock market index as the proxy for the mean-variance efficient market portfolio suggest that this model may not best describe the cross-variation of average stock returns. The need to better explain expected returns has led to the inclusion of numerous variables as potential sources of risk in the return generating process. According to Fama and French (1992), the ICAPM of Merton (1973) was the "fishing license" that allowed asset-pricing models to be structured as multi-factor models.

To include presumably priced risk factors, there is a need to associate financial market movements with macroeconomic events. As stocks returns are deemed to be higher in "good" times and lower in "bad" times, expected returns should be related to or driven by changing economic conditions as captured by macroeconomic factors. The Fama-French (1993) three-factor model is the first popular asset-pricing model that fulfils the condition that the added factors are part of the aggregate wealth in the economy. Liew and Vassalou (2000) find that value (HML or high minus low) and size (SMB or small minus big) are significant explanatory variables of future output growth (i.e., of business cycles). In contrast, the momentum-related risk factor added by Carhart (1997) to obtain his four-factor model has no apparent macroeconomic grounding although its addition helps to explain the momentum anomaly.

A number of other sources of risk are proposed to more accurately price stocks. Jagannathan and Wang (1996) find that human capital should be taken into account when explaining variations in expected stock returns. Harvey and Siddique (2000) and Dittmar

(2002) find that investors also incorporate coskewness and cokurtosis as factors when pricing securities. As researchers search for new risk variables to better describe expected stock return cross-variations, the problem of data snooping becomes a real issue. Thus, an economic explanation for factors helping to shape the distribution of securities' returns may be found, without being influential out of the sample used in the study. Furthermore, Kothari, Shanken and Sloan (1995) argue that survivorship bias exists in the data used to test the multi-factor linear pricing models.

The stochastic discount factor (hereafter SDF) formulation is considered as a competing paradigm to beta pricing formulations for empirical work in asset pricing. Under the same distributional assumptions, the GMM approach within the SDF framework and multivariate regression approach are equivalent when the same moments are estimated. Nevertheless, the GMM method is more attractive than the latter to estimate "true" risk-adjusted fund returns. First, the GMM relies on weaker construction conditions since there is no need to hypothesize about the distributions followed by the pricing errors. Second, the multifactor models rely on strong assumptions such as the rationality and the efficiency of markets. According to Cochrane (2005), pricing is undeniably rational if the SDF mirrors the macroeconomic conditions correctly, where Arrow-Debreu prices of securities reflect the economy state. If the SDF approach prices the assets in the investment opportunity set, then financial markets are efficient, regardless of the choice of benchmarks and their mean-variance efficiency. Furthermore, Söderlind (1999) shows that a portfolio performance measure equivalent to Jensen's alpha is obtained using a Hansen and Jagannathan (1991) SDF that is a linear combination of individual returns.

We begin by investigating the performance of individual U.S. equity mutual funds between January 1962 and June 2006 relative to nine benchmark models within the SDF framework. Our study is related to Dahlquist and Söderlind (1999) and Farnsworth *et al.* (2002) in that we estimate SDF parameters to measure fund performance. Our work differs from their work in terms of study period, and choice of SDF candidates for testing the existence of abnormal returns from active management. While our work is close to that of Fletcher and Forbes (2004), we apply our models to U.S. equity mutual funds and not U.K. unit trusts, and *we do allow* the SDF coefficients to vary over time when we measure conditional risk-adjusted returns. We test the ability of each SDF candidate, which is related to an asset-pricing model, to provide neutral performance when no managerial ability is at play.

This paper has four major findings. First, the three highest ranked models based on Hansen-Jagannathan (HJ) distances (first ranking criterion) in descending order of appropriateness are the Carhart model, the APT model and the Cubic, with the CAPM model in the ninth rank under both settings (conditional and unconditional). Second, the three highest ranked models based on the Hansen-Jagannathan (HJ) boundaries (second ranking criterion) in descending order of appropriateness are the four-factor Carhart model, the three-factor Fama-French (henceforth FF) model and the Labor-Cubic model, and ending with the APT under the unconditional setting. Conditioning results in minor changes in ranking. Third, the three highest ranked of the nine candidate models based on average absolute pricing errors (third ranking criterion) in descending order of appropriateness are the CAPM, the FF model and the Carhart model under both settings. Finally, the three highest ranked models based on the percentage of significant alphas (fourth ranking criterion) in descending order of appropriateness are the Carhart, Labor-Quadratic and Labor-Cubic models, with the Labor-CAPM and CAPM model in the eighth and ninth ranks for both settings.

The remainder of the paper is organized as follows. In the next section, we introduce the SDF approach and describe the need for the generalized method of moments in the general asset pricing framework. In the third section, we present the methodology of mutual fund performance using the SDF approach and the ten candidate models for the SDF. In the fourth section, we describe the mutual fund sample and the data used herein. In the fifth section, we present and discuss our empirical results. In the sixth section, we report the results of robustness tests. We conclude with a summary of our findings and their implications.

## 2.2. STOCHASTIC DISCOUNT FACTOR APPROACH

### 2.2.1 The Stochastic Discount Factor

Asset-pricing models are based on two central concepts: the no-arbitrage principle and/or financial market equilibrium. The theorems of Harrison and Pliska (1981) provide the foundation for the law-of-one-price evaluation method based on the seminal work of Harrison-Kreps (1979). Harrison-Kreps show that there is a price process of an admissible investment strategy that is compatible with market equilibrium, if and only if, there is a martingale for some equivalent probability measure when appropriately normalized. In the absence of arbitrage, the equilibrium price of an asset equals the expectation of its discounted future values using risk-neutral probabilities.

According to Harrison and Kreps (1979), the general asset-pricing (GAP) model requires rather weak market conditions of either the law of one price or the no arbitrage principle. The GAP model implies the canonical asset-pricing equation according to which any gross return discounted by a market-wide random variable has a constant conditional expectation: the pricing kernel or stochastic discount factor.

In an Arrow-Debreu economy, the SDF constitutes the state-price density and reflects the intertemporal marginal rate of substitution in the CCAPM. The SDF is called the marginal value of wealth or a "hunger" measure for wealth by Cochrane (2005). SDFs are positively related with economic conditions.

### 2.2.2 The GAP Framework and Mutual Fund Performance

The SDF approach is used to measure portfolio performance given its equivalence to factor pricing models and its weaker distributional assumptions on the pricing errors. The use of GMM to estimate all parameters simultaneously avoids the errors-in-variables problem associated with the traditional regression method. The system consists of all relevant orthogonality moment conditions to reflect the mean-variance efficient frontier in financial markets,[3] augmented with a similar condition applied to the fund (or funds) of interest. If the pricing errors of the fund, on average, are neutral, then the fund belongs to the portfolio frontier. Otherwise, the fund either expands the frontier when positive, or leads to a sub-optimal combination of individual assets when negative.

Söderlind (1999) shows that the estimation of mutual fund performance under the (un)conditional GAP framework is related to the metric introduced by Jensen (1968) to measure stock-picking ability. Thus, when we apply the SDF approach, we estimate a modified Jensen alpha while avoiding a potential bias from market timing and the econometric errors that may occur with linear estimation. The unconditional SDF-based measure is used to test the average performance of portfolio managers after controlling

[3] The pricing kernel is assumed to price all assets on the market at equilibrium. Hence, there is no need to specify a mean-variance efficient frontier. Empirically, the latter is proxied by a number of benchmark strategies (hereafter primitive assets) that are deemed to encompass all investment opportunities available to investors and reflect the dynamics of the financial asset universe.

for the impact of the economy on their trading strategies. The conditional measure is used to test the ability of managers to better use publicly available information to generate returns that outperform naive trading strategies based on the same information set.

## 2.3. METHODOLOGY

According to Harrison and Kreps (1979) and Harrison and Pliska (1981, 1983), there is a martingale equivalent measure in equilibrium that prices all financial securities, such that:

$$E_t\left(m_{t+1} r_{t+1}\right) = 0 \tag{1}$$

where $E_t$ is the conditional expectation operator; $m_{t+1}$ is the future pricing kernel prevailing at t+1 given the information set at time t, and $r_{t+1}$ is the excess return on the risky versus risk-free asset at time t+1. To implement this fundamental pricing model, we: (i) use sample analogs instead of the population moments; (ii) measure ex-post first moments of discounted fund returns rather than ex-ante moments conditional on the available information set; and (iii) estimate expectations over time and not over states of the world. Hence, we apply the law of iterated expectations assuming that asset returns are random variables measurable on the probability space $(\Omega, F, F_t, P)$, and constant on the atoms of the sub-σ-algebras $F_t$. The canonical equation becomes:

$$E\left(m_{t+1} r_{t+1}\right) = E\left(E_t\left(m_{t+1} r_{t+1}\right)\right) = 0 \tag{2}$$

### 2.3.1 Setup

When applied to mutual fund performance measurement, the GMM system involving equilibrium pricing equations and instrumental variables $Z_t$ becomes:

$$E\left(m_{t+1} r_{t+1} \mid Z_t\right) = 0 \tag{3}$$

$$E\left(m_{t+1} r_{pt+1} \mid Z_t\right) = \alpha_p \tag{4}$$

where $m_{t+1}$ is the pricing kernel, $r_{t+1}$ is the vector of N primitive asset excess returns at time t+1, $r_{pt+1}$ is the mutual fund excess return, and $\alpha_p$ is the average unconditional abnormal performance of the fund when $Z_t$ is a constant, and average conditional performance when $Z_t$ is a set of economy-reflecting variables. According to the semi-strong from of market efficiency (Fama, 1971, 1998), the average conditional alpha must be neutral, even if the unconditional abnormal return is positive. Trading rules that respond mechanically to economic readings and historical return patterns should not obtain significant positive risk-adjusted rewards. However, if the average conditional alpha is significantly positive, this provides evidence that active managers can use economic variables to forecast risk-adjusted returns that outperform appropriate benchmarks.

When the general pricing framework is based on excess rather than gross returns, the model is not constrained to price rates of return on a discounting security (the numéraire). As a result, the inverse of the gross risk-free return is assigned to the mean of the SDF: $E\ (m_{t+1}|Z_t)=1/R_{f,t}$. If the pricing errors are denoted by $f_{t+1}$, then the system becomes:

$$E(f_{t+1}|Z_t)=0 \tag{5}$$

where

$$f_{t+1}=\begin{pmatrix} m_{t+1}r_{t+1} \\ m_{t+1}r_{p,t+1}-\alpha_p \\ m_{t+1}-1/R_{f,t} \end{pmatrix}$$

The mimicking portfolio makes the portfolio-based descriptions of the marginal value of wealth a more legitimate method with regard to its effectiveness in performance evaluation. According to Cochrane (2005),[4] the mimicking portfolio theorem states that if we assume that the pricing kernel is a linear function and the model is well-specified, then we can work with a mimicking portfolio resulting from the regression of the SDF on asset returns. This mimicking portfolio will work better in sample and in practice using the better-measured data for asset returns than that for consumption-related variables.

Ayadi and Kryzanowski (2005) show that the performance statistics and inferences are sensitive to the kernel specification model, when estimating performance under the same framework. Thus, we measure the relative effectiveness of nine candidate models to reflect economic conditions and to price the IO set in order to identify the best performing models for assessing mutual fund performance using the GMM method (in the spirit of Fletcher and Forbes, 2004; and Farnsworth *et al.*, 2002).

We investigate the predictability of asset returns by assessing conditional performances. We translate the co-variation of the SDFs and the risk factors by the inclusion of lagged short-term interest rates (Ferson and Schadt, 1996; Kryzanowski et al., 1997; Ayadi and Kryzanowski, 2005).[5] Empirically, we choose to account for instrumental variables using the linear method as in Cochrane (1996) and we impose the time-variability of factor coefficients to reflect variability in risk and excess returns.

### 2.3.2 Candidate SDF Specifications

<u>CAPM</u>. Dybvig and Ingersoll (1982) show that the Sharpe-Lintner model is equivalent to the SDF model when the pricing kernel is a linear function of the excess returns on the market portfolio, $r_{mt}$, as follows:

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[4] According to Cochrane (2005), the linear function of mimicking portfolios for some economic risks is a plausible alternative for the more common ratio of intertemporal levels of consumption (e.g., the consumption-CAPM).

[5] Due to saturation ratio considerations, we do not include the dividend yield of the equity index as an instrumental variable (see Appendix A).

$$m_t = a(z_{t-1}) + b(z_{t-1}) r_{mt} \tag{6}$$

where $z_{t-1}$ is a vector of information variables (ones) in an (un)conditional setting.

Labor-CAPM. Jagannathan and Wang (1996) broaden the market portfolio to account for the growth in per capita labour income $r_{lt}$ to proxy for the human capital factor since salary and wages represent a major part of the U.S. economy. The SDF specification based on the Labor-CAPM is as follows:

$$m_t = a(z_{t-1}) + b(z_{t-1})' \begin{pmatrix} r_{m,t} & r_{l,t} \end{pmatrix}' \tag{7}$$

FF and Carhart Models. The FF model acquired legitimacy among empirical researchers because the size and value factors ($r_{smb,t}$ and $r_{hml,t}$, respectively) may correspond to a plausible measure of the marginal utility of wealth (Cochrane, 2005). Carhart (1997) accounts for return persistence by adding the momentum risk factor $r_{wml,t}$ to the FF model to obtain:

$$m_t = a(z_{t-1}) + b(z_{t-1})' \begin{pmatrix} r_{m,t} & r_{smb,t} & r_{hml,t} & r_{wml,t} \end{pmatrix}' \tag{8}$$

Four-factor APT. We implement the APT model of Ross (1976) by using mimicking portfolios for four predetermined risk factors: residual market portfolio return ($r_{mres,t}$); term structure ($r_{term,t}$); unexpected change in industrial output ($r_{prod,t}$) (Breeden, 1979); and unexpected change in inflation ($r_{\inf,t}$) (Chan, Foresi and Lang, 1996). Specifically:

$$m_t = a(z_{t-1}) + b(z_{t-1})' \begin{pmatrix} r_{mres,t} & r_{term,t} & r_{prod,t} & r_{\inf,t} \end{pmatrix}' \tag{9}$$

Quadratic kernel. Harvey and Siddique (2000) find that coskewness commands a significant risk premium. Hence, the quadratic pricing kernel, which is consistent with the three-moment or quadratic-CAPM, is formulated as:

$$m_t = a(z_{t-1}) + b(z_{t-1})' \begin{pmatrix} r_{m,t} & r_{m,t}^2 \end{pmatrix}' \tag{10}$$

Cubic kernel. This model adds a cubic term beyond the linear and quadratic ones to capture cokurtosis (Dittmar, 2002) in order to account for the investor preference for thin- compared to heavy-tailed asset return distributions. This model is formulated as:

$$m_t = a(z_{t-1}) + b(z_{t-1})' \begin{pmatrix} r_{m,t} & r_{m,t}^2 & r_{m,t}^3 \end{pmatrix}' \tag{11}$$

Quadratic and Cubic LCAPMs. Dittmar (2002) allows for nonlinearities in the human capital factor and finds that it substantially improves the pricing kernel's ability to describe the cross-section of returns. When the third moment of labor income growth, which reflects the price of systematic skewness of the human-capital component within aggregate wealth, is included the quadratic LCAPM pricing kernel specification is:

$$m_t = a(z_{t-1}) + b(z_{t-1})' \begin{pmatrix} r_{m,t} & r_{l,t} & r_{m,t}^2 & r_{l,t}^2 \end{pmatrix}' \tag{12}$$

When the high kurtosis of the return on labor compared to that on the market return is captured by including the fourth moment of returns on the human capital factor (Dittmar, 2002), the SDF specification becomes:

$$m_t = a(z_{t-1}) + b(z_{t-1})' \begin{pmatrix} r_{m,t} & r_{l,t} & r_{m,t}^2 & r_{l,t}^2 & r_{m,t}^3 & r_{l,t}^3 \end{pmatrix}' \tag{13}$$

### 2.3.3 Estimation Method and Statistical Tests

The first moment of model conditions is estimated using sample averages over the study period.[6] The $N+2$ moment conditions are denoted by the following system of equations:

$$g_T = \frac{1}{T}\sum_{t=1}^{T} f_t = 0_{N+2} \tag{14}$$

where $T$ is the number of pricing errors in the time series and $N$ is the number of primitive assets under consideration. The number of parameters in the model, $p$, is driven by the restrictions on the SDF specification. In the linear three-factor case, $\mathrm{p}=3\times(\mathrm{K}+1)+1$, where $K$ is one (zero) in the (un)conditional setting.

Hansen's (1982) generalized method of moments (GMM) is used to test the hypothesized neutral performance of mutual funds. We estimate the model parameters and test the overidentifying orthogonality conditions simultaneously using the minimization of the function of the weighted squared pricing errors. We assess the iterated GMM estimator given its superior finite sample properties compared to the standard estimator (Ferson and Foerster, 1994).

Hansen (1982) has established that the GMM estimators are optimal if a consistent estimate of the asymptotic variance-covariance matrix of the sample analogs of moment conditions is used. We followed Newey and West (1994) and estimate the spectral density matrix at frequency zero of sample averages of pricing errors. This

[6] The general equilibrium exists if the discounted asset return is a martingale difference sequence. Also, the GMM distribution theory requires that the SDF, the asset prices and the payoffs must be stationary random variables so that sample averages converge to population means. Consequently, we tested the stationarity of the primitive assets as well as the mutual funds time series of monthly returns (Cochrane, 2001). Using the Dickey-Fuller limiting distributions at the 95% confidence level, we find a percentage of equity funds whose return series are cointegrated of 2.07% (or 310 funds out of 14,996). All 10 industry-sorted portfolio returns series are stationary using the augmented Dickey-Fuller tests. The Phillips-Perron correction for autocorrelation and heteroscedasticity yields slightly different figures with a percentage of 2.09% for equity funds.

weighting matrix has been proven to be positive, semi-definite and a consistent estimator since it accounts for heteroscedasticity and serial autocorrelation within the moment condition time series. Larger weights are assigned to low-order lagged autocorrelation terms to reflect a greater impact of closer autocorrelations than further ones. We test the classical weighting schemes used to estimate spectral density matrices using three kernel types: Bartlett window (Newey and West, 1987), Parzen window (Gallant, 1987) and Quadratic Spectral kernel (Andrews, 1991).

We impose an additional condition on the estimation system which is the positivity of the SDF in both the unconditional and conditional versions of the model. Hansen and Jagannathan (1991) argue that the absence of arbitrage opportunities (nonnegative payoffs with negative prices) imposes positivity on the SDF almost surely in a conditional asset-pricing model (Dahlquist and Söderlind, 1999, p. 352). Our objective is to ensure a maximum level of accuracy in both the SDF and the abnormal performance estimates.

## 2.4. SAMPLE OF FUNDS AND DATA COLLECTION

### 2.4.1 Mutual Fund Dataset

Our sample consists of all 14,996 alive, dead and surviving U.S. open-ended equity funds drawn from the CRSP survivorship-bias free mutual fund database with regularly-reported monthly returns in the period from January 1962 through June 2006.[7] Whether a fund is an equity fund is based on the not fully-revealing objective codes provided by Wiesenberger for funds from 1962 to 1990, the widened set of Wiesenberger

[7] Alive and dead funds are those that started up before May 2006 and were and were not still operating as of June 2006, respectively. Surviving funds are those that were alive over the full evaluation period.

objective codes from 1991 to 1993, and the S&P codes (or in their absence the ICDI codes) thereafter.[8] Changes in investment objectives are treated as fund terminations.

Monthly mutual fund returns are net of management fees and adjusted for dividend or interest distributions, but are gross of commissions, front-end and back-end loads. Their excess returns are calculated using the total returns on 30-day U.S. Treasury Bills available from the Ibbotson Associates database.[9]

### 2.4.2 Investment Opportunity (IO) Set of Primitive Assets

The investment opportunity (IO) set of primitive assets initially is proxied by ten value-weighted industry portfolios: Consumer Nondurables, Consumer Durables, Manufacturing, Energy, HiTech Business Equipment, Telecom, Shops, Health, Utilities and Others (e.g., Mines, Hotels, Entertainment, Finance, etc.). The excess portfolio returns over those for 30-day U.S. Treasury Bills are obtained from the "Kenneth French data library".

### 2.4.3 Risk Factors and Information Variables[10]

The value-weighted portfolio of all NYSE, AMEX and NASDAQ stocks from CRSP is used as the proxy for the market portfolio. The previous month's growth in the two-month moving average of labour income from the Bureau of Economic Analysis is used as the proxy for the human capital return.[11] We also use the continuously compounded growth rate of the U.S. industrial production index available from the U.S. Board of Governors of the Federal Reserve System, and the monthly change in the CPI-U

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[8] Information for fund style is missing for a number of funds. When it was possible to infer fund style or investment objective from information on asset holdings, we added the fund to our sample. This process resulted in the addition of 147 funds to the sample.

[9] The U.S. T-bill index is extracted from the *Wall Street Journal* for 1977-2007, and is the CRSP U.S. government bond file for 1926-1976.

[10] See Table 1 for simple statistics for the data series for the risk factors.

[11] As in Jagannathan and Wang (1996), a lagged variable is used since labour information is released with a one-month delay. Labour income is the difference between personal and dividend income, all divided by the population size, as reported in a table in the *National Income and Product Account* section.

index (Consumer Price Index for All Urban Consumers) available from the Bureau of Economic Analysis. Term structure is measured by the difference in returns of the U.S. long-term government bond index and 30-day T-bills.

To form mimicking portfolios for the industrial production and inflation factors in the APT model, the sample realizations of statistical factors are first identified by estimating the first five eigenvectors of the cross-products matrix of the cross-section of returns on all securities traded on the NYSE, AMEX and NASDAQ over the study period (Connor & Korajczyk, 1986, 1988; Ferson & Korajczyk, 1995). The economic shocks (demeaned risk factors) are then regressed on the five demeaned eigenvectors. The resulting coefficients from the rotational matrix are then multiplied by the original eigenvectors to get the mimicking portfolio excess returns that proxy for industrial production and inflation risk sources.

The size and value factors are based on self-financing portfolios sorted by market capitalization (SMB) and book-to-market ratios (HML). The momentum factor (WML) is based on zero-net investment portfolios long in winners and short in losers. These three factors are obtained from the "Kenneth French data library".

As one test of robustness, we implement the four-index model as in Elton et al. (1999) and Ayadi and Kryzanowski (2008), where the factors are the three Fama-French risk factors and a bond factor. The Merrill Lynch U.S. Broad Market Index, which includes U.S. Treasury, quasi-government, corporate, securitized and collateralized securities, is used to proxy for the bond market in the EGB model. Since the index began at the end of 1975, this led to the restriction of our study period to thirty years (1976-2006).

One lagged instrument is used for public information. The lagged stochastically detrended risk-free rate is defined as the return difference between the lagged 30-day U.S. Treasury bill and the lagged two-month moving average to decrease the persistence of the original yield (Dahlquist and Söderlind, 1999).

## 2.5. RESULTS

The primary objective of the GMM estimation is to test whether the suggested SDF specification prices all primitive assets and the mutual fund(s) under consideration so that we can better distinguish between model failure and market inefficiency.

### 2.5.1 Model Performance Based on HJ Distances (First Ranking Criterion)

We first compare the SDF candidate models using the Hansen-Jagannathan (HJ) (1997) distance $D$ (first ranking criterion), which equals the square root of the quadratic function used in the standard GMM estimation when the parameters used are one-step estimators and the weighting matrix is the inverse of the second moment of the primitive asset returns to down-weight noise generated by the moment conditions. [12] Or:

$$D = \left[ E\left(m_{t+1} r_{t+1} \mid Z_t\right)' E\left(R_t{}' R_t\right)^{-1} E\left(m_{t+1} r_{t+1} \mid Z_t\right) \right]^{1/2} \tag{15}$$

This metric is interpreted as the distance between the sample SDF estimates and the space of real SDFs (i.e., the necessary correction to the proxy SDF in order to make it consistent with the data). Thus, the model with the lowest Hansen-Jagannathan distance $D$ is considered to best price the investment opportunity set.

[12] The weighting matrix is invariant across all models tested, so the distance measure can be used to directly compare the performance of the different candidate models, rank different pricing theories and identify the ones that best reflect the value of money and SDF movements.

For both settings (see figure 1),[13] we find that the three highest ranked of the nine candidate models on this criterion in descending order of performance are the Carhart model, APT model and the Labor-Quadratic model, with the CAPM occupying the lowest rank for both settings. While the distances for five models improve with conditioning, the relative ranks are unchanged.

**[Please place figure 2.1 here.]**

### 2.5.2 Model Performance Based on HJ Boundary (Second Ranking Criterion)

We now conduct Hansen and Jagannathan (HJ) (1991) volatility boundary tests to assess the relevance of each model. If a given SDF does not satisfy the restriction imposed on its lower-bound variability, then the SDF cannot satisfy the fundamental pricing equation and the related theoretical pricing model is not supported. We apply the following formula for this purpose:

$$Var(m) \geq \left[1' - E(m)E(R')\right]\sum{}^{-1}\left[1 - E(m)E(R)\right] \tag{16}$$

where $m$ is the empirical SDF, $R$ is the vector of gross returns for the ten primitive assets, and $\Sigma$ is the estimate of their asymptotic variance-covariance matrix.

The results from applying the second performance criterion suggested by Hansen and Jagannathan (1991) are depicted in Figure 2 for the equity funds reporting at least 180 months of data (i.e. more than 15 years of business activity and subsequently referred to as 180-funds). This tool examines the behavior of the empirical stochastic discount factors depending on the model tested and the considered setting. Based on the percentage of the SDFs lying in the admissible region, we find that the three highest

[13] There are no substantial differences between the results related to the quadratic spectral window and those related to the Bartlett and Parzen ones. Consequently, we chose to report the outcomes of the optimization procedure related to the quadratic spectral kernel only. This type of window has been proven to lead to a faster convergence of the quadratic spectral density matrix estimator.

ranked models in descending order of performance are the Carhart, the FF and the Labor-Cubic (the Labor-CAPM) models under the unconditional (conditional) setting. The APT is the poorest performer with only 2.95% of the SDFs lying in the admissible region for both settings. The percentages decrease marginally, with conditioning, from 87.95% to 87.84% for the Carhart model, and dramatically from 83.07% to 64.77% for the FF model.

**[Please place figure 2.2 here.]**

### 2.5.3 Model Performance Based on Average Absolute Error (Third Ranking Criterion)

These somewhat conflicting inferences from the measures of misspecification and membership in the mean-variance admissible region for the SDFs raise the issue of whether or not the models describing the pricing kernels are appropriate. To further explore this issue, we use a third ranking criterion, the average absolute pricing error (AAE). Based on the results reported in Figure 3 for the unconditional setting, we find that the three highest ranked of the nine candidate models on this criterion in descending order of performance are the CAPM, FF model and Carhart model, with the Cubic, Labor-Cubic and Labor-Quadratic models occupying the lowest ranks. The top three rankings change their order and become Carhart model, CAPM and FF model for the conditional setting. Thus, the AAE criterion suggests that the three models based on the first and second moments of risk factors perform better than the models that account for macroeconomic factors or the higher-order moments of the market risk factor.

**[Please place figure 2.3 here.]**

### 2.5.4 Model Performance Based on SDF Alphas (Fourth Ranking Criterion)

We now evaluate the empirical probability distributions of alphas for the funds with at least 180 data return observations for each model under both settings. Based on Figure 4, the fund performances are mostly negative except for the Cubic model. The cross-sectional distributions of alphas for the unconditional setting are right-skewed for the APT and Carhart models, left-skewed for the Cubic model and virtually symmetric for the other six models. In contrast, the cross-sectional distributions of alphas for the unconditional setting are right-skewed for the CAPM, Labor CAPM and Quadratic model, left-skewed for the Cubic and Labor-Cubic models, and reasonably symmetric for the other four models. The alpha distributions for the Carhart and FF models exhibit thicker right tails.

**[Please place figure 2.4 here.]**

An examination of the number of cases where the average alpha is statistically significant at the 95% confidence level shows that the number of occurrences where the alphas are significantly different from zero range between 16 (0.11%) and 195 (1.30%) out of 14,996 equity funds (see Table 3). In addition, we find that the three highest ranked of the nine candidate models on this criterion in descending order of performance are the Carhart, the Labor-Quadratic (APT) and the Labor-Cubic (FF) under the unconditional (conditional) setting, with the Labor-CAPM and CAPM occupying the eight and ninth ranks for both settings.

**[Please place table 2.3 here.]**

## 2.6. ROBUSTNESS TESTS

### 2.6.1 Portfolios of Funds

Since the individual fund results may be affected by cross-sectional correlation in returns, we apply GMM optimization to two portfolios of funds.

Based on the HJ distances (first ranking criterion) for both settings, the three highest ranked models in descending order of performance are the Carhart, the FF and the APT models for the equally-weighted portfolios (hereafter EW) and the size-weighted portfolios (hereafter SW) of all 180 funds, and the subsamples of surviving, alive and dead equity funds. The least performing model for both settings for this criterion, is the Labor-CAPM for SW portfolio of surviving funds and EW portfolio of dead funds and the CAPM for EW and SW portfolios of alive funds.

For both settings, we find that the empirical SDF lies on the HJ boundary (second ranking criterion) only for the Carhart and FF models for the EW portfolios, and only for the Carhart model for the SW counterparts. The results of applying the HJ boundary test to the portfolios corroborates the superior appropriateness of the Carhart and FF models for the EW and SW portfolios of alive and dead funds for both settings, and the Carhart model for the EW and SW portfolios of surviving funds for both settings. The superiority of the Carhart over the FF model is greater for the alive and dead funds in a conditional setting. Hence, the Carhart model remains the most appropriate specification for the pricing kernel according to the HJ boundary test based on the portfolio results.

Based on the AAE (third ranking criterion) for both settings, the three highest ranked models are the Carhart, the FF and the CAPM (Labor-Quadratic) models for EW (SW) portfolios and the APT is the lowest ranked model for all portfolios of funds. For the EW and SW portfolios of surviving, alive and dead equity funds, the two top models exchange their respective ranks in some instances.

### 2.6.2 The EGB Model

As a further test of the robustness, we use a four-index model as in Elton et al.(EGB) (1999) and Ayadi & Kryzanowski (2008), which replaces the momentum factor in the Carhart model with a broad-based bond market index. The objective is to examine whether results change in terms of SDF volatility and abnormal performance compared to the rest of the tested candidates. Based on the first ranking criterion (HJ distances), the EGB model is ranked third after the Carhart and APT models for both settings.

The percentages of cases where the SDF mean-standard deviation for this additional model is inside the HJ boundary (second ranking criterion) are 5.09% for both settings (see table 4). While the EGB model does not outrank the Carhart and FF model under the unconditional setting, the latter comes second behind the Carhart model under the conditional setting, it ranks behind the Carhart model with a percentage of 78.32% for the 180-funds in the conditional setting.

**[Please place table 2.4 here.]**

The ranking of the EGB based on the AAE (third ranking criterion) is sixth under the conditional setting and least under the conditional setting. The percentage of significant alphas (fourth ranking criterion) at the 5% level resulting from the EGB model is only 0.98% (147 funds) under the unconditional setting and even lower at 0.07% (11 funds) under the conditional setting. The percentages rise to 16.96% and 1.27% for the unconditional and conditional settings, respectively, for the 180-funds. All significant alphas are negative regardless of the setting, and conditioning results in some of the significant alphas becoming insignificant. Thus, after conditioning for common knowledge, the resulting inference is that fund managers do not add even value to cover their costs.

### 2.6.3 Alternative Investment Opportunity (IO) Set of Primitive Assets

As a further test of robustness, we replace the ten value-weighted industry portfolios by the 125 size-, value- and momentum-sorted equity portfolios of Wermers

(2004). The objective for the use of an alternative set of primitive assets based on style-based portfolios is to examine changes in the rankings of the candidate models and the alphas of the fund managers. Based on the HJ distances (first ranking criterion), we find that the three highest ranked models in descending order of performance are the CAPM, FF model and the Carhart model for both settings, with the Cubic-Labor (Cubic) occupying the lowest rank under the unconditional (conditional) setting.

While the cubic (24.90%) and quadratic (22.84%) models yield more cases inside the cup based on the HJ boundary test (second ranking criterion) with these style-sorted benchmarks than with the former IO set, the differences between the proportions of permissible cases yielded by the different candidate models are not statistically significant. Based on the AAE measure (third ranking criterion), the FF and the CAPM are the top-ranked models, followed by the Labor-CAPM, with the APT model occupying the lowest rank for both settings.

**[Please place figure 2.6 about here]**

The percentages of significant alphas (fourth ranking criterion) are negligible and range between 1.09% (CAPM) and 2.19% (APT) of the whole sample, of which 33.97% (CAPM) and 49.68% (Quadratic-Labor) are positive, under the conditional setting. This result confirms the overall conclusion that any significant performance is not likely to be due to superior ability or the lack thereof.

**[Please place table 2.5 about here]**

The relaxation of the constraint that the SDF is positive (the no-arbitrage assumption) shows that the volatility of the SDF is substantially higher, as found in Fletcher (2010). This constraint has a significant effect on the variation of the pricing kernel over time for all nine models, with the cubic and quadratic candidates becoming top ranked (with 80.51% and 81.03% of cases inside the cup, respectively). The Carhart model followed by the Labor-Cubic model exhibits the statistically lowest cross-sectional average AAE, with the Quadratic model occupying the lowest rank. Based on the HJ distances, the Carhart and APT models are the top-ranked models, with the Labor-Cubic (Labor-Quadratic) model yielding the highest HJ distances under the unconditional (conditional) setting.

## 2.7. CONCLUSION

This paper finds that the stochastic discount factor (SDF) approach is consistent with the market efficiency hypothesis. Expected mutual fund returns are unpredictable and money managers do not demonstrate superior ability to time the market and exploit mispricings and misperceptions. It is statistically not feasible to extend short-run abnormal performance over the long-run since US equity mutual funds are zero-alpha performers.

With regard to the different SDF specifications, we find that the Carhart model (followed by the FF model) is the best suited for assessing the performance of the mutual fund dataset examined herein. Use of the Carhart model results in the smallest average pricing errors and produces the largest number of cases in the admissible region of SDF mean-variance with the ten value-weighted industry portfolios as the investment opportunity set. The relative performance of each model is sensitive to the choice of the portfolios forming the investment opportunity set. The Carhart model continues to be highly ranked when the investment opportunity set is based on style-sorted portfolios, but the non-linear specifications improve their ranks especially with the second and third criteria; namely, the HJ boundaries and the AAE.

As predicted, conditioning information has an effect on the results. Conditioning lowers the number of funds with significant alphas. Our results raise several follow-up questions. First, should different instrumental variables be used in the pricing equations for equity funds? Second, is the lagged detrended riskfree rate an adequate indicator of economic conditions? We leave their study for future work.

# CHAPTER 3

# US MUTUAL FUND M&As

## 3.1. INTRODUCTION

Business combinations represent an efficient avenue for growth. If the bid price is fair, mergers can allow for synergies in the employed physical and human capital and may lead to abnormal performances that are not obtainable with separate entities. The visibility of the newly created business, the range of products offered, the quality of the service, the targeted market, the geographic diversification, and the expertise of the new management team are all arguments in favour of merger activity.[14] This stylized fact is supported in the literature for firms in, for example, manufacturing and services (e.g., Asquith *et al.*, 1983; Jensen and Ruback, 1983; Andrade *et al.*, 2001).

As Jayaraman *et al.* (2002) argue the exponential growth in the mutual fund industry has led to consolidation in the financial services industry since the early 2000s. Jayaraman *et al.* (2002) find that target funds are significantly smaller in asset size, incur higher expense ratios, and perform poorly compared to acquiring funds over the four-year study period (1994-1997). The target (acquiring) fund's performance improves (deteriorates) in the first year post-merger and the expense ratio for the combined fund is similar to that of the acquiring fund pre-merger. Perold and Salomon (1991) link the higher size of assets under management (AUM) after merger to greater scale economies resulting from decreased fixed operating costs. As one of their measures of agency costs, Ferris and Yan (2009) report that public fund families engage in a significantly larger

[14] We use the terms 'merger' and 'M&As' (mergers and acquisitions) interchangeable throughout this paper.

number of acquisitions undifferentiated by the type of acquired fund than private fund families over the period of 1993-2004. However, their study differs from ours in that Ferris and Yan do not conduct an event-like study of the performance of either the acquiring or the acquired funds.

The objective of this paper is to extend the work of Jayaraman *et al.* (2002) by examining the pre-merger conditions of each M&A participant separately and the post-M&A impact of the merger on the acquiring funds for 6,680 M&As over the period 1962-2009. To this end, we examine the effects of M&As and termination activities in terms of costs, reputation, efficiency and risk in the mutual fund industry to test whether wealth transfer persists over a 48-year test period. As the most important concern for unitholders is the risk-return tradeoff, we test if fund performance improves when unitholders of the target fund become acquiring fund unitholders, and the extent to which risk changes post-M&A. Since a target unitholder needs to decide whether to maintain his or her position or to liquidate it, we identify the determinants of M&A success, extending the work of Jayaraman *et al.* (2002) where the determinants of the occurrence of M&As are studied. Potential determinants examined include the sizes, performances, asset flows, expense ratios and investment objectives of the M&A participants. Thus, our findings provide some initial guidance in whether a target unitholder should exit or remain with the surviving fund post-M&A. It also provides some guidance to sponsors who wish to increase AUM though external growth.

We estimate the conditional abnormal performance of target and acquiring funds using the four-factor Carhart (1997) model. To obtain efficient estimates, we use Hansen's (1982) generalized method of moments (GMM) and an estimator of the spectral density matrix as the weighting matrix. Consistent with the literature, we find that, while the unitholders of targets benefit more than their counterparts in the acquiring funds unitholders from M&As, the performance improvement is small. Cost efficiency and superior management ability through M&As are more pronounced over shorter and more recent periods than over the full 48-year period. The semi-variance of monthly returns for acquirers changes post-M&A. Explanatory variables considered in a logistic regression to determine the significant forces driving successful M&As include: the ages of the target and acquiring funds at transaction dates to proxy for their reputations, the sizes of the bidder and the target fund, the past performance of the target fund, the average MER of the bidder and the target, the average net asset flow for the target prior to the M&A, dummy bull/bear market indicators to proxy for the timing of the deal, the Investment Style (hereafter IS) of the target and merger type (within vs. across-IS and within vs. across-family).

The paper makes two contributions to the literature. First, it finds that the abnormal performance improvement around the M&As primarily benefits target unitholders, but that the increase in risk post-M&A is incompatible with a significantly higher abnormal performance. Fund risk increases post-M&A for the unitholders of acquirers and is unchanged for unitholders of targets. The latter finding is consistent with the continuity or smooth transition hypothesis. The mean-variance efficiency of high-risk bidder funds deteriorates while that of low-risk bidder funds remains unchanged. Thus, M&As only affect unitholders of high-risk bidder funds adversely. The window of opportunity and smooth transition hypotheses are supported since the target's reputation (as proxied by its age), target's size and timing of the deal are significantly related to prospective post-M&A outperformance.

The remainder of the paper is organized as follows. Section 2 develops the hypotheses to be tested. Section 3 describes the characteristics of the studied sample. Section 4 reports and analyzes abnormal performance and risk around the M&As. Section 5 presents the specification of the logistic regressions to examine the determinants of successful fund M&As and analyzes the empirical results. Section six provides concluding remarks.

## 3.2. TESTED HYPOTHESES

### 3.2.1. Window of Opportunity

Sapp and Tiwari (2004) show that the smart money effect documented by Gruber (1996) and Zheng (1999) is explained by the stock return momentum phenomenon. This provides the underpinning for the window of opportunity hypothesis. If investors chase past winners and targets are primarily past losers and the fund M&As occur during bullish times, then they provide opportunities for the acquirer fund to enlarge their AUM (including the attraction of new money).

### 3.2.2. Smooth Transition

Pollet and Wilson (2008) find that fund managers increase their ownership interest as the fund grows, rather than focusing on new bets, except to accommodate liquidity constraints. Thus, if two entities of the same type enter into an M&A, the newly incumbent managers are more likely to continue with their same investment strategies.

We would expect that the bidder's strategy would prevail post-M&A if the motivation driving the fund M&A is: (i) the target's past poor performance, or (ii) is predicated on a strategic move across family. If consummated successfully, both types of motivated M&As should have a positive impact on the wealth of unitholders but with unitholders of the target (bidder) benefiting most from the first (second) motivation.

The smooth transition hypothesis emanates from the premise that mutual fund sponsors need to ensure that changes to increase returns with unchanged risk are noticed by existing unitholders (particularly, those that remained in the fund regardless of its past performance). Whether the M&A is within- or across-family, any changes in investment strategy need to be gradual, fully disclosed and explained to the unitholders in order to keep current AUM and to attract new fund inflows. The smooth transition hypothesis is tested by examining risk levels, MERs and the types of assets held for target and bidder funds around fund M&A.

#### 3.2.3. Diseconomies of Scale

The literature finds that smaller funds tend to outperform larger funds due to diseconomies of scale (Chen et al., 2004). We hypothesize that M&A success increases if the bidder is smaller. We subsequently test this hypothesis using a logistic regression analysis.

#### 3.2.4. Fund Flow Effect

Dickson, Shoven, and Sialm (2000) demonstrate that shareholder flows negatively affect after-tax returns of mutual funds. Hence, we expect that the average fund flow into target mutual funds during the one year pre-M&A will be negatively related to the subsequent probability of success of the M&A. This hypothesis is related to the hypothesis that the probability of M&A success and positive abnormal risk-adjusted returns are positively related to poorer performance of the target fund.

### 3.3. SAMPLE, DATA AND SOME DESCRIPTIVE STATISTICS

#### 3.3.1. Data Collection

From the CRSP survivorship-bias-free mutual fund database for the period January 1962 to May 2009, we extract 8,410 mutual funds with "merger" as the delisting cause (i.e. M or M? codes) that also report the identifier of the new entity. The sample is reduced to 7,151 mergers after excluding those funds with missing monthly returns or monthly returns reported on an irregular basis.

The resulting sample is matched with investment style data using multiple sources of information. Wiesenberger Policy codes are the primary source prior to 1993 and Strategic Investment thereafter until December 1999. Lipper objective code data are used from December 1999. Thomson-Reuters group codes are used to check the coherence of information from the different sources for data from 2008. We manually assign investment objectives to 65 M&As based on the asset classes held by the missing-style funds or their headers, and are unable to assign an investment objective to 96 M&As. Hence, our sample of M&As with style information consists of 7,055 combinations of target and acquiring funds with regular monthly returns and fund style information reported over their business life. Our information-coherence checks result in the exclusion of 375 M&As where the necessary monthly returns before the delisting date of the target fund are missing.

### 3.3.2. Descriptive Statistics

Descriptive statistics on the monthly returns of the samples of target and acquiring funds are reported in table 1 for the final sample of 6,680 M&As.[15] The number of acquiring funds of 4,459 is lower than the number of successfully targeted funds of 6,680 due to several instances where more than one targeted mutual fund is merged into the

[15] The sample of 7,151 M&As contains 387 M&As where the delisting dates of target funds either do not coincide with the inception dates of merged funds or do not belong to the regularly-reported monthly returns time interval of the surviving funds. Hence, ignoring the investment style information makes the size of the raw sample equal to 6,764 cases.

same surviving fund. Specifically, we identify 912 cases with one acquired target, 283 cases with two acquired targets, 86 cases with three acquired targets, 41 cases with four acquired targets, and finally one case with 13 acquired targets (see table 2). Also, 1,206 funds change from being the acquirer to being the acquired over the study period.

**[Please place tables 3.1 and 3.2 about here.]**

As reported in table 2, the M&A participants have different investment styles for 225 of the M&As. Equity target funds exhibit the greatest number of changes (95 cases) with 77 of them acquired by hybrid funds, ten by bond funds, seven by convertibles funds and one by a money market fund. The targeted bond funds have only 32 cases of investment style changes, 12 to equity, 11 to hybrid, eight to money market and one to convertibles funds. Only two and five of the target money market funds became equity and bond funds, respectively. Sixty-five, three and one target hybrid funds became equity, bond and convertibles funds, respectively. Eleven, three and eight target convertible funds became equity, bond and hybrid funds, respectively.

The absence of Total Net Assets (TNA) information used to investigate average transaction sizes results in the elimination of 2,059 M&As, involving 4,621 targets and 3,256 acquiring funds. Over the study period for every year, we calculate the 2.5%, 25%, 75%, 97.5% TNA percentiles, and the time-series average of each series of percentiles for the sample of acquired (and acquiring) funds. Table 3 reports the average number of funds involved in annual M&As, the two extreme percentiles and the median, for the total sample and the five subsamples based on investment style over the whole period 1962-2009 and for the four subperiods (1971-1980, 1981-1990, 1991-2000, 2001-2009) with non-zero percentages.

The 97.5% percentile of target fund sizes is on average one-the fifth of the size of the corresponding merged funds (306.67 vs. 1,646.86 million USD). Mutual fund assets acquired in the last decade have increased and represent on average seven times their homologs in the 1970s (311.22 vs. 42.63 million USD). On average, 159 targets are involved each year in a M&A over the total study period. The annual number is 400 M&As over the most recent period 2001-2009. Merger fund activity (not) differentiated by investment style is more important in number during the last decade compared to the distant past. The average equity fund target at the 97.5% percentile of size of 181.04 million USD is lower than that of all other categories of funds except convertibles ones. With regard to merged funds, money market funds register the highest average 97.5% percentile of TNA over the whole period. During the most recent decade, equity funds are ranked second with an average of 2,700.90 million USD.

**[Please place table 3.3 about here.]**

The management expense ratio (MER) is defined as the ratio of total investment that shareholders pay for the fund's operating expenses which include the 12b-1 fees. The MER of a mutual fund may change over time either because of a changing level of operating efficiency or due to competitive forces. Table 4 reports the cross-sectional statistics of time-series averages of MERs for the 6,464 fund M&As (6,464 targets and 4,307 merged entities) with MER information. On average, the expenses incurred by target fund unitholders exceed those of their merged fund counterparts (1.45% vs. 1.34%) for the whole sample and for all but the money market and convertible funds subsamples. This suggests that higher operating costs may be a trigger for some of the mergers. The maximum MERs and kurtosis are substantially larger for target funds (7.51% and 4.09%)

than for merged funds (3.82% and 2.50%). With more extreme data points, target mutual funds are a less homogeneous group compared to the resulting merging funds.

**[Please place table 3.4 about here.]**

Monthly income distributions are one of the selection criteria used by investors seeking short-term income on a regular basis. We obtain 2,037 usable cases with such data and 941 cases (941 targets and 638 merged funds) that also have investment style information. We transform dollar amounts into percentages for each month-end date and every fund, and aggregate all types of income distributions to obtain a single monthly income distribution rate for each fund. Based on table 5, the 858 bond funds have an average rate of income distribution of 0.47% for target funds and 0.45% for merged funds. The average life of included funds is nine years for targets and five years for merged funds, and is largest for money market funds. Tests of whether monthly income distributors represent a suitable candidate for a successful merger are inconclusive. Since the end-of-fiscal-year distributions tend to be higher than those for the rest of the year due to the multiple types of income payments, the rates are consequently higher which adds outliers to each time-series of fund distributions and results in kurtosis being substantially higher than the normal three-level. Furthermore, fat tails are more pronounced for target than for merged funds and for hybrid funds.

**[Please place table 3.5 about here.]**

Based on the monthly numbers and volumes of M&As that satisfy our inclusion criteria, the maximum monthly volume of in-sample M&As in the 1970s of 157 million USD was in December 1979 and in the 1980s of 1,417.20 million USD was in December

1980.[16] Over the remaining months of both decades, number of M&As and their volumes are small (between zero and 108 million USD). In contrast for the 1990s and 2000s, maximum monthly M&A volume of 3,518.18 and 7,499.60 million USD occurred in October 1994 and August 2005, respectively. The annual number of M&As is very low at the beginning of the studied period and starts to increase after 1987 (i.e., the year of the so-called “Market Crash of 1987”), and declines dramatically around 1999 (i.e., near the end of the tech bubble). The peak in numbers is reached in 2007 with 775 cases. Relative to active funds, on average, only 1% of the mutual funds cease operations annually due to a M&A. In the 2000s, M&As occur more often since they exceed 2% of active funds for 90% of the time. The percentages are rarely higher than two percent in the 1990s, but are larger than 1% for 90% of the time. Also, the annual volume distribution is similar to that of the absolute number of mergers. As the number of funds increases over time, so does the relative size of the merged funds. The average relative size peaks at 1.06% in 1980, and stabilizes at a level of 0.17% in the 1990s and 2000s.

Finally, we examine whether the monthly M&A activity is seasonal. Based on the sample autocorrelations and partial autocorrelations of first-order differences in logarithmic number of changes, mutual fund M&As are generated by an autoregressive process. This could be an indication of merger waves. The monthly merger quartiles and maxima over the whole period show that the month of May has the highest number of M&As, followed by February and October. The subperiods spanning the period 1981 to 2009 reveal a similar pattern with a predominance of M&As in July and December for the first decade.

[16] All volume and size analyses involve only the 4,621 usable cases for which returns, investment style and TNA information are available.

### 3.4. ABNORMAL PERFORMANCE AND RISK

#### 3.4.1 Methodology

The gains from M&A activity are examined first by testing the significance of any abnormal performance shift from the pre- to post-M&A periods for both target and acquirer funds. Given the evidence of performance persistence in the mutual fund industry (Christopherson *et al.*, 1998, Fletcher and Forbes, 2002), performance is estimated using the general asset pricing model with the four-factor Carhart linear model specification for the stochastic discount factor. The investment opportunity set is represented by ten value-weighted industry portfolios (as in Fletcher and Forbes, 2004).[17] The number of moment conditions becomes 12 with the inclusion of the monthly return on the risk-free security $R_{ft+1}$ and the subject mutual fund conditions.[18] The addition of the risk-free security ensures that the SDF takes sensible values (around one) and sums to the numéraire or reference security condition. The addition of the subject mutual fund conditions allows for a test of whether the subject fund is part of the optimal investment opportunity set (abnormal performance is neutral), improves it (abnormal performance is significantly positive) or contains a suboptimal array of securities (abnormal performance is significantly negative).

The set of orthogonality conditions are as follows:

$$\begin{cases} E_t(m_{t+1}R_{ft+1}) = 1 \\ E_t(m_{t+1}r_{t+1}) = 0 \\ E_t(m_{t+1}r_{pt+1}) = \alpha_{pt} \end{cases}$$

[17] Industries included are Non Durables, Durables, Manufacturing, Energy, HiTech, Telecom, Shops, Health, Utilities and other, whose data are obtained from the Kenneth French Library.

[18] We refer to moment conditions as orthogonality conditions and average pricing errors interchangeably, and stochastic discount factor and pricing kernel interchangeably.

where $m_{t+1}$ is the pricing kernel prevailing from time t to time t+1; $r_{pt+1}$ is the excess monthly return of the subject mutual fund over the risk-free rate; and $\alpha_{pt}$ is the measure of abnormal performance attributed to the fund manager. The market timing effect on performance is isolated by estimating conditional performance (Ferson and Schadt, 1996) using the lagged stochastically detrended risk-free rate as the instrumental variable to reflect macroeconomic conditions (Cochrane, 2001).

Unlike a merger announcement for two corporate participants in efficient markets, such an announcement does not have an "immediate" effect on performance for fund M&As.[19] Thus, the event-study method is modified to examine the average abnormal performance of targets and acquiring funds (pre- and post-M&A) over much longer pre- and post-event windows. After testing for the normality of the SDF return distributions, we conduct paired tests of the estimated alphas in pre- and post-periods for the full sample and five fund categories over the full time period and each of the five decades enclosed therein.

### 3.4.2 Abnormal Performance

#### 3.4.2.1 Average performances over fund lifetimes

The median SDF alpha of the target funds is 0.06% whereas the median abnormal performance of the acquiring fund is 0.13% pre-M&A and 0.02% post-M&A. The paired tests, which are reported in table 6, show that, on average, differences in SDF alphas are statistically significant. The sample standard deviations of SDF alphas are comparable for both entities (between 0.90% and 1.00%). Nevertheless, the negative skewness of the SDF alphas for target and pre-M&A acquiring funds, coupled with substantial kurtosis

[19] See appendix B for more details about the mechanics of a US mutual funds merger, as dictated by the Investment Company Act 1940.

levels, show a tendency for extreme and negative abnormal performance pre- versus post-M&A. The acquiring funds yield the highest percentages of positive (0.01%) and negative (0.52%) significant SDF alphas prior to the M&As. The difference in the percentage of significant SDF alphas between target and post-M&A bidders (p-value=0.02) and between post- and pre-M&A bidders (p-value<0.01) is significant. The primary conclusion from the overall sample is that the abnormal performance distribution for the acquiring funds change upon M&A. The thinner left tails post M&A could result from economies of scale due to larger AUM or from the strategic changes made to offer the most suitable product to existing unitholders of both entities.

**[Please place table 3.6 about here.]**

When examined by decade (see Table 6), the median SDF alpha of targets equals 0.05% (-0.22%) and of acquirers equals 0.37% (0.15%) pre-M&A and -0.03% (0.06%) post-M&A during the 1960s (1970s). In the two first decades of the study, differences in SDF alphas are not significant between targets and post-M&A bidders and between pre- and post-M&A bidders. In the 1980s, the median SDF alpha of the acquiring funds equals 0.09% pre-M&A and 0.07% thereafter, but the percentage of significant SDF alphas for post-M&A bidders equals 9.63% (3.61% positive and 6.02% negative) whereas that of the pre-M&A bidders reaches 1.23%, all positive. Acquiring funds tend to yield more negative abnormal performance post- M&A confirming the performance deterioration (significant at 0.01 level) around M&As revealed by the medians. Consequently, the integration experiences are not as seamless as they should have been through the M&A process. The 1990s show the same pattern as the 1980s for median SDF alphas, but the SDF alphas of targets and pre-M&A bidders are on average statistically higher than those for acquirers. This indicates a time-dependent discontinuity in performance for the pre-M&A unitholders of the acquirers after the M&As.

The 2000s are characterized by the neutrality of the performance of acquiring funds post-M&A given no abnormal SDF alphas compared to low but positive percentages pre-M&A. Results show that negative and significant SDF alphas are neutralized post-M&A (from 1.83% to 0.00%) and that targets also benefit from the same phenomenon with their SDF alphas moving from 1.76% to 0.00%. The changes are statistically significant at 0.01 level. However, the median SDF alphas tell a different story. The median SDF alphas of acquirers move significantly from 0.12% to 0.01% post-M&A, and those for targets are significantly higher at 0.05%.

Bond (money market) funds exhibit significant performance improvement post-M&A, with a median SDF alpha of 0.06% (-0.05%) for targets, 0.09% (-0.02%) for acquiring funds pre-M&A and 0.10% (-0.01%) post-M&A. The empirical SDF alphas exhibit positive skewness and high kurtosis pointing to the likelihood of extreme values and the preponderance of high abnormal performances. The money market targets have a tendency to underperform with 7.14% of them having significant negative SDF alphas. In contrast, only 0.15% of bond target funds exhibit significantly negative SDF alphas. This changes post-M&A since the percentage for these two fund types falls significantly to respectively 1.90% (0.01 level) and 0.00% (0.10 level). The same gain is experienced by acquiring funds for pre-existing money market but not bond unitholders (0.10 level for the former). Finally, pre-M&A acquiring fund median SDF alphas are higher (and of a different sign) than those post-M&A for equity (0.32% vs. -0.06%), hybrid (0.30% vs. -

0.15%) and convertibles (0.15% vs. -0.15%) funds. The shifts are statistically significant for all but the convertibles funds.

#### 3.4.2.2 Average performances over shorter time periods

The 1-year SDF alphas are the result of a risk-adjusted return optimization based on only one year of data. The objective is to examine whether the effects of synergies, the benefits of a smooth transition and of economies of scale, if any, are captured by the abnormal performance metrics over the short-, mid- and long-term. Table 7 reports results for targets and acquiring funds (pre- and post-M&A). The bottom target fund posts a -4.92% SDF alpha over one year prior to M&A, and only -2.18% over 10 years. The opposite outcome occurs for the top fund with an SDF alpha of 5.65% over one year and 2.78% over ten years. For bidders post-M&A, the bottom fund yields -5.09% abnormal performance after one year and -1.08% after 10 years; both are not significantly different from the bottom bidder fund pre-M&A.

**[Please place table 3.7 about here.]**

Median SDF alphas over the short- and longer run for the sample of target funds are all negative and significantly lower than their corresponding values for post-M&A bidders (see table 8). Through the decades, only the 2000s yield significant differences between SDF alphas around M&As (medians of -0.10% to -0.04%, respectively). M&As in the 1990s do not experience a substantial change in short-term performance as changes appear to take from 3 to 7 years post-M&A.

Within-family M&As yield palpable changes by the first year as median SDF alphas move from -0.09% to -0.03%, and for all terms except ten years (because of missing information about the type of some cases). Across-family mergers take more time to deliver significant performance improvement; namely two years, where the median moves from -0.18% to -0.01%. Like within-family mergers, this result is obtained for the rest of the post-M&A time periods.

The sample subdivided by deal size shows no important changes in the short-run in both tails. This result changes after two years for the top 30% (at 0.01 level) and the top 10% (at 0.10 level). For the rest of the post-M&A time periods, performance improvement occurs for both tails of the distribution of deal sizes, except for the ten-year term.

An examination of the SDF alphas by asset class types shows that the first gainers from M&A synergies are the equity and money markets funds, where median SDF alphas increase from -0.21% and -0.07% to -0.13% and -0.01%, respectively. In the second year post-M&A, the hybrid funds experience a performance improvement at the 0.05 level, bond funds join the list in the third through tenth year post-M&A.

**[Please place table 3.8 about here.]**

### 3.4.3 Risk of the M&A Participants

Overall, the risk of targets (0.12%) is significantly lower than that of acquirers (0.21%), and the risk of bidders (0.10%) is significantly lower pre- versus post-M&A, especially in the 1990s and 2000s, at the 0.01 level. The median risk of target equity funds equals 0.28%, and is significantly lower than that for bidders (0.43%) at the 0.01 level. This characteristic is shared by all other asset class categories of funds with the exception of the money market funds where targets are significantly riskier than their acquirers at the 0.01 level. Also, all bidder asset class categories (except for fixed income) are significantly less risky pre- versus post-M&A, especially in the 1990s and 2000s, at the 0.01 level. .

**[Please place table 3.9 about here.]**

### 3.4.4 Risk-Return Trade-off

Multiple comparisons of SDF alphas resulting from ANOVA analyses (Hochberg and Tamhane, 1987) confirm that the average target underperforms their acquirers pre- and post-M&A at the 0.05 level. On average, pre-M&A bidders are significantly less risky than their targets and post-M&A, and target risk does not increase post-M&A.

The probability distribution of a Sharpe-like ratio (the ratio of SDF alpha to the square root of semi-variance) is depicted in Figure 1. The distribution of this Sharpe-like ratio for target funds is slightly right-skewed. The distribution of Sharpe-like ratios for acquirers pre-M&A has a similar dispersion and thicker tails than that for the target funds. The right-skewness is more visible and reflects a higher likelihood of better returns for a unit of risk borne by bidder unitholders prior to M&As. The distribution of Sharpe-like ratios of post-M&A acquirers exhibit leptokurtic left skewness. In contrast, the distributions of Sharpe-like ratios over post-M&A periods ranging from one year to ten years differ. The right tails of the distributions for post-M&A bidders are virtually always thicker than their counterparts for pre-M&A bidders and targets and all modes are negative.

**[Please place figures 3.1 & 3.2 about here.]**

The frontiers of the portfolios in the mean-variance domain exhibit variations in the second-order stochastic dominance rankings according to the levels of risk, as proxied by the square root of the semi-variance. Based on Figure 3, the M&A is the most beneficial to all unitholders at very low levels of riskiness since the post-M&A bidder offers the highest SDF alphas and the target offers the lowest. The target is still better off being acquired to maximize the benefits for its unitholders at intermediary levels of risk, although the portfolio acquirers at this risk level is less efficient post- versus pre-M&A. At high levels of risk, the M&As lead to a suboptimal frontier where the target funds pre-M&A dominate the acquiring funds post-M&A. Thus, the success of mutual fund M&As appears to depend on the level of risk of both targets and acquirers. Those with low levels of risk could be promising candidates for a potential improvement in portfolio mean-variance efficiency via M&As. To further test the robustness of these findings, we examine the first-order stochastic dominance of portfolios of acquirers and targets over different levels of risks for the cases posting significant SDF alphas.

**[Please place figure 3.3 about here.]**

Figure 4 depicts the cumulative distribution functions of significant SDF alphas for six categories of risk: bottom 10%, bottom 25%, bottom 50%, top 50%, top 25% and top 10%. We find that for low levels of risk, there are no significant differences between the different entities. For the top levels of risk, the pre-M&A bidders have the most dominant portfolios, although the differences between the post-M&A bidders and targets are not striking. Thus, for more risky mutual funds, the targets posting significant alphas do not experience an important change (whether positive or negative) in the mean-variance efficiency of their portfolios. In contrast, the bidders do lose and the pre-M&A unitholders are better off divesting before the M&A finalizes. For less risky funds, it is unclear whether there is a considerable improvement or deterioration in the mean-variance efficiency of the portfolios.

**[Please place figure 3.4 about here.]**

## 3.5. DETERMINANTS OF M&A SUCCESS

### 3.5.1 Methodology

In this section, we test possible determinants of a successful mutual fund M&A by conducting a logistic regression where the dependent variable *M&A* $Success_i$ is a dummy variable which takes the value of 1 if the average objective-adjusted return is strictly positive and zero otherwise for participant *i*.[20] This mimics an investor whose goal is to choose a better performing fund from among an array of mutual funds that match his liquidity needs, investment horizon and risk tolerance, as proxied by a set of products offering the same investment style. The objective-adjusted monthly return is obtained as the raw return of the subject fund for month *t* minus the mean monthly return of all active funds offering the same investment style for month *t*.

We consider a number of potential determinants of M&A success. We include the age of both the target $Age_{Ti}$ and the acquirer $Age_{Pi}$ in years measured at the deal completion date of merger *i*. Fund age is used as a proxy for reputation as it indicates whether the incumbent investment advisor has been able to attract or retain assets under management (AUM). The asset sizes of the acquirer and the target at the deal date, $Size_B$ and $Size_T$, are included to capture the ability of managers and advisors for the acquirer and target funds to satisfy existing investors and to appeal to prospective investors. The average net asset flow of the target prior to the deal date, $Flow_{Ti}$, is included to reflect the (in) ability of target funds to sustain or grow the asset base without the M&A (Del Guercio and Tkac, 2002; Jayaraman, 2002).

The past performance of the target fund, $Alpha_{Ti}$, is included based on its expected negative relationship with the odds of M&A success. If the target is acquired

[20] The Newton-Raphson optimization method is used to implement the iterative process of parameter estimation. A heteroskedasticity and autocorrelation consistent estimator of the asymptotic variance-covariance matrix of the residuals is also used. See Hosmer and Lemeshow (2000) for more details.

because of relatively poor past performance, the probability of better performance post-M&A should be higher. This variable is measured over different time periods ranging from one to ten years pre-M&A and over the whole lifetime if it exceeds ten years. We include the following three risk measures: $\sigma_P$ or the pre-M&A risk of the bidder; $\sigma_T$ or the target risk; and $\sigma_B$ or the post-M&A risk of the bidder where $\sigma$ is the square root of the semi-variance to capture downside risk.

The average expense ratios of acquiring and target funds, $MER_B$ and $MER_T$, are included with expected negative and positive signs respectively since they capture the operational efficiency of acquiring funds relative to target funds. The dummy variable, $Family_i$, which is equal to 1 for a within-family fund and to 0 otherwise, is included to test whether within-family M&As are the reflection of a desire to eliminate weak, redundant and unappealing funds, or across-family M&As which may be a response to a lack of diversity in the products offered by the acquiring fund family. The categorical variable, $IS_{Ti}$, stands for the investment style of the target fund for M&A $i$. The categorical variable, $Delta_i$, is a dummy variable equal to 1 for an across-IS M&A and to 0 otherwise, and is included to capture the effects of the different risk tolerances of unitholders by opting for one or the other of the categories of mutual funds.

The dummy variable reflecting market conditions, $Market_i$, is equal to one for the bull market state at the time of the deal conclusion and to zero otherwise.[21] This indicator is included to examine if funds exploit windows of opportunity by completing M&As based on early year tournament performance and during bull versus bear markets.

The model to be estimated for merger $i = 1..N$ is as follows:

[21] See Appendix C for a definition of the variable $Market_i$.

$$Pr(M\&A\ Success_i) = \alpha + \beta_1(Age_{Ti}) + \beta_2(Age_{Pi}) + \beta_3(Flow_{Ti}) + \beta_4(Alpha_{Ti}) + \beta_5(MER_{Bi})$$
$$+\beta_6(MER_{Ti}) + \beta_7(\sigma_{Bi}) + \beta_8(\sigma_{Pi}) + \beta_9(\sigma_{Ti}) + \beta_{10}(Size_{Bi}) + \beta_{11}(Size_{Ti})$$
$$+\beta_{12}(Family_i) + \beta_{13}(IS_{Ti}) + \beta_{14}(Delta_i) + \beta_{15}(Market_i) + \varepsilon_i$$

Table 10 reports the descriptive statistics of the non-categorical independent variables.[22] The number of observations varies from 6,680 to 4,621 because of the missing information about the characteristics of M&A participants and deal features. The median age of targets in the whole sample is about six years at the transaction date whereas the mean age of bidders at the same date is about seven years. The prior average fund flows of targets are on average negative with a minimum of -$237.07 million over the year preceding the M&A. The average MER for bidders (1.31%) is lower than that of targets (1.45%). The average bidder's downside risk equals 4.68 post-M&A versus 3.48% pre-M&A. The average size of a bidder is about nine times the average size of a target.

**[Please place table 3.10 about here.]**

In order to include coherent measures of risk and performance for all entities we use the same length of time for estimates of semi-variances and for the indicators of positive/negative/neutral performances of the targets and the bidders. We examine the explanatory power of the above-mentioned features of the deal, the bidders and the targets pre- and post-M&A, for different time periods of 1, 2, 3, 5 and 7 years. The results are reported and analyzed in the next section.

### 3.5.2 Empirical Findings

The logistic regression results for merger success likelihood are summarized in Table 11. For the 95 cases with the necessary data over the 7-years post-M&A, M&A

[22] Correlation matrix of independent variables is available upon request.

success is positively related to target past performance (0.05 level) and prior fund flow (0.10 level). This does not support the expectation that negative net flows experienced by targets pre-M&A would be an indicator of post-M&A acquirer success over the long run. Also, prior seven-year performance of targets is directly related to M&A success. The profitability of the targets pre-M&A has explanatory power for 7-year outperformance post-M&A.

**[Please place table 3.11 about here.]**

For the 320 cases with the necessary data over the 5-years post-M&A, M&A success is positively related to the target's risk pre-M&A (0.05 level). For bond funds, M&A success is positively related to the bidder's risk pre-M&A, and the bidder's size, and negatively related to the bidder's risk post-M&A and MER. In other words, the largest, least risky and least costly bidders should be the most successful in bond fund M&A activities for a horizon of five years. For equity funds, M&A success is negatively related to the bidder's age at the deal date, the bidder's risk pre-M&A, the target's size and to the *Family* variable, and positively related to the target's risk and the bidder's size. Hence, the across-family M&As, and the smallest and riskiest equity funds (on average $31 million) are targets for the largest and least risky bidders that are more likely to result in M&A success when measured over the five years post-M&A.

For the 986 cases with the necessary data over the 3-years post-M&A, M&A success is positively related to the target's age at the deal date, its prior performance, the bidder's risk pre-M&A and the bull/bear market indicator, and negatively related to the post-M&A bidder's risk and the *Family* variable. For equity funds, the coefficient signs for the risk, prior performance, and *Family* variables and their respective statistical significance are the same as for the whole sample. For bond funds, M&A success is negatively related to prior target fund flows and post-merger bidder's risk and positively related to the bidder's risk pre-M&A, bidder's size and market state. For hybrid funds, risky bidders prior to the deal completion are more likely to have successful fund M&As when the deals occur during bullish markets.

For the 2,504 cases with the necessary data over the 1-year post-M&A, results show that good performing, risky and costly targets result in higher probabilities of M&A success. Paradoxically, bidders need to be small, risky prior to the M&A and less costly to affect positively the probability of success. Contrary to the longer-term results, the within-family M&As occurring in bearish markets exhibit a higher likelihood of outperformance one year post-deal. For equity funds, the well-established, good performing and risky targets are a statistically significant determinant of M&A success when the M&A involves same-family entities. Also, on average, the bidder's size in equity fund M&A successes is about $342 million whereas it is about $445 million for M&A failures. For bond funds, M&A success is positively related to the age of the bidder, the target's prior performance, the bidder's risk pre-M&A, and the target's MER. The odds of outperformance for bond funds are negatively related to the bidder's risk post-M&A, the bidder's MER and the market state.

For the 2929 cases with the necessary data over the entire lifetime of funds post-M&A, M&A success is positively related to prior performance and the target's MER, and negatively related to the target's and bidder's risk, and the bidder's MER. The relationship of M&A success with these fund performance and risk metrics are relatively unchanged for most of the various post-M&A periods examined. The robustness of the results for the various regressions are important because they include all cases whether they survived only a limited term or still existed seven or more years after the M&A.

Considering the window of opportunity hypothesis, we find that the bull/bear market indicator is a significant force driving M&A success. Its effect is negative over the short-term (1-year post-M&A), and becomes positive over the longer run (2-, 3-years post-M&A). We conclude that the window of opportunity is a viable hypothesis if we concentrate on the mid-term performance of a fund. Nevertheless, the *Family* indicator is significant and positive one year post-M&A, and negative 3-years post-M&A. In order to further examine these disparities in regression outcomes for different periods post-M&A, we conduct robustness tests in the following section.

## 3.6. ROBUSTNESS TESTS

### 3.6.1 Subsample of M&As

As a robustness test for our analysis of the determinants of merger success, we focus on a subsample of M&A cases. We refer to the 7-year sample as the merger cases involving funds that survived, and reported monthly TNA and returns on a regular basis for 7 years or longer. The logistic regressions are implemented using only the 218 data points meeting the 7-year condition, with the definitions of the independent variables remaining unchanged. We start with the dependent variable as the objective-adjusted returns post-M&A, then we consider an alternative proxy for the odds of success. The alternative proxy is a dummy variable based on the SDF alpha, taking a value of one if the SDF alpha is statistically significant and positive, and zero otherwise.

#### 3.6.1.1 Objective-adjusted returns as the dependent variable

The target size remains irrelevant in the determination of the success of fund M&As. The positive relation between target performance prior to M&A and the odds of

M&A success over the 1-year and 7-year periods post-M&A is robust to the change of the sample. Similarly, the negative relationship between the bidder risk of the fund post-M&A and the success of the deal is confirmed for the 1- and 3-year terms. The target's MER remains a significant explanatory variable for M&A success after the first and second years of the deal. Also, the bull-bear market indicator (*Family* indicator) is positively related to post-M&A outperformance after three (one) years of the deal completion.

**[Please place table 3.12 about here.]**

The target's fund flow prior to the deal conclusion date is still positively related to the probability of success for the 7-year term. The attractiveness of the target prior to the M&A is significantly related to the outperformance of the acquirer over the longer run. This result contradicts the fund-flow effect hypothesis, but is consistent with the positive relationship between target's prior performance and M&A success.

#### 3.6.1.2 The SDF alpha as the dependent variable

Regardless of the definition of the dependent variable, the age of the bidder remains irrelevant in the determination of the success of the M&As for terms of 1 to 7 years post-M&A. Also, the signs of the relationships between the three measures of risk and the odds of M&A success are robust to this test of sample selection for the 1-year term. Specifically, the estimated coefficient is positive for the target's risk and bidder's pre-merger risk and negative for the bidder's post-merger risk one year post-M&A. Also, there is a consistent positive relationship between the bull-bear market indicator three years post-M&A and the target's prior performance two and three years post-M&A, and the success of the M&A.

**[Please place table 3.13 about here.]**

### 3.6.2 Alternative pricing kernel specification for bond funds

In this section, we examine the robustness of our performance results for bond funds using a 4-index bond model kernel specification as in, for example, Ayadi and Kryzanowski (2008).[23] Based on untabulated results, we find a 1- and 3-year performance improvement for target bond fund shareholders. The 2-year (7-year) SDF alphas decline (increase) significantly for the target and the merging funds post-M&A. The 4-factor model results corroborate those of the momentum model for the 3- and 7-year terms only. Deals completed in the 1980s involving bond funds yield significant performance decreases post-M&A for terms of 2- and 3-years (7-years) for target (merging) fund shareholders. In contrast, M&As in the 2000s yield a significant positive change in performance after three and five years post-M&A for the shareholders of both entities. The bottom deal-size decile shows a negative change 3 years after M&A for target shareholders, whereas the top deal-size decile shows a positive (negative) change for a 1- (2-) year term post-M&A for the target (merging) fund shareholders.

Based on the SDF alphas obtained using the 4-index model, the success determinants regression shows that the market conditions indicator is a consistent explanatory variable for M&A success over all terms. The relationship is negative supporting the hypothesis that successful bond fund M&As occur in bear markets. The pre-M&A risk of the bidder is positively related to M&A success for 2-, 5- and 7-year periods following the M&A. Only the negative relationship between the bull-bear market indicator at the 2-year term and the odds of success is robust to the definition of the

[23] Other factor models have also been proposed to examine bond fund performance (.e.g., Chen, Ferson and Peters, 2009).

discount factor. For bond funds, the *Family* indicator only has significance in the shorter-term. Its positive estimated coefficient infers that within-family M&As involving bond funds are more likely to be successful 1-year post-M&A.

We run the logistic regression with alternative independent variables that are limited to the following M&A participant characteristics: age, risk, MER for both entities and prior performance for the target. The use of a four-index bond model and the momentum models yield positive relationships between the target risk and the post-M&A outperformance after 2 years of the deal (p-value= 0.06 and 0.00, respectively), and between target MER and success after 3 years of the deal (p-value= 0.10 and 0.04, respectively). The outcomes for both models show a negative relationship between prior performance at the 5- (p-value= 0.01 and 0.00, respectively) and 7-year (p-value= 0.01 and 0.03, respectively) terms and the odds of M&A success.

### 3.6.3 Alternative pricing kernel specification for money market funds

In this section, we examine the robustness of our performance results for money market funds using a 1-factor (Treasury bill rate of return) kernel specification. Based on untabulated results, we find performance improvements for periods of 1 to 7 years post-M&A for target shareholders of money-market funds. No noticeable changes in performance occur for merging fund shareholders over all terms. Deals completed in the 1980s lead to an increase (decrease) in the SDF alpha for the 1-year (5- and 7-year) term for target (merging fund) shareholders. For deals completed in the 1990s, the increase in performance occurs 2 years post-M&A for target shareholders, and a significant decrease occurs after 7 and 10 years post-M&A for both M&A participants.[24] Deals during the

[24] We did not examine the ten-year term for the other asset classes due to the small sample size for these subsamples.

2000s yield a performance improvement for all post-M&A terms (except the 10-year term) for the target, and only for the first year post-M&A for the merging fund. Size deciles show that the smallest deals exhibit no significant alpha changes, but that the largest decile of deals has an SDF alpha increase for the 1- and 7-year terms for target shareholders.

Using the same definition of the dependent variable and the outcome of the 1-factor model, the key variables for the success of money market fund M&As are the bidder MER (negative for all terms) and the target fund flows pre-M&A (negative for 2- to 7-year terms). For the 1 and 2-year terms post-M&A, the target MER is positively related to the odds of success. Hence, the operating inefficiency of the target leads to outperformance in the short-term, but the operating efficiency of the bidder leads to performance success in both the short-and long-runs. Also, the funds-flow effect hypothesis is not rejected for this category of funds. The relationships between bidder MER for all terms, as well as the post-M&A bidder risk at the 5-year term, and the odds of success are robust to the choice of the specification of pricing kernel for money market fund performance evaluation. We also run the regression with a smaller number of regressors drawn from the characteristics of both M&A participants. These include age at the deal date, the prior performance of the target, the risk over the corresponding term, and the average MER. The dependent variable is first based on the one-factor model and second based on the momentum model. The bidder MER remains significantly and negatively related to the post-M&A performance (probability values range from 0.00 to 0.09) for all terms and both models. Also, the target risk at the 1-year term, and the bidder post-M&A risk at the 5- and 7-year terms are positively related to the success odds for both models.

### 3.7. CONCLUSION

This study examines M&A activity in the US mutual fund industry over a 48-year period. The performance enhancement hypothesis is tested for GMM estimates of abnormal performance under the stochastic discount factor approach. We find little evidence of significant abnormal performance, but its occurrence primarily benefits target unitholders as shown in the literature for other industries.

The smooth transition hypothesis is not supported based on various downside risk comparisons since the acquirer's and the target's risk increases significantly around an M&A. The pre- to post-M&A shift in risk is not compatible with a significantly higher abnormal performance. Furthermore, acquirers displaying greater risk tolerance, in terms of portfolio holdings post-M&A, have less efficient asset portfolios.

Determinants of success vary somewhat as the period over which abnormal performance post-M&A is estimated**.** Data over the lifetimes of funds prove that the fund flow effect hypothesis can not be rejected in that M&A success is negatively related to the mean fund flows prior to M&A. Over a 1-year period post-M&A, the diseconomies of scale hypothesis is accepted. Also, M&A success is negatively (positively) related to the market state at the time of the deal conclusion over the short-term (longer term) post-M&A showing that the window of opportunity hypothesis could not be rejected. Finally, we find a consistent negative (positive) relationship between post-M&A bidder risk (target past performance) and M&A success.

Tests of robustness find that the bidder's size, the target's MER and the family indicator are significantly (and positively) related to M&A success as measured by objective-adjusted returns when the sample is reduced to only acquiring funds who survived for at least seven years post-M&A. Post-M&A risk of the bidder negatively affects the odds of success. The target's MER and the bidder's size at the deal date are important in predicting M&A success over the first three years post-M&A for this seven-year subsample. Reputation as proxied by the size and the level of expenses imposed on target shareholders pre-M&A also has significant power in explaining the longer-term outperformance of surviving funds.

# CHAPTER 4

# EQUITY FUND FLOWS AND PERFORMANCE AROUND ECONOMIC RECESSIONS

## 4.1. INTRODUCTION

The literature reports an asymmetric relationship between performance and net fund flows. The relationship is positive for outperformance and net fund flows, implying that investors chase winners (Sapp and Tiwari, 2004). In contrast, values in the far left tail of the performance distribution have little impact on net fund flows (Ippolito, 1992; Sirri and Tufano, 1998). In other words, investor demand for additional mutual fund investments is inelastic to performance below a certain minimum threshold. Lynch and Musto (2003) explain this phenomenon by investor perceptions that bad and very bad returns signal a potential change in strategy, hence the magnitude of their difference has little predictive power.

Each of the last two decades has experienced an economic recession that has impacted fund performance and possibly the relation between net fund flows and performance conditioned on the state of the economy. Given that the literature has not sufficiently addressed the nature of this relationship to date, the primary purpose of this paper is to examine the relationship between recessionary period fund performance and subsequent non-recessionary period net fund flows for U.S. equity mutual funds around the two most recent U.S. economic recessions. This allows us to address two related questions. First, are subsequent non-recessionary period net fund flows to equity funds related to their absolute and/or objective-adjusted[25] (henceforth relative) return performances during recessionary periods? Are funds that are able to outperform peers during economic recessions able to attract more net cash flows during subsequent economic "good times"?

We conjecture that absolute and relative returns are the only variables observed and used by fund investors through updated factsheets made available to them on a monthly or quarterly basis. We focus on these variables because fund investors are much less likely to resort to sophisticated (risk-adjusted) estimation methods for fund performance when making their fund allocation decisions.

We study the relationship between performance and net fund flows (henceforth, the "two variables") over their whole distributions, and over their lower and upper tails separately. The dependence between variables is examined via correlations and the copulas method. The linear correlation measures (parametric and non-parametric) provide a first assessment of the relationship (if any) between the variables. Since "copulas contain all the information about the dependence structure of a vector of random variables" (Rodriguez, 2007, p.403), we invoke a normal joint distribution assumption between these two variables and simulate bivariate Gaussian copulas. Then, we relax the normality assumption and use the non-parametric method to estimate empirical copulas. We also estimate empirical survival copulas to cover the right tails of the distributions of the two variables.[26]

This paper contributes to the literature by examining the behavior of net fund flows and fund performances around two recent economic recessions in the U.S. Previous

[25] Thereafter, we use "objective-adjusted", "peer-relative" and "relative" interchangeably to indicate that the variable is adjusted for the investment objective benchmark.
[26] See Genest *et al.* (2009) for a review of the literature on the use of copulas in finance.

papers study the relations between current fund flows and future fund performance (Gruber, 1996; Zheng, 1999), or the reverse relationship by controlling for certain variables such as participation costs (Huang *et al.*, 2007) or management changes (Chevalier and Ellison, 1999). To our knowledge, the dependence between these two variables has not been studied using the copulas method, especially around "economic recessions", where the ability of funds to weather adverse economic conditions may be rewarded in subsequent non-recessionary periods through increased net fund flows.

Our major findings show significant differences between both covered recessionary periods and between both return and fund flows measures. First, the Early 2000 Recession yields a positive correlation between during-recessionary period absolute returns and post-recessionary period absolute fund flows and a negative linear dependence between objective-adjusted variables, suggesting that higher performance during downturns is rewarded by subsequent higher money flows on an absolute basis and that investors direct less new cash to outperformers on a peer-relative basis. On absolute and relative bases, performance positively impacts post-Great Recession fund flows according to the non-parametric measures. Second, extreme left and right regions of the tails of the peer-relative distributions are associated with negative dependence for both recessionary periods. Median Gaussian copulas for the absolute variables show a positive (negative) dependence in the 1% left (right) tail for the Early 2000 Recession. The right and left 1% tail dependence for the Great Recession is positive. Empirical copulas in the extreme left tail exhibit a positive dependence for the Early 2000 Recession and independence for the Great Recession between performance and new cash. Third, survival copulas show an overall positive dependence on an absolute basis and a negative dependence on an objective-adjusted basis in the right region. Fourth, our initial findings are robust to the use of estimated *Student* copulas between bootstrapped variables instead of Gaussian copulas and the choice of the announcement date that a recession has begun instead of the official date of the recession.

The remainder of the paper is organized as follows. The sample, data and some summary statistics are presented in the next section. The test methodology used herein is described in section three. Section four presents and analyzes the empirical results. Section five concludes the paper.

## 4.2. SAMPLE, DATA AND SAMPLE CHARACTERISTICS

The paper examines the relation between absolute and relative net fund flows and return performance for U.S. equity funds with Lipper objective codes around two U.S. economic recessions officially identified by the National Bureau of Economic Research (NBER).[27] They are the Early 2000 economic recession that covered the eight-month period of March 2001 to November 2001 and the Great Recession that covered the 18-month period of December 2007 to June 2009. A fund is excluded from each recession-specific sample if: (1) monthly returns and Total Net Assets (TNA) are not available for the fund around the specific economic recession, and (2) the class of assets invested in by the fund is not equity. To ensure that only equity funds are included in the sample and to avoid any selection errors embedded in the original data source, we only include the funds whose equity holdings exceed 75% of their portfolio holdings.

[27]A recession is bound by a peak and a trough in economic activity. According to the NBER dating committee, these turning points are determined using four broad indicators: industrial production, real manufacturing and retail trade sales, real personal income less transfer payments, and payroll employment.

The monthly fund flows are calculated using monthly TNA and returns data obtained from the CRSP survivor-bias-free U.S. mutual fund database.[28] Dates are also subject to verification since some inconsistencies have been detected; e.g., incoherence between inception (call) and attrition (end) dates. Interpolation is used when TNA information is missing but monthly values are reported around the missing month. The redundancy problem in the sample is eliminated by constructing a size-weighted return of different classes of shares of funds when they are associated with a unique portfolio.[29] The TNA are needed to construct the benchmarks in order to calculate the objective-adjusted performance and fund flows.

The sample of equity funds is subdivided into 12 categories of fund objectives according to various combinations of capitalization (large, mid, small, and multi) and value (growth, core and value) following the Morningstar categorization.[30] Objective-adjusted (relative) returns and fund flows are obtained by first constructing size-weighted portfolios of mutual funds in each of the 12 categories of investment styles without requiring included funds to have survived the recession or to have been operating prior to the recession. The monthly return or net fund flows of the matched size-weighted portfolio is then subtracted from the corresponding return or net fund flows for the subject fund. The final sample of 4,766 funds consists of 417 small-growth, 470 small-core, 214 small-value, 382 mid-growth, 270 mid-core, 140 mid-value, 646 large-growth,

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[28] Specifically, $Fund\ Flow_t = \left[TNA_t - TNA_{t-1}(1+r_t)\right] / TNA_{t-1}$, where $TNA_t$ is the total net assets at the end of month t; and $r_t$ is the monthly return for month t.

[29] Each portfolio in the CRSP database, whether associated or not to a different class of shares for the same underlying portfolio, is assigned a unique identifier. The portfolio mapping is available as of year 2003; hence all cases prior to this date are not subject to the size-weighting treatment. The effect of this deficiency will be tested in a subsequent version of this paper.

[30] The exact Lipper objective codes corresponding to the sub-sample selection criteria are the following : LCVE (Large-Value), LCCE (Large-Core), LCGE (Large-Growth), MCVE (Mid-Value), MCCE (Mid-Core), MCGE (Mid-Growth), SCVE (Small-Value), SCCE (Small-Core), SCGE (Small-Growth), MLVE (Multi-Value), MLCE (Multi-Core) and MLGE (Multi-Growth).

727 large-core, 394 large-value, 450 multi-growth, 298 multi-core and 358 multi-value funds.

Table 1 reports the summary statistics for monthly returns and fund flows around both recessions (events). Dispersions of returns (absolute and relative) for the pre- and post-Early 2000 Recession are significantly higher than those prevailing during the recession. They are not significantly different for the Great Recession. The skewness of absolute returns is statistically higher and positive post-Great Recession than pre- and within-recessionary periods ($p<0.001$), but statistically unchanged around the Early 2000 Recession. For relative returns, the skewness and kurtosis are not statistically different between the three periods for both recessions. For the Early 2000 Recession, absolute (relative) returns of the large-growth funds show a substantial change in kurtosis from period to period, moving from 17.25 (9.22) to 60.15 (35.90) and decreasing back to 8.92 (5.99) subsequently.[31]

**[Please place Table 4.1 about here]**

Among the second through fourth moment, only the pre- and post-event skewness measures of absolute fund flows are significantly different (lower and negative) than for the recessionary periods. The objective-adjusted fund flows yield a different interpretation. The Early 2000 Recession yields a significantly higher standard deviation (263.69% and 118.65% respectively) and kurtosis (61.10 and 13.27 respectively) pre- and post-event; and higher positive skewness measures post-event (1.72). The fund flows around the Great Recession exhibit higher standard deviations (339.40%) and less prevalent extreme values (5.29) post-event.

[31] For the sake of brevity, results of subsample characteristics are not reported in the paper but are available upon request.

The left percentiles of the absolute within-recessionary period net fund flows are significantly higher than their post-recessionary period counterparts for both recessionary periods ($-10.43 million versus $-184.64 million for the Early 2000 Recession and $-115.83 million versus $-221.88 million for the Great Recession), accompanied with a different pattern for the left percentiles of returns (-3.24% versus -5.67% for the first recession and -5.08% versus 0.44% for the second recession). The resulting inference is that the most risk-averse investors react to a downturn in the form of massive post-recessionary period share redemptions, when the poor fund performance becomes more extreme in the Early 2000 Recession and improves in the Great Recession. The objective-adjusted variables do not show any significant difference between the left percentiles of fund flows, and exhibit substantial changes in returns (-2.41% versus -3.64%) around the Early 2000 Recession. In contrast, there are significant changes in the left percentile of objective-adjusted fund flows ($-413.13 million versus $-1053.47 million) and not their returns (-1.86% versus -1.50%) during the Great Recession.

The 99% percentile of absolute fund flows for the within-Early 2000 Recession of $177.25 million is significantly higher than its subsequent post-recessionary period values. In contrast, there is no significant change in the 99% percentile of absolute returns (1.71% versus 1.88%). Nevertheless, the 1% right tail of the objective-adjusted fund flows for the within-Early 2000 Recession of $82.09 million is significantly lower than its post-recession value ($407.07 million), even though the objective-adjusted returns for the same distribution region are not statistically different (2.17% versus 2.21%). This outcome suggests that volatility during the downturn causes greater positive extremes in fund flows on an absolute basis, because of the greater level of risk attached to mutual fund investment. Even with an unchanged performance post-recession, depressed investor sentiment leads to lower extreme net flow levels post-recession. On an objective-adjusted basis, the net fund flow extreme levels are higher but not accompanied with higher adjusted returns. The sample shows that growth-oriented funds are the most representative of this phenomenon with a change in objective-adjusted fund flows from $106.88 to $697.61 million and returns from 1.90% to 2.34% from the within to the post-recessionary period.

Around the Great Recession, the 99% percentile absolute net fund flow decreases significantly from $151.24 million to $54.89 million while the absolute returns increase from -0.62% to 6.83%. Objective-adjusted variables for the Great Recession show muted changes. This result shows how investors shaped their behavior differently in the late versus early 2000 recession. Even with a significantly higher performance, the eroded confidence of mutual fund investors kept the extreme new cash levels from flowing to equity mutual funds following the more recent recession.

Table 1 shows that absolute fund flows during the Great Recession are as volatile and more leptokurtic (81.15 versus 62.46) and less positively skewed (3.56 versus 6.64) compared to their counterparts during the Early 2000 Recession. Absolute returns dispersion, asymmetry and the prevalence of extreme values are not statistically different from one recession to the other. Nevertheless, for the Early 2000 Recession, objective-adjusted returns reflect higher volatility (0.83% versus 0.57%) and objective-adjusted fund flows reflect higher skewness (0.97 versus -1.56) and kurtosis levels (8.50 vs 5.79) than for the Great Recession. Therefore, on an objective-adjusted basis, more return variability is associated with unchanged fund flow volatility but increased higher-order moments.

## 4.3. METHODOLOGY

Correlations between event mean returns and post-event mean fund flows are measured using three metrics. While the Pearson correlation is an effective way to represent comovements between variables if they are linked by linear relationships, it may be severely flawed in the presence of non-linear links. In order to test whether the relationship between performance in recessionary periods and net cash flows in the following recovery periods is robust regardless of the method utilized to measure co-movements, we examine non-parametric dependence measures. We estimate Spearman's rho and Kendall tau, which do not depend on the marginal probability distributions (Cherubini *et al.*, 2004).

As a further check, we examine the relationship between recessionary period performance and subsequent recovery period net fund flows using copulas. This enables us to tackle the problem of specification of marginal univariate distributions separately from the specification of the comovement and dependence of the variables. For this reason, copulas are also called dependence functions (Deheuvels, 1978). The use of copula functions enables us to capture non-linear relationships among variables, if any.

We estimate copulas on bootstrapped variables by sampling with replacement over 1000 paths. We begin with the Gaussian copula to determine the characteristics of the relationship between returns and net fund flows. With the Gaussian copula, we can preserve the dependence structure typical of a multivariate normal distribution by modifying only the marginal distributions, which can be allowed to display skewness and fat-tail behavior consistent with the observed data.

According to Sklar's theorem, any joint probability distribution can be written in terms of a copula function taking the marginal distributions as arguments and, conversely, any copula function taking univariate probability distributions as arguments yields a joint distribution. Therefore, in order to estimate empirical copulas, we compute the empirical joint distributions (i.e. their joint cumulated frequencies). All estimations are based on means of recession-period returns and post-recession-period net fund flows over time periods of equal length.

We determine level curves (1%, 5%, 50% and 75%) corresponding to the joint cumulative distributions. We consider the theoretical Fréchet bounds for level curves by estimating those corresponding to extreme cases of independence and perfect dependence; namely, product, minimum and maximum copulas (Fréchet, 1935, 1951; Hoeffding, 1940). For the 1% level, we superpose the following curves:

(1) Perfect positive dependence or comonotonicity

$$\{ (x, y) : \min(F_1(x), F_2(y)) = 1\% \}$$

(2) Perfect negative dependence or countermonotonicity

$$\{ (x, y) : \max( F_1(x) + F_2(y) - 1, 0) = 1\% \}$$

(3) Independence

$$\{ (x, y) : F_1(x) F_2(y) = 1\% \}$$

(4) Empirical: as translated by the couples (x,y)

$$\{ \ (x,y): F(x,y) = C(F_1(x), F_2(y)) = 1\% \ \}$$
$$\begin{aligned}
&\textit{where } x \textit{ refers to means of returns during recessionary period}\\
&\qquad y \textit{ refers to means of fund flows subsequent to recessionary period}\\
&\qquad F(x,y) \textit{ refers to the joint cumulative distribution function of } x \textit{ and } y\\
&\qquad F_1(x) \textit{ refers to the marginal distribution function of } x\\
&\qquad F_2(y) \textit{ refers to the marginal distribution function of } y\\
&\textit{and } C \textit{ refers to the copula relating } x \textit{ and } y \textit{ such as}:\\
&\qquad C(v,z) = \Pr(U_1 \le v, U_2 \le z)\\
&\textit{where } U_1 \textit{ and } U_2 \textit{ are standard uniform variables}\\
&\qquad v = F_1(x) \quad \textit{and } z = F_2(y)
\end{aligned}$$

We also estimate survival copulas, which are defined as follows:

$$\overline{C}(v,z) = v + z - 1 + C(1-v, 1-z)$$

When computed at $(1 - v,\ 1 - z)$, we obtain the probability for two standard uniform variates with copula $C$ that are greater than $v$ and $z$ respectively:

$$\begin{aligned}
\overline{C}(1-v,1-z) &= \Pr(U_1 > v, U_2 > z)\\
&= \overline{F}(F_1^{-1}(v), F_2^{-1}(z))
\end{aligned}$$
$$\textit{where } \overline{F} \textit{ is the complement to } F$$

As defined above, the survival copula represents the joint survival probability of two variables beyond thresholds $x$ and $y$. The objective is to examine the relationship between recessionary-period performance and post-recessionary period net cash flows in the upper tail.

## 4.4. EMPIRICAL RESULTS

Based on Table 2, the three correlation measures for the absolute variables are positive but only significant for the Early 2000 recession. In contrast, the three sets of correlations between within-recessionary period relative performance and post-recessionary period net fund flows are significant but negative for the Early 2000 recession and positive for the Great Recession. The Early 2000 Recession results are driven by the small-core, large-growth, multi-growth and multi-value funds, whereas the Great Recession results are driven by multi-growth funds.

**[Please place Table 4.2 about here]**

These results are only suggestive for a number of reasons. First, the correlations are based on the whole distributions, and idiosyncrasies associated with either recession can provide different inferences. Second, the Great Recession was much longer than the Early 2000 recession (18 versus 8 months), which could have affected the perceptions of investors and their sentiments. A behavioural argument to this disparity between the two examined recessionary periods is that investors regained an appetite for risk by the end of the Great Recession and re-injected cash in the mutual fund industry given the perception that the downturn had ended and financial markets were in recovery. The median relative return for the Early 2000 Recession of 0.01%, which is statistically higher than -0.06% for the Great Recession homolog, suggests either a change in investor sentiment or a substantial difference in the tail-dependence between performance and fund flows (see Table 1). We now examine the latter conjecture.

Table 3 and figure 1 report on the distributions of Gaussian copulas between bootstrapped recession period returns and post-recession period fund flows. Based on the relative variables, the median copulas for the 1% left and right tails are significantly different for both recessions with a lower negative value for the left tail for the Early 2000 recession and for the right tail for the Great Recession. For the absolute variables, similar comparisons for each considered quartile-tail produce similar results in terms of significance. While the left tail median copulas are positive for both recessions, those for the right tails are negative for the Early 2000 Recession and positive for the Great Recession.[32]

**[Please place Table 4.3 and Figures 4.1 & 4.2 about here]**

Figure 3 shows the cumulative joint distribution functions of returns and net fund flows, and the level curves for copulas at values of 1%, 5%, 50% and 75% for both recessions. At low probability levels, there are irregularities in the empirical joint distributions, whereas the shape of the level curves is closer to normal distributions at higher levels. For absolute (objective-adjusted) monthly during-recessionary period returns lower than -1% for the Early 2000 Recession, there is a 1% probability that post-recession period monthly fund flows will be lower than $-100.85 million ($-82.18 million). The impact of such negative absolute (objective-adjusted) monthly performance is accompanied by fund flows less than $-218.80 million ($-60.86 million) for the Great Recession.

**[Please place Figure 4.3 about here]**

The survival copulas analysis shows that there is 1% probability that post-recessionary period fund flows will be higher than $-130.94 million ($-6.00 million) when absolute (objective-adjusted) monthly during-recessionary period returns are higher than -1% for the Early 2000 Recession. In the Great Recession, the associated fund flows amount to $-214.99 ($-120.88) million. The 32% percentile of absolute returns

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[32] Given that the within-recessionary average performance and post-recessionary period fund flows do not follow normal marginal distributions, we estimated *Student* copulas between bootstrapped variables. The outcomes are qualitatively similar to the outcomes using Gaussian copulas. The left-tail median copulas are positive for absolute variables and both crises, whereas the right-tail median copulas are negative for the Early 2000 Recession and positive for the Great Recession. Relative variables show negative dependence, on average, at the 1% left and right tails for both recessions.

corresponds to the 2nd percentile of net fund flows during the Early 2000 Recession, and the 75th percentile of absolute returns corresponds to the 2nd percentile of net fund flows during the Great Recession. The relationships between the two variables differ for objective-adjusted returns. Specifically, the 3rd percentile of objective-adjusted returns matches the 24th percentile for net fund flows for the Great Recession, and the 9th percentile of objective-adjusted returns associates with the 19th percentile of net fund flows for the Early 2000 Recession. Given this separation between joint and marginal distributions, we draw two inferences: first, the absolute and objective-adjusted variables exhibit different relationships, and the relationships for the Early 2000 Recession and Great Recession are significantly different.

Figure 4 depicts the copulas and survival copulas at 1% superposed with the Fréchet bounds and independence curves. For absolute returns, the empirical copulas at the 1% level are significantly far from the so-called bounds and from the independence curve for the Early 2000 Recession. The empirical absolute variables infer a positive relationship between during-recessionary period absolute returns and post-recessionary period net fund flows at the tail. This result differs for the Great Recession where the data show independence between absolute-return performance and net fund flows. For the objective-adjusted variables, the empirical copulas at 1% are significantly different from perfect concordance (but not from independence) for the Great Recession. In contrast, the empirical 1% level curve for the objective-adjusted variables lies between perfect positive correlation ($p$-value$<0.001$) and independence ($p$-value$=0.03$) for the Early 2000 Recession.

**[Please place Figure 4.4 about here]**

Survival copulas at the 1% level for the absolute variables are significantly far from the bounds and independence curve (p-value<0.001), which indicates a positive relationship between during-recessionary period returns and post-recessionary period fund flows. This result is found for both recessions separately. For the objective-adjusted variables in the Great Recession, the survival rate curve at 1% is significantly away from the bounds (p-values<0.001) but not significantly distinct from the independence curve (p-value=0.89). The corresponding result differs for the Early 2000 Recession, where the relationship is significantly negative (see Table 4).

**[Please place Table 4.4 about here]**

Based on the copulas between absolute variables at 1% for the different categories of funds for the Early 2000 Recession, there is a positive dependence between during-recessionary period returns and post-recessionary period net fund flows for core funds (except those that are large) and value funds (except those that are small). Growth funds do not show a consistent relationship, since the relationship is positive for small and medium funds, non-existent for large funds, and negative for not-size-sorted funds.[33] The large and multi-cap funds and the value funds in the two remaining size categories yield independence for the Great Recession. In contrast, the relation is negative for small and medium, growth and core funds. On an absolute basis, only large- growth and core funds and small-value funds exhibit a similar independent relationship around both recessions. The sign of the relationship changes from positive to negative for small and medium, growth and core funds from the Early 2000 Recession to the Great Recession, and disappears for the other categories of funds.

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[33] When p-values are not mentioned, we implicitly mean that they are lower than 0.05.

The relationships between the objective-adjusted variables for the Early 2000 Recession show that small and medium funds yield positive dependence when holdings are in the growth and core category, but do not exhibit dependence when funds are invested in value funds. Not-size-sorted funds yield three types of relationships: negative for growth, positive for core and no relationship for value funds. For the Great Recession, only small-value, multi-cap- value and core funds maintain the same type of relationship as for the Early 2000 Recession. The relationships for small growth and core funds turns from positive to negative, and that for medium growth and core funds turns from positive to no relationship (see Table 4).

Finally, the survival copulas for the absolute variables for the Early 2000 Recession exhibit a positive dependence except for small- and medium-value funds. The relationships based on the Great Recession are positive except for small-value, mid- core and value, and multi-cap- growth and core funds which exhibit independence. Based on the survival copulas and using objective-adjusted variables for the Early 2000 Recession, all core funds as well as small-growth, large-value and multi-value funds exhibit positive relationships. For the Great Recession, only small-, mid- and large- growth funds keep the same relationships of respectively positive, none and negative. Also, independence is exhibited by all but multi-cap core funds and all but mid-value funds.

### 4.5. ROBUSTNESS TESTS

In this section, we conduct robustness tests for the relationships between performance in bad times and fund flows in subsequent good times. Instead of considering the official dates of the beginning and end of each recession, one could claim that the announcement dates may have more impact on investor demand for mutual funds. The Business Cycle Dating Committee members of the National Bureau of Economic Research meet regularly in order to determine the trough or the peak in business activity of the US economy. Consequently, the committee publishes a report about the dates of turning points in the US economy. For the Early 2000 Recession, the peak was announced in November 2001 and the trough was announced in July 2003, changing the duration of this event from 8 months to 20 months. For the Great Recession, the peak was announced on December 2008 and the trough was announced on September 2010, changing its duration from 18 months to 19 months. All these findings are untabulated but are available upon request.

For both recessions, dispersions of post-crisis absolute fund returns are significantly higher than their within-recessionary period homologs. The skewness of absolute returns is statistically higher and positive post-Great Recession than for the pre- and within-recessionary period (p-value= 0.02), but statistically unchanged around the Early 2000 Recession (as reported earlier using the official dates). For relative returns, the skewness and kurtosis are not statistically different between the three periods for both recessions.

For both measures of fund flows and both events, the dispersion of net fund flows is significantly higher post-recessionary period than within, as was reported earlier for the official dates. Skewness of absolute fund flows is lower and negative post-Early 2000 Recession than within-recessionary period, but unchanged elsewhere. Kurtosis post-recessionary period is unchanged for the Early 200 Recession (absolute and relative), but significantly exceeds its counterpart within the most recent recession (absolute and relative).

The left percentiles of the absolute post-recessionary period net fund flows are unchanged relative to their within-recessionary period homologs for both events, whereas the left percentiles of absolute returns increase substantially around recessions (p-value < 0.001). This result confirms the inelasticity of demand at the far left of the distribution of returns documented in the literature. Nevertheless, objective-adjusted variables show that the left percentiles of within-recessionary period fund flows are higher than their post-event counterparts for both recessions (p-value=0.05 for each event). The left percentile of objective-adjusted returns follows the same pattern in the Great Recession only.

The right percentile of absolute fund flows and returns for both recessions are significantly lower than their subsequent post-recessionary period values. Although, there is no significant change in the right percentile of objective-adjusted fund flows, the corresponding percentile of returns decreases around the Early 2000 Recession (p-value = 0.05). The Great recession relative variables follow the same pattern as the absolute ones.

Absolute and relative fund flows post-Great Recession are more volatile (548.72 versus 21.36), more negatively skewed (-8.48 versus -4.56) and more leptokurtic (208.89 versus 80.91) than their counterparts in the post-Early 2000 Recession. Absolute returns reflect higher volatility during the Great Recession (1.03% versus 0.59%), a lower and negative skewness (-1.20 versus 0.42) and a statistically similar kurtosis (4.67 versus 4.12) than their counterparts in the Early 2000 Recession. The second and third moments of objective-adjusted returns follow the same pattern, but the prevalence of extreme values is significantly lower in the Great Recession compared to the Early 2000 one (4.97 versus 5.78).

Parametric correlations between during-recession performance and post-recessionary fund flows are not significant for the sample as a whole. Non-parametric correlations are positive and significant with objective-adjusted variables or the Early 2000 Recession and with absolute variables for the Great Recession. When we consider the subcategories of funds, we find that with absolute variables, the three sets of correlations are significantly positive for large-core and multi-value funds in the Early 2000 Recession. With objective-adjusted variables for the same event, parametric and non-parametric correlations are positive and significant for mid-core, large-growth and core, multi-growth and core funds, but negative for small-growth funds. For the second crisis, there is no instance where all sets of correlations are significant. With absolute variables, the Spearman and Kendall measures are significantly positive for small-value, large-growth and multi-value funds. With objective-adjusted variables, large-growth funds keep the positive correlations with respective p-values of 0.04 and 0.05, but multi-value funds show negative correlations with respective p-values of 0.01 and 0.02.

The median of Gaussian copulas for the 1% left tail is significantly lower (higher) around the Early 2000 Recession compared to the Great Recession with (relative) absolute variables. The 1% right tails do not show any difference between the two events and are significantly positive.

The empirical copulas at the 1% level show that absolute (relative) returns lower than -1% are associated with net fund flows lower than -0.07 million (-18.09 million) dollars for the Early 2000 Recession and lower than 0.72 million (-147.69 million) dollars for the Great Recession. The survival copulas analysis for when returns are higher than -1% shows that there is a 1% probability that post-recessionary period absolute (relative) fund flows are higher than -1.02 million (-14.23 million) dollars for the Early 2000 Recession and 5.32 million (-573.88 million) for the Great Recession.

The positive dependence between within-recessionary period absolute returns and post-recessionary period fund flows for the Early 2000 Recession is consistent with the outcome of the analysis using the official economic trough and peak dates. This relationship is driven by growth-oriented, as well as mid- and multi-value funds. Also, the independence between both variables for the Great Recession confirms the results found with the initial period delineations. This relationship is driven by mid- and large-growth funds.

We find the same relationships as found earlier using the relative variables. For the Early 2000 Recession, the results are driven by small-growth, mid-core, large-core, multi-growth and multi-value funds. For the Great Recession, the results are driven by mid-growth, mid-value, large-growth and multi-growth funds.

Survival copulas at the 1% level for the absolute variables indicate a positive dependence between within-recessionary period returns and subsequent fund flows for both recessions. Although the sign of the relationship remains the same with relative variables for the Early 2000 Recession, the right-tail dependence fades in the most recent recession. This independence is driven by small-value, mid-growth, mid-core, large-core, large-value and multi-value funds.

## 4.6. CONCLUSION

We study the relationship between performance and net fund flows for U.S. equity mutual funds for both the Early 2000 Recession and the Great Recession. We use the copulas method in order to examine the dependence in the tails of distributions in order to draw inferences about whether or not the behavior of new cash inflows subsequent to such downturns is significantly related to the performance during such periods of turmoil.

The triggers of each recession differed. The Early 2000 Recession stems from the dissipation of the price bubble for high-tech stocks. The Great Recession was more global since it was triggered to a large extent by excessive non-transparent securitization of mortgage debts which ultimately affected real estate markets and the banking system.

For the Early 2000 Recession, there is a positive correlation between during-recessionary period absolute returns and post-recessionary period absolute fund flows and a negative linear dependence between objective-adjusted measures of these variables. Higher absolute fund performance during this economic downturn is subsequently followed by higher money flows. In contrast, investors seem to direct less new cash to outperformers after this recession when the assessment is on a peer-relative basis. For the Great Recession, the non-parametric absolute and relative relationships between these two variables are positive and significant but the parametric linear relationships are not significant.

At the tails of the distributions of peer-relative variables, extreme left and right regions exhibit negative dependence for both recessions. Median Gaussian copulas for the absolute variables show a positive dependence in the 1% left tail for the absolute variables for both recessions, and negative and positive dependence in the 1% right tail for the Early 2000 Recession and Great Recession, respectively. Empirical copulas show a positive dependence in the extreme left tail for the Early 2000 Recession, due primarily to value and core funds when measured on an absolute and objective-adjusted basis, respectively. The Great Recession is characterized by the independence of fund performance and subsequent fund flows, driven primarily by value funds for absolute measurements and medium funds for relative measurements. The survival copulas show an overall positive dependence on an absolute basis (including the upper tails), and a negative dependence in the right region driven primarily by growth funds for the objective-adjusted measurements.

# CHAPTER 5

# CONCLUSION

In this thesis, we study three major issues in the US mutual fund industry: (1) performance evaluation, (2) the M&A activity and (3) the fund flow behaviour subsequent to recessions. In the first essay, we find that the stochastic discount factor (SDF) approach is consistent with the market efficiency hypothesis. Expected mutual fund returns are unpredictable and money managers do not demonstrate superior ability to time the market and exploit mispricings and misperceptions. With regard to the different SDF specifications, we find that the four-factor Carhart model (followed by the three-factor Fama-French model) is best suited for assessing the performance of the mutual fund dataset. The use of the Carhart model results in the least pricing errors on average and produces the largest number of cases in the admissible region of SDF mean-variance.

In the second essay, we examine M&A activity in the US mutual fund industry over a 48-year period. The performance enhancement hypothesis is tested for GMM estimates of abnormal performance under the SDF approach. We find little evidence of significant abnormal performance, but its occurrence primarily benefits target unitholders as shown in the literature for other industries. The smooth transition hypothesis is not supported based on various downside risk comparisons since the acquirer's and the target's risk increases significantly post-M&A. The pre- to post-M&A shift in risk is not compatible with a significantly higher abnormal performance. Furthermore, acquirers displaying greater risk tolerance, in terms of portfolio holdings post-M&A, have less efficient asset portfolios. Data over the lifetimes of funds can not reject the fund-flow effect hypothesis that M&A success is negatively related to the mean fund flows prior to M&A. Also, M&A success is negatively (positively) related to the market state at the time of the deal conclusion over the short-term (longer term) post-M&A showing that the window of opportunity hypothesis could not be rejected. Finally, we find a consistent negative (positive) relationship between post-M&A bidder risk (target past performance) and M&A success.

In the third essay, we study the relationship between performance and net fund flows for U.S. equity mutual funds for both the Early 2000 Recession and the Great Recession. We use the copulas method in order to examine the dependence in the tails of distributions in order to draw inferences about whether or not the behavior of new cash inflows subsequent to such downturns is significantly related to the performance during such turmoils. For the Early 2000 Recession, there is a positive correlation between during-recessionary period absolute returns and post-recessionary period absolute fund flows and a negative linear dependence between objective-adjusted measures of these variables. Higher absolute fund performance during this economic downturn is subsequently followed by higher money flows. In contrast, investors seem to direct less new cash to outperformers after this recession when the assessment is on a peer-relative basis. For the Great Recession, the non-parametric absolute and relative relationships between these two variables are positive and significant but the parametric linear relationships are not significant.

At the tails of the distributions of peer-relative variables, extreme left and right regions exhibit negative dependence for both recessions. Median Gaussian copulas for the absolute variables show a positive dependence in the 1% left tail for the absolute variables for both recessions, and negative and positive dependence in the 1% right tail for the Early 2000 Recession and Great Recession, respectively. Empirical copulas show a positive dependence in the extreme left tail for the Early 2000 Recession, due primarily to value and core funds when measured on an absolute and objective-adjusted basis, respectively. The Great Recession is characterized by the independence of fund performance and subsequent fund flows, driven primarily by value funds for absolute measurements and medium funds for relative measurements. The survival copulas show an overall positive dependence on an absolute basis (including the upper tails), and a negative dependence in the right region driven primarily by growth funds for the objective-adjusted measurements.

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## APPENDICES

### Appendix A: Saturation Ratios

Dahlquist and Söderlind (1999) define the saturation ratio as the total number of observations divided by the number of parameters to be estimated (including the number of parameters in the weighting matrix).[34] Bekaert and Urias (1996, p. 846) point out that GMM-systems with saturation ratios below ten are likely to have low power, even though they are common in empirical finance. We seek to maximize the power of our tests by maintaining suitable saturation ratios. We apply the GMM estimation on only one fund at a time. We repeat the iterative estimation process for every single equity and bond mutual fund to test the appropriateness of each candidate model, jointly with the existence of abnormal performance. Maintenance of an appropriate saturation ratio is one of the reasons why we choose to use only one information variable (short-term interest rate) to test the conditional version of the proposed candidate models.

Given the ten-level barrier suggested in the literature, a suitable saturation ratio in our tests lies between 68 and 73 data points. We find that 44% (i.e., 6,553) of the equity funds and 55% (i.e., 4,295) of the bond funds meet this condition. It is noteworthy that surviving funds offer large saturation ratios (between 72.00 and 79.11), making the subsample in question a reference for model ranking and testing. Given that the power of the tests applied to this subsample is stronger, it could buttress our acceptance of the null hypothesis of no superior ability in managing mutual funds when test statistics confirm it.

[34] It is equal to the ratio of the product of the number of conditions and length of data, divided by the number of parameters to be estimated. For example, for a fund with 100 posted monthly returns and a CAPM-like model in the unconditional setting, the saturation ratio of the GMM system equals: $n_c*T/((n_v + 1)*k +1 + n_c*(n_c + 1)/2)=12*100/(2*1 + 1 + 12*13/2) = 15$.

## Appendix B: Some Institutional Detail on US Mutual Funds Mergers

Rule 17a-8, which was promulgated under the Investment Company Act of 1940, defines *Merger* as the merger, consolidation, or purchase or sale of substantially all of the assets between a registered investment company (or a series thereof) and another company. The parties of a merger are called the surviving company[35] and the merging company, respectively. A merger consists of the transfer of all of the merging fund's assets attributable to a certain class of shares to the surviving ("acquiring") fund. The board of directors communicates with shareholders in order to vote on an Agreement and Plan of Reorganization for the Fund.[36]

The Board of Directors of the merging company determines that the interests of the merging company's existing shareholders will not be diluted as a result of the merger, given all pertinent factors. In making this determination, the directors have to approve procedures for the valuation of assets to be transferred. These procedures are used by an Independent Evaluator in order to assess the fair value of any securities (or other assets) for which market quotations are not readily available, as of the date of the merger.

Participation in the merger has to be approved by the vote of a majority of the outstanding voting securities unless: (1) all policies and advisory contracts between the merging company and the investment advisers are not materially different for the merging and surviving companies; (2) elected directors of the merging company comprise a majority of the directors of the surviving company; and (3) 12b-1 distribution fees of the surviving company are not greater than those of the merging company.

[35] Surviving Company means "a company in which shareholders of a Merging Company will obtain an interest as a result of a Merger" (Rule 17a-8, Investment Company Act 1940).
[36] See Appendix B of "Board Consideration of Fund Mergers", June 2006.

If the plan of merger is approved, the shareholders of the merging funds become shareholders of the Surviving fund. The Surviving fund generally has management policies similar to the acquired fund.

## Appendix C: Bull-Bear Market Indicator

Over the study period (1962-2009), the value-weighted portfolio of all non-ADR securities traded on the NYSE, NASDAQ and AMEX constitutes the basis for the determination of bull/bear market conditions. Since there are no generally accepted formal definitions of bull and bear markets, we chose to adopt the one suggested by Lunde and Timmermann (2004), inspired by Sperandeo (1990), Chauvet and Potter (2000) and the financial press. The corresponding algorithm allows the identification of turning points from one state to another (from bull to bear and vice versa).

Lunde and Timmermann (2004) use the stochastic process tracking the stock price as the underlying variable to determine the turning points. Suppose that the initial state at time $t_0$ is the bull state and symbolize the corresponding market state indicator as $I_{t_0} = 1$ and assign to $P_{t_0}^{\max}$ the initial price $P_{t_0}$. Let $\tau_{\min}$ and $\tau_{\max}$ be the stopping-time variables defined as follows:

$$\tau_{\max}(P_{t_0}^{\max}, t_0 | I_{t_0} = 1) = \inf\{t_0 + \tau : P_{t_0+\tau} \geq P_{t_0}^{\max}\};$$
$$\tau_{\min}(P_{t_0}^{\max}, t_0, \lambda_2 | I_{t_0} = 1) = \inf\{t_0 + \tau : P_{t_0+\tau} < (1-\lambda_2)P_{t_0}^{\max}\}$$

where $\tau \geq 1$

If $\tau_{\max} < \tau_{\min}$ then we update the local maximum price: $P_{t_0+\tau_{\max}}^{\max} = P_{t_0+\tau_{\max}}$ and $I_{t_0+1} = ... = I_{t_0+\tau_{\max}} = 1$

If $\tau_{\min} < \tau_{\max}$ then we update the local minimum price: $P^{\min}_{t_0+\tau_{\min}} = P_{t_0+\tau_{\min}}$ and $I_{t_0+1} = ... = I_{t_0+\tau_{\min}} = 0$

In the contrary configuration, where $I_{t_0} = 0$ and $P^{\min}_{t_0} = P_{t_0}$, the stopping-time variables are defined as follows:

$$\tau_{\min}(P^{\min}_{t_0}, t_0 | I_{t_0} = 0) = \inf\{t_0 + \tau : P_{t_0+\tau} \leq P^{\min}_{t_0}\};$$
$$\tau_{\max}(P^{\min}_{t_0}, t_0, \lambda_1 | I_{t_0} = 0) = \inf\{t_0 + \tau : P_{t_0+\tau} > (1+\lambda_1) P^{\min}_{t_0}\}$$

If $\tau_{\min} < \tau_{\max}$ then we update the local minimum price: $P^{\min}_{t_0+\tau_{\min}} = P_{t_0+\tau_{\min}}$ and $I_{t_0+1} = ... = I_{t_0+\tau_{\min}} = 0$

If $\tau_{\max} < \tau_{\min}$ then we update the local maximum price: $P^{\max}_{t_0+\tau_{\max}} = P_{t_0+\tau_{\max}}$ and $I_{t_0+1} = ... = I_{t_0+\tau_{\max}} = 1$

The scalar $\lambda_1$ ($\lambda_2$) represents the threshold of movements in stock prices that trigger a switch from bear (bull) to bull (bear) market. Based on the financial press, as in Lunde and Timmermann (2004), we consider the conventionally used values and apply the filter (0.20, 0.20). Hence, the state changes occur when stock price increases/decreases by 20%.

## TABLES

### Table 2.1. Summary statistics

This table provide various summary statistics for the nine risk factors time series employed to describe the pricing kernel. M stands for the market portfolio return. L stands for the human capital factor. SMB and HML are the size and value self-financing portfolios as constructed in Fama-French (1993). WML stands for the momentum trading strategy return. I stands for inflation-mimicking portfolio return. IP represents the Industrial Production-mimicking portfolio return. T represents the term structure-mimicking portfolio return. RM is the residual market risk factor, obtained after controlling for the four preceding risk sources. The statistics describing the following factors are in order: mean, standard deviation, skewness, kurtosis, minimum, maximum and first-order autocorrelation. They are calculated on the basis of the study period: January 1962 up to June 2006.

| | Mean | Standard Deviation | Skew. | Kurt. | Min. | Max. | $\rho_1$ |
|---|---|---|---|---|---|---|---|
| Market (M) | 0.0045 | 0.0443 | -0.4764 | 4.9417 | -0.2313 | 0.1605 | 0.04830 |
| Labor income (L) | 0.0050 | 0.0040 | -0.6874 | 9.8721 | -0.0205 | 0.0185 | 0.41743 |
| Size factor (SMB) | 0.0023 | 0.0320 | 0.5294 | 8.4349 | -0.1658 | 0.2187 | -0.08155 |
| Value factor (HML) | 0.0047 | 0.0288 | -0.0057 | 5.5719 | -0.1266 | 0.1371 | 0.06231 |
| Momentum factor (WML) | 0.0084 | 0.0399 | -0.6471 | 8.4710 | -0.2505 | 0.1840 | -0.07063 |
| Inflation (I) | 0.0000 | 0.0289 | 0.0372 | 5.3188 | -0.1064 | 0.1432 | -0.01442 |
| Industrial production (IP) | 0.0015 | 0.0284 | 0.3026 | 5.1713 | -0.0989 | 0.1398 | 0.00544 |
| Term structure (T) | -0.0001 | 0.0006 | -0.0496 | 4.7707 | -0.0031 | 0.0024 | 0.14381 |
| Residual market risk (RM) | -0.0001 | 0.0009 | -0.1287 | 4.5664 | -0.0042 | 0.0031 | 0.00688 |

**Table 2.2. Hansen-Jagannathan Volatility Bounds Diagnosis**

This table reports the percentage of cases (funds) with SDFs that are considered "variable enough" for the nine candidate models in (un)conditional settings for all non-missing-data equity mutual funds, as well as the special cases of funds with at least 180 data points. The objective is to eliminate outliers stemming from cases where the funds report very few monthly returns over their lifetime. CAPM stands for the single-factor linear pricing kernel. FAFR stands for the three-factor Fama-French model. APT stands for the arbitrage pricing theory-based model. LCAPM stands for the Jagannathan and Wang (1996) labor-CAPM. WML stands for the four-factor Carhart model. CUB stands for the non linear cokurtosis-based model as proposed by Dittmar (2002). QUAD stands for the non-linear coskewness-based model as proposed by Harvey and Siddique (2000). L-CUB and L-QUAD represent labor-cubic and labor-quadratic models respectively, as proposed by Fletcher and Forbes (2004).

| **Percentage of cases where the mean-std is inside the HJ boundary (%)** | | | | |
|---|---|---|---|---|
| | Unconditional | | Conditional | |
| Models | All | More than 180 obs | All | More than 180 obs |
| CAPM | 0.88 | 7.61 | 0.74 | 10.11 |
| FAFR | 5.32 | 83.07 | 4.38 | 64.77 |
| APT | 0.18 | 2.95 | 0.18 | 2.95 |
| LCAPM | 0.73 | 10.00 | 0.75 | 10.23 |
| WML | 6.64 | 87.95 | 6.64 | 87.84 |
| CUB | 0.73 | 9.89 | 0.73 | 10.00 |
| QUAD | 0.73 | 9.89 | 0.74 | 10.11 |
| L-CUB | 0.75 | 10.23 | 0.73 | 10.00 |
| L-QUAD | 0.73 | 10.00 | 0.74 | 10.11 |

**Table 2.3. The percentages of significant alphas**

This table reports the percentages of significant alphas for the nine candidate models for the (un)conditional setting. The sample size is 14,996 equity funds. Statistical significance is measured at the 5% level. CAPM stands for the single-factor linear pricing kernel. FAFR stands for the three-factor Fama-French model. APT stands for the arbitrage pricing theory-based model. LCAPM stands for the Jagannathan and Wang (1996) labor-CAPM. WML stands for the four-factor Carhart model. CUB stands for the non linear cokurtosis-based model as proposed by Dittmar (2002). QUAD stands for the non-linear coskewness-based model as proposed by Harvey and Siddique (2000). L-CUB and L-QUAD represent labor-cubic and labor-quadratic models respectively, as proposed by Fletcher and Forbes(2004).

| Models | Unconditional | Conditional |
|---|---|---|
| CAPM | 1.30 | 1.13 |
| FAFR | 1.09 | 0.41 |
| LCAPM | 1.22 | 0.83 |
| APT | 1.00 | 0.13 |
| WML | 0.76 | 0.11 |
| CUB | 1.12 | 0.79 |
| QUAD | 1.11 | 0.69 |
| L-CUB | 0.99 | 0.57 |
| L-QUAD | 0.95 | 0.50 |

**Table 2.4. Results for the four-index EGB model**

This table reports the percentages of funds whose mean-standard deviation are inside the HJ boundary and the percentages of funds with significant alphas for the (un)conditional setting for the four-index model for the full sample of equity funds and subsamples thereof consisting of funds with at least 180 observations. The four factors in this model are: the stock market portfolio, the size portfolio, the value portfolio and the broad-based bond market portfolio. The sample sizes are 14,968 equity funds, respectively. Statistical significance is measured at the 5% level. Results are calculated on the basis of the subperiod January 1976 up to June 2006.

| | Unconditional | | Conditional | |
|---|---|---|---|---|
| | All | More than 180 obs | All | More than 180 obs |
| Mean-std inside the HJ boundary (%) | 5.09 | 78.32 | 5.09 | 78.32 |
| Significant alphas (%) | 0.98 | 16.96 | 0.07 | 1.27 |

**Table 2.5. Alternative Investment Opportunity Set : 125 Wermers (2004) benchmarks**

The table represents the outcome of the SDF alpha estimation under (un)conditional setting and the HJ boundary test for equity funds (for the period 1975-2006) with an alternative IO set. *Permissible%* stands for the percentage of cases in the permissible region according to the HJ boundary. *Permissible% (180-funds)* stands for the same measure for funds reporting 180 datapoints or more. *Sig alphas* stands for the percentage of SDF alphas significant at the 95% confidence level. *Positive Sig alphas* represents the percentage of positive alphas among the significant cases. The addition of the mention 180-funds means that the measures concern only the funds that report 180 datapoints or more.

| | | | UNCONDITIONAL SETTING | | | |
|---|---|---|---|---|---|---|
| Models | Persmissible % | Permissible% (180-funds) | Sig alphas (%) | Positive sig alphas (%) | Sig Alphas (180-funds) % | Positive sig alphas (180-funds) % |
| FAFR | 0.04 | 0.00 | 1.53 | 42.27 | 70.06 | 42.27 |
| CAPM | 0.00 | 0.00 | 1.10 | 32.48 | 68.26 | 32.48 |
| JW | 0.04 | 0.00 | 1.86 | 41.48 | 60.54 | 41.48 |
| WML | 0.02 | 0.00 | 1.79 | 41.92 | 53.83 | 41.92 |
| APT | 0.00 | 0.00 | 2.25 | 48.48 | 67.21 | 48.48 |
| Cub | 0.85 | 24.73 | 2.03 | 45.08 | 62.90 | 45.08 |
| Quad | 0.74 | 20.75 | 1.95 | 41.55 | 58.92 | 41.55 |
| Cub-L | 0.81 | 22.98 | 2.07 | 46.51 | 62.32 | 46.51 |
| Quad-L | 0.69 | 19.26 | 2.01 | 45.55 | 59.84 | 45.55 |
| | | | CONDITIONAL SETTING | | | |
| Models | Permissible% | Permissible % (180-funds) | Sig alphas (%) | Positive sig alphas (%) | Sig Alphas (180-funds) % | Positive sig alphas (180-funds) % |
| FAFR | 0.04 | 0.00 | 1.41 | 35.47 | 65.91 | 35.47 |
| CAPM | 0.00 | 0.00 | 1.09 | 33.97 | 66.10 | 33.97 |
| JW | 0.04 | 0.00 | 2.01 | 44.18 | 64.18 | 44.18 |
| WML | 0.02 | 0.00 | 1.93 | 45.71 | 57.85 | 45.71 |
| APT | 0.00 | 0.00 | 2.19 | 46.23 | 65.43 | 46.23 |
| Cub | 0.87 | 24.9 | 2.17 | 49.05 | 66.11 | 49.05 |
| Quad | 0.74 | 20.75 | 1.96 | 44.21 | 59.13 | 44.21 |
| Cub-L | 0.81 | 22.84 | 2.10 | 47.87 | 62.76 | 47.87 |
| Quad-L | 0.70 | 19.47 | 2.13 | 49.68 | 63.52 | 49.68 |

**Table 3.1. Descriptive statistics of target and merged funds rates of return over the period 1962-2009**

The table reports the cross-sectional average of mutual funds time-series descriptive statistics, except for the number of target and merged funds (*n*). Both samples of targets and merged funds are subdivided into five subsamples according to their investment style: equity, bond, money market, hybrid (or asset allocation), and convertible. "T" stands for the cross-sectional average of the number of regularly posted monthly returns for every in-sample fund. "Mean" represents the cross-sectional average of monthly return time-series means. "Median" is the cross-sectional average of monthly return time-series medians. "Min" is the cross-sectional average of monthly return minima. "Max" is the cross-sectional average of monthly return maxima. "Sigma" is the cross-sectional average of monthly returns time-series standard deviations. "Skew" is the cross-sectional average of (conventional) skewness measures of monthly returns. "Kurt" is the cross-sectional average of kurtosis measures of monthly returns. "Rho" is the cross-sectional average of first-order time series autocorrelations. All numbers are in percentages except for n, size, Skew, Kurt and Rho. Monthly returns, which are from the US Mutual Fund survivorship-bias-free CRSP database, are calculated as the change in the Net Asset Value per share including reinvested dividends from one month to the next and net of management expenses.

| | n | T | Mean | Median | Min | Max | Sigma | Skew | Kurt | Rho |
|---|---|---|---|---|---|---|---|---|---|---|
| Target Funds (statistics concern the period starting from inception up to merger completion) | | | | | | | | | | |
| Total | 6680 | 90 | 0.27 | 0.42 | -10.68 | 9.63 | 3.81 | -0.33 | 4.16 | 0.13 |
| Equity | 3727 | 84 | 0.15 | 0.33 | -16.05 | 14.22 | 5.74 | -0.31 | 4.07 | 0.07 |
| Bond | 2082 | 96 | 0.42 | 0.53 | -3.75 | 3.84 | 1.31 | -0.40 | 4.47 | 0.11 |
| Money | 423 | 117 | 0.39 | 0.39 | 0.15 | 0.70 | 0.14 | 0.05 | 3.22 | 0.88** |
| Hybrid | 420 | 91 | 0.47 | 0.67 | -8.38 | 6.67 | 2.73 | -0.52 | 4.40 | 0.05 |
| Convertible | 28 | 78 | 0.06 | 0.14 | -9.26 | 7.50 | 3.20 | -0.44 | 4.71 | 0.14 |
| Merged Funds (statistics concern the period starting from the transaction dates up to either the end date of the study period or the delisting date) | | | | | | | | | | |
| Total | 4459 | 65 | 0.16 | 0.60 | -11.53 | 8.51 | 4.12 | -0.57 | 4.30 | 0.25 |
| Equity | 2530 | 98 | 0.23 | 0.53 | -13.43 | 10.69 | 3.88 | -0.37 | 3.28 | 0.13 |
| Bond | 1300 | 108 | 0.25 | 0.33 | -3.68 | 3.00 | 0.91 | -0.43 | 4.17 | 0.08 |
| Money | 322 | 145 | 0.22 | 0.24 | 0.01 | 0.49 | 0.12 | -0.02 | 2.03 | 0.73** |
| Hybrid | 294 | 100 | 0.23 | 0.46 | -8.26 | 5.28 | 2.14 | -0.55 | 3.60 | 0.13 |
| Convertible | 13 | 111 | -0.02 | 0.16 | -13.81 | 7.93 | 3.26 | -0.91 | 6.61 | 0.19 |

**significant at the 0.05 level.

### Table 3.2. Number of mergers with different participant investment styles

The table represents the cases where a target fund is acquired by a mutual fund with a different investment style or objective. Investment styles are defined by the class of assets held by the mutual fund over the business life of the funds. The five investment styles are: Equity, Bond, Money Market, Hybrid and Convertible. To illustrate, 95 of the 3727 target equity funds merged with different-style funds (10 became bond funds, 1 a money market fund, 77 hybrid funds and 7 convertible funds).

| Style of Target | Style of Acquiring Fund | | | | | Style changes |
|---|---|---|---|---|---|---|
| | Equity | Bond | Money Market | Hybrid | Convertibles | Total |
| Equity | | 10 | 1 | 77 | 7 | 95 |
| Bond | 12 | | 8 | 11 | 1 | 32 |
| Money Market | 2 | 5 | | 0 | 0 | 7 |
| Hybrid | 65 | 3 | 0 | | 1 | 69 |
| Convertibles | 11 | 3 | 0 | 8 | | 22 |

## Table 3.3. Descriptive statistics for the size of the targets and merged funds at deal month-end dates

The table reports the time-series averages of the cross-sectional percentiles of the target and merged fund sizes at the time of the M&A transaction. The 2.5%, 50% and 97.5% percentiles of the fund Total Net Assets (TNA) are calculated each year over the period 1962-2009. The reported numbers are averages of these percentiles across time over the whole study period in table 3a, and for each of the four subperiods of 1971-1980, 1981-1990, 1991-2000 and 2001-2009 in table 3b. The figures related to the subperiod 1962-1970 are omitted since all their values are equal to zero. Both samples of targets and merged funds are subdivided into five subsamples according to their investment style: equity, bond, money market, hybrid (or asset allocation), and convertible. All averages of percentiles are in millions USD. By convention, the very small funds whose size is less than $100,000 report 0.01 as a monthly Total Net Assets. "*n*" stands for the average monthly (integer) number of target or merged funds over the respective periods. It is noteworthy that these statistics involve only those mutual funds for which the regularly reported monthly return, the investment style and TNA information are available.

**Table 3.3a.**

| Period | Targets | | | | Acquiring funds | | | |
|---|---|---|---|---|---|---|---|---|
| | n (annually) | 2.5% | 50% | 97.5% | n (annually) | 2.5% | 50% | 97.5% |
| | Total sample (4,621 cases) | | | | Total sample (3,256 cases) | | | |
| 1962-2009 | 159 | 57.70 | 67.21 | 306.67 | 165 | 82.28 | 157.71 | 1646.86 |
| 1971-1980 | 1 | 42.63 | 42.63 | 42.63 | 1 | 36.95 | 36.95 | 36.95 |
| 1981-1990 | 2 | 298.27 | 309.21 | 321.02 | 2 | 422.12 | 498.76 | 660.84 |
| 1991-2000 | 61 | 1.05 | 15.37 | 400.56 | 61 | 7.19 | 107.79 | 1688.29 |
| 2001-2009 | 400 | 0.10 | 7.88 | 311.22 | 400 | 1.04 | 73.32 | 2581.42 |

**Table 3.3b.**

| Period | Targets | | | | Acquiring funds | | | |
|---|---|---|---|---|---|---|---|---|
| | n (annually) | 2.5% | 50% | 97.5% | n (annually) | 2.5% | 50% | 97.5% |
| | Equity (2818) | | | | Equity (1989) | | | |
| 1962-2009 | 113 | 3.01 | 10.64 | 181.04 | 112 | 15.45 | 81.95 | 1434.48 |
| 1971-1980 | 1 | 4.50 | 4.50 | 4.50 | 1 | 36.95 | 36.95 | 36.95 |
| 1981-1990 | 2 | 3.85 | 3.96 | 6.90 | 2 | 36.25 | 46.17 | 250.21 |
| 1991-2000 | 24 | 5.30 | 17.16 | 162.73 | 23 | 19.38 | 113.28 | 824.18 |
| 2001-2009 | 258 | 0.10 | 7.30 | 287.14 | 256 | 0.89 | 71.27 | 2700.90 |
| | Bond (1395) | | | | Bond funds (941) | | | |
| 1962-2009 | 61 | 4.58 | 13.76 | 255.21 | 63 | 23.88 | 130.81 | 1628.90 |
| 1971-1980 | 1 | 18.54 | 19.13 | 19.72 | 0 | 0 | 0 | 0 |
| 1981-1990 | 35 | 3.25 | 14.72 | 350.05 | 2 | 192.78 | 205.38 | 217.99 |
| 1991-2000 | 108 | 0.19 | 10.74 | 264.04 | 31 | 11.82 | 170.01 | 1580.39 |
| 2001-2009 | 61 | 4.58 | 13.76 | 255.21 | 107 | 2.16 | 76.70 | 1959.60 |
| | Money Market (113) | | | | Money Market (102) | | | |
| 1962-2009 | 8 | 184.56 | 249.85 | 1022.0 | 7 | 825.42 | 1256.14 | 6408.23 |
| 1971-1980 | 1 | 157.00 | 157.00 | 157.00 | 0 | 0.83 | 0.83 | 0.83 |
| 1981-1990 | 1 | 762.60 | 762.60 | 762.60 | 1 | 813.22 | 813.22 | 813.22 |
| 1991-2000 | 4 | 176.68 | 282.84 | 1025.07 | 4 | 1452.78 | 1869.81 | 3459.85 |
| 2001-2009 | 14 | 4.34 | 61.41 | 1249.71 | 13 | 292.90 | 919.96 | 11333.26 |
| | Hybrid (282) | | | | Hybrid (216) | | | |
| 1962-2009 | 17 | 45.54 | 58.51 | 254.08 | 18 | 104.08 | 285.41 | 1602.90 |
| 1971-1980 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1981-1990 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1991-2000 | 5 | 110.37 | 128.68 | 223.91 | 5 | 248.17 | 494.05 | 1154.12 |
| 2001-2009 | 25 | 0.16 | 9.39 | 275.19 | 28 | 3.21 | 139.37 | 1917.05 |
| | Convertibles (13) | | | | Convertibles (8) | | | |
| 1962-2009 | 3 | 4.25 | 6.40 | 10.37 | 2 | 14.31 | 40.93 | 100.01 |
| 1971-1980 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1981-1990 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1991-2000 | 1 | 15.46 | 15.46 | 15.46 | 3 | 5.85 | 8.69 | 29.35 |
| 2001-2009 | 3 | 1.45 | 4.14 | 9.10 | 2 | 17.13 | 51.68 | 123.57 |

### Table 3.4. Descriptive statistics of the MER of the targets and merged funds

The table reports cross-sectional statistics for management expense ratios (MERs) of the target and merged funds with regularly posted monthly returns, investment style and MER information. All numbers are in percentages except for the skew and kurt measures. For mutual funds reporting different MERs throughout their business life, the time-series average of MERs is used in the cross-sectional computations.

| | Mean | Median | Minimum | Maximum | Sigma | Skew | Kurt |
|---|---|---|---|---|---|---|---|
| **Targets** | | | | | | | |
| Total sample (6464) | 1.45 | 1.41 | 0.00 | 7.51 | 0.69 | 0.49 | 4.09 |
| Equity (3565) | 1.73 | 1.73 | 0.00 | 7.51 | 0.65 | 0.48 | 5.29 |
| Bond (2051) | 1.12 | 1.00 | 0.00 | 5.38 | 0.54 | 0.72 | 5.12 |
| Money Market (417) | 0.57 | 0.53 | 0.00 | 1.75 | 0.30 | 1.35 | 5.57 |
| Hybrid (407) | 1.50 | 1.46 | 0.00 | 4.09 | 0.59 | 0.07 | 3.08 |
| Convertibles (24) | 1.52 | 1.68 | 0.25 | 2.25 | 0.64 | -0.65 | 2.14 |
| **Merged entities** | | | | | | | |
| Total sample (4307) | 1.34 | 1.28 | 0.00 | 3.82 | 0.60 | 0.32 | 2.50 |
| Equity (2417) | 1.59 | 1.54 | 0.13 | 3.82 | 0.56 | 0.20 | 2.62 |
| Bond (1279) | 1.06 | 0.92 | 0.00 | 3.09 | 0.46 | 0.53 | 2.47 |
| Money Market (318) | 0.60 | 0.55 | 0.11 | 1.70 | 0.31 | 1.21 | 5.01 |
| Hybrid (280) | 1.30 | 1.25 | 0.00 | 2.40 | 0.54 | 0.02 | 2.21 |
| Convertibles (13) | 1.57 | 1.52 | 0.82 | 2.20 | 0.45 | -0.08 | 1.91 |

**Table 3.5. Descriptive statistics on the income distributions of the targets and merged funds**

The table reports cross-sectional averages of time-series statistics for income distributions of target and merged funds. Income distributions include all types of distributions converted to percentages by dividing by Net Asset Value per share: capital gains, dividends and interest income. We calculate time-series statistics (number of data points, mean, median, minimum, maximum, standard deviation, skewness and kurtosis) for each in-sample fund, and then we compute their cross-sectional averages. All numbers are in percentages except for n, skew, kurt. "*n*" stands for the number of funds involved in the calculations. "Total sample" for both target and merged funds includes all funds where only regular monthly returns and distribution information are available. We subdivide the sample into five subsamples according to their investment style. Thus, the number of cases only includes those funds where all three variables are available: returns, investment style and income distributions (941 targets and 638 merged funds).

| | n | T | Mean | Median | Min | Max | Sigma | Skew | Kurt |
|---|---|---|---|---|---|---|---|---|---|
| | **Target Funds** | | | | | | | | |
| Total Sample | 2037 | 89 | 0.50 | 0.43 | 0.26 | 2.16 | 0.30 | 2.76 | 21.04 |
| Equity (16) | 16 | 54 | 0.90 | 0.58 | 0.21 | 8.80 | 1.33 | 3.94 | 23.91 |
| Bond (858) | 858 | 86 | 0.47 | 0.44 | 0.28 | 1.65 | 0.18 | 3.08 | 23.67 |
| Money Market (49) | 49 | 110 | 0.36 | 0.35 | 0.14 | 0.67 | 0.13 | 0.30 | 2.69 |
| Hybrid (12) | 12 | 63 | 0.53 | 0.27 | 0.18 | 10.54 | 1.31 | 5.68 | 42.00 |
| Convertibles (6) | 6 | 71 | 0.53 | 0.53 | 0.28 | 2.34 | 0.29 | 1.40 | 11.95 |
| | **Acquiring Funds** | | | | | | | | |
| Total Sample | 848 | 60 | 0.64 | 0.45 | 0.26 | 2.35 | 0.56 | 1.97 | 11.69 |
| Equity (13) | 13 | 39 | 0.64 | 0.28 | 0.19 | 4.82 | 1.10 | 2.27 | 8.57 |
| Bond (564) | 564 | 61 | 0.45 | 0.40 | 0.27 | 1.19 | 0.17 | 1.98 | 11.60 |
| Money Market (47) | 47 | 67 | 0.32 | 0.32 | 0.08 | 0.71 | 0.15 | 0.36 | 3.45 |
| Hybrid (13) | 13 | 47 | 0.51 | 0.33 | 0.21 | 4.55 | 0.76 | 2.20 | 13.20 |
| Convertibles (1) | 1 | 37 | 0.71 | 0.18 | 0.11 | 9.25 | 1.73 | 3.89 | 18.17 |

### Table 3.6. SDF performance based on the Carhart model

The first three columns report the median of SDF alphas for T (target) funds; Pre-B (pre-merger bidder) funds and Post-B (post-merger bidder) funds. All numbers are in percentages. "EQ" stands for Equity funds; "BD" stands for Bond funds; "MM" stands for Money market funds; "HY" stands for hybrid funds and "CV" stands for convertibles funds. The second panel reports paired tests of SDF alphas both between target and post-merger bidders and between pre-merger and post-merger bidders. The last column shows t- or z-statistics, testing the differences between SDF alphas depending on the normality or not of the corresponding series distributions. $^{*}$, $^{**}$ and $^{***}$ signify statistical significance based on the p-values at the 0.10, 0.05 and 0.01 levels, respectively. The SDF alphas results from GMM optimization of the orthogonality conditions on pricing errors. The SDF specification is linear in four factors: market, size, value and momentum. The weighting matrix is the estimator of the spectral density of moment conditions, and the window type employed is the quadratic spectral.

| | Median Alpha (in %) | | | Percentage of Positive Significant Alphas (%) | | | Percentage of Negative Significant Alphas (%) | | | Comparison tests between SDF alphas | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | T | Pre-B | Post-B | T | Pre-B | Post-B | T | Pre-B | Post-B | T/Post-B | Pre-B/Post-B |
| All | 0.06 | 0.13 | 0.02 | 0.01 | 0.03 | 0.01 | 0.52 | 0.42 | 0.13 | 0.00 | 0.81 |
| 60s | 0.05 | 0.37 | -0.03 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | - | - |
| 70s | -0.22 | 0.15 | 0.06 | 0.00 | 0.00 | 11.76 | 0.00 | 0.00 | 0.00 | -1.51 | -1.51 |
| 80s | 0.05 | 0.09 | 0.07 | 0.00 | 1.23 | 3.61 | 1.20 | 0.00 | 6.02 | $-1.76^{*}$ | -1.00 |
| 90s | 0.10 | 0.16 | 0.04 | 0.32 | 1.22 | 0.24 | 0.57 | 1.55 | 2.75 | 0.38 | $2.86^{***}$ |
| 00s | 0.05 | 0.12 | 0.01 | 0.11 | 0.59 | 0.00 | 1.76 | 1.83 | 0.00 | $2.43^{**}$ | $5.61^{***}$ |
| EQ | 0.12 | 0.32 | -0.06 | 0.00 | 0.03 | 0.00 | 0.05 | 0.27 | 0.00 | - | 1.05 |
| BD | 0.06 | 0.09 | 0.10 | 0.00 | 0.00 | 0.05 | 0.15 | 0.05 | 0.00 | -1.02 | -1.02 |
| MM | -0.05 | -0.02 | -0.01 | 0.24 | 0.00 | 0.00 | 7.14 | 3.81 | 1.90 | 1.01 | - |
| HY | 0.20 | 0.30 | -0.15 | 0.00 | 0.24 | 0.00 | 0.00 | 0.24 | 0.00 | - | 1.03 |
| CV | -0.10 | 0.15 | -0.15 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 3.57 | - | - |

## Table 3.7. Distribution of SDF alphas over various post-M&A terms

The table shows the SDF alphas estimated for various post-M&A terms of one to ten years. N stands for the number of observations for each term. Bottom stands for the poorest performing fund in the subsample, 1%, 25%, Median, 75% and 99% stand for the corresponding percentiles of the alpha distributions; and Top stands for the best-performing fund in the subsample. Panel A shows the target funds SDF alpha results over the terms 1Y to 10Y. The abnormal performance is estimated using the stochastic discount factor approach using a subperiod, for each fund, corresponding to a specific term. For example, 1Y-SDF alphas for target funds are estimated using the data one year prior to the M&As. Panel B shows results for acquiring funds subsequent to the M&As. Panel C shows results for acquiring funds prior to the M&As. All numbers are in percentages except for *n*.

| | n | Bottom | 1% | 25% | Median | 75% | 99% | Top |
|---|---|---|---|---|---|---|---|---|
| Panel A: Target funds | | | | | | | | |
| 1 Y | 4445 | -4.92 | -2.71 | -0.43 | -0.11 | 0.21 | 1.89 | 5.65 |
| 2 Y | 4639 | -4.50 | -2.47 | -0.47 | -0.15 | 0.06 | 1.67 | 4.12 |
| 3 Y | 5133 | -2.72 | -1.86 | -0.45 | -0.18 | 0.01 | 0.99 | 2.40 |
| 5 Y | 4064 | -2.82 | -1.30 | -0.36 | -0.14 | 0.02 | 0.62 | 5.80 |
| 7 Y | 2953 | -2.16 | -1.24 | -0.37 | -0.11 | 0.05 | 0.43 | 3.58 |
| 10 Y | 1639 | -2.18 | -1.22 | -0.36 | -0.10 | 0.04 | 0.28 | 2.78 |
| Panel B: Acquiring funds (post- M&A ) | | | | | | | | |
| 1 Y | 4428 | -5.09 | -2.51 | -0.38 | -0.06 | 0.21 | 1.91 | 4.68 |
| 2 Y | 3718 | -4.63 | -2.16 | -0.37 | -0.08 | 0.16 | 1.75 | 3.81 |
| 3 Y | 3962 | -2.23 | -1.49 | -0.27 | -0.04 | 0.18 | 1.08 | 1.93 |
| 5 Y | 2902 | -2.39 | -1.12 | -0.24 | -0.07 | 0.09 | 0.72 | 2.43 |
| 7 Y | 1863 | -1.58 | -1.01 | -0.18 | 0.00 | 0.16 | 0.79 | 2.39 |
| 10 Y | 892 | -1.08 | -0.92 | -0.13 | -0.01 | 0.10 | 0.31 | 1.70 |
| Panel C: Acquiring funds (pre- M&A) | | | | | | | | |
| 1 Y | 4308 | -5.16 | -2.53 | -0.29 | -0.02 | 0.26 | 2.01 | 5.28 |
| 2 Y | 4518 | -3.77 | -1.86 | -0.35 | -0.06 | 0.15 | 1.41 | 3.23 |
| 3 Y | 5151 | -2.31 | -1.53 | -0.31 | -0.09 | 0.07 | 1.10 | 1.99 |
| 5 Y | 4295 | -2.43 | -1.17 | -0.24 | -0.07 | 0.09 | 0.93 | 2.21 |
| 7 Y | 3364 | -1.93 | -1.04 | -0.24 | -0.03 | 0.10 | 0.58 | 1.32 |
| 10 Y | 2159 | -1.25 | -0.81 | -0.22 | -0.04 | 0.07 | 0.34 | 1.44 |

## Table 3.8. Median SDF alphas in each category for targets and post-merger bidders

The table shows the median SDF alphas over terms ranging from 1 to 10 years for the whole sample, as well as by subsample divided according to: the decade at which the deal occurred; within versus across-family M&As; M&A deal size; and by target investment style. All numbers are in percentages except for *p-values*.

| | 1Y | | | 2 Y | | | 3 Y | | | 5 Y | | | 7 Y | | | 10 Y | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | T | PostB | p-value | T | PostB | p-value | T | PostB | p-value | T | PostB | p-value | T | PostB | p-value | T | PostB | p-value |
| All sample | -0.11 | -0.06 | <0.01 | -0.15 | -0.08 | <0.01 | -0.18 | -0.04 | <0.01 | -0.14 | -0.07 | <0.01 | -0.11 | 0.01 | <0.01 | -0.10 | -0.01 | <0.01 |
| By the decade in which the M&A occurred | | | | | | | | | | | | | | | | | | |
| 1970s | -0.11 | -0.14 | 0.51 | -0.64 | 0.05 | 0.37 | -0.55 | 0.04 | 0.04 | -0.17 | -0.02 | 0.20 | -0.32 | 0.01 | 0.18 | -0.34 | -0.01 | 0.41 |
| 1980s | -0.16 | -0.03 | 0.98 | 0.06 | -0.13 | 0.06 | -0.13 | 0.05 | 0.36 | 0.01 | 0.00 | 0.73 | -0.14 | -0.04 | 1.00 | -0.20 | -0.36 | 0.58 |
| 1990s | -0.08 | -0.08 | 0.94 | -0.16 | -0.15 | 0.41 | -0.15 | -0.10 | <0.01 | -0.10 | -0.04 | <0.01 | -0.04 | -0.02 | <0.01 | -0.03 | -0.02 | 0.28 |
| 2000s | -0.10 | -0.04 | 0.01 | -0.15 | -0.05 | <0.01 | -0.20 | -0.01 | <0.01 | -0.15 | -0.03 | <0.01 | -0.12 | 0.08 | <0.01 | -0.11 | - | - |
| By within vs across family M&As | | | | | | | | | | | | | | | | | | |
| Within | -0.09 | -0.03 | <0.01 | -0.08 | -0.03 | <0.01 | -0.13 | 0.01 | <0.01 | -0.09 | 0.08 | <0.01 | -0.04 | 0.16 | <0.01 | -0.03 | - | - |
| Across | -0.08 | -0.05 | 0.49 | -0.18 | -0.01 | <0.01 | -0.20 | 0.02 | <0.01 | -0.15 | -0.02 | <0.01 | -0.13 | 0.09 | <0.01 | -0.13 | - | - |
| By the size of the M&A deal | | | | | | | | | | | | | | | | | | |
| Bottom 10% | -0.07 | -0.06 | 0.76 | -0.17 | -0.18 | 0.98 | -0.31 | -0.10 | <0.01 | -0.27 | -0.08 | 0.01 | -0.25 | 0.12 | 0.01 | -0.18 | -0.23 | 1.00 |
| Bottom 30% | -0.09 | 0.00 | 0.30 | -0.17 | -0.13 | 0.28 | -0.30 | -0.08 | <0.01 | -0.27 | 0.00 | <0.01 | -0.29 | 0.10 | <0.01 | -0.17 | -0.06 | 0.41 |
| Top 30% | -0.05 | -0.07 | 0.30 | -0.19 | -0.09 | <0.01 | -0.32 | -0.04 | <0.01 | -0.28 | -0.05 | <0.01 | -0.34 | 0.01 | <0.01 | -0.55 | -0.04 | 0.02 |
| Top 10% | -0.03 | -0.07 | 0.23 | -0.17 | -0.09 | 0.10 | -0.37 | -0.04 | <0.01 | -0.28 | -0.04 | <0.01 | -0.45 | 0.00 | <0.01 | -0.31 | 0.06 | 0.33 |
| By target IS category | | | | | | | | | | | | | | | | | | |
| EQ | -0.21 | -0.13 | 0.03 | -0.29 | -0.16 | <0.01 | -0.32 | -0.15 | <0.01 | -0.29 | -0.17 | <0.01 | -0.35 | -0.23 | <0.01 | -0.40 | -0.29 | 0.01 |
| BD | 0.00 | -0.01 | 0.96 | -0.05 | -0.02 | 0.25 | -0.05 | 0.13 | <0.01 | 0.02 | 0.09 | <0.01 | 0.07 | 0.17 | <0.01 | 0.05 | 0.11 | 0.01 |
| MM | -0.07 | -0.01 | <0.01 | -0.07 | -0.02 | <0.01 | -0.06 | -0.02 | <0.01 | -0.06 | -0.02 | <0.01 | -0.05 | -0.02 | <0.01 | -0.05 | -0.03 | 0.03 |
| HY | -0.14 | -0.11 | 0.95 | -0.19 | -0.13 | 0.05 | -0.23 | -0.12 | <0.01 | -0.19 | -0.13 | <0.01 | -0.14 | -0.11 | 0.21 | -0.21 | -0.03 | <0.01 |
| CV | -0.29 | -0.21 | 0.48 | -0.12 | -0.15 | 0.51 | -0.32 | 0.14 | 0.21 | -0.26 | -0.08 | 0.18 | 0.01 | -0.17 | 0.44 | -0.12 | - | 1.00 |

## Table 3.9: Risk of the M&A participants

The table reports the descriptive statistics of the semi-variance of monthly returns for T (target) funds; Pre-B (pre-merger bidder) funds; and Post-B (post-merger bidder) funds. All numbers, in the Risk metric panel, are in percentages except for Skewness and Kurtosis of the semi-variances. "EQ" stands for Equity funds; "BD" stands for Bond funds; "MM" stands for Money market funds; "HY" stands for hybrid funds and "CV" stands for convertibles funds. The "Paired tests" panel reports paired tests of fund risk measures both between target and post-M&A bidders and between post- and pre-M&A bidders. The second panel shows t- or z-statistics depending on the normality or not of the corresponding series distributions. $^{*}$, $^{**}$ and $^{***}$ signify statistical significance based on the p-values at the 0.10, 0.05 and 0.01 levels, respectively.

| | Median (%) | | | Standard Deviation (%) | | | Skewness | | | Kurtosis | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Semi-variance of monthly returns** | | | | | | | | | | | | |
| Fund type | T | Pre- B | Post- B | T | Pre- B | Post- B | T | Pre-B | Post-B | T | Pre-B | Post-B |
| All | 0.12 | 0.10 | 0.21 | 0.56 | 0.38 | 0.53 | 6.95 | 7.16 | 4.34 | 95.47 | 92.97 | 40.11 |
| EQ | 0.28 | 0.23 | 0.43 | 0.69 | 0.45 | 0.57 | 5.90 | 6.51 | 3.93 | 68.32 | 73.97 | 35.01 |
| BD | 0.01 | 0.01 | 0.02 | 0.04 | 0.05 | 0.31 | 8.75 | 10.71 | 16.08 | 108.99 | 156.06 | 294.11 |
| MM | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.02 | 1.54 | 17.20 | 15.98 | 5.17 | 318.21 | 278.80 |
| HY | 0.07 | 0.07 | 0.19 | 0.14 | 0.15 | 0.30 | 12.88 | 10.00 | 3.18 | 216.32 | 147.79 | 22.05 |
| CV | 0.08 | 0.05 | 0.24 | 0.32 | 1.10 | 0.38 | 3.71 | 1.80 | 1.31 | 17.39 | 4.42 | 3.74 |

**Paired tests: Comparison tests between SDF alphas**

| z | All | EQ | BD | MM | HY | CV | 60s | 70s | 80s | 90s | 00s |
|---|---|---|---|---|---|---|---|---|---|---|---|
| T/Post-B | -12.32$^{***}$ | -18.96$^{***}$ | -11.64$^{***}$ | 8.29$^{***}$ | -15.15$^{***}$ | -2.53$^{***}$ | 0.11 | 1.33 | 0.97 | -2.70$^{***}$ | -13.15$^{***}$ |
| Pre-B/Post-B | -16.76$^{***}$ | -28.66$^{***}$ | 9.91$^{***}$ | 14.15$^{***}$ | -13.38$^{***}$ | -2.32$^{**}$ | 0.33 | -0.55 | -0.94 | -2.86$^{***}$ | -19.26$^{***}$ |

## Table 3.10: Descriptive statistics for the independent variables

The table reports the descriptive statistics for the independent variables, which are the pre-selected candidate indicators of mutual fund M&A success. $Age_T$ stands for target age (in years); $Age_B$ stands for bidder fund age at the deal date (in years); $Flow_T$ is the average net asset flow of target funds one year prior to the M&A deal; $MER_B$ stands for average expense ratio of acquiring funds post-M&A, $MER_T$ is the average expense ratio of the target prior to the M&A; $\sigma_B$ stands for the risk of the post-M&A bidder; $\sigma_P$ stands for risk of the pre-M&A bidder; $\sigma_T$ stands for the risk of the target; $Size_B$ stands for asset size of the acquiring fund, and $Size_T$ stands for the asset size of the target at the M&A deal date.

| | $Age_T$ | $Age_B$ | $Flow_T$ | $MER_B$ | $MER_T$ | $\sigma_B$ | $\sigma_P$ | $\sigma_T$ | $Size_B$ | $Size_T$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Observations | 6680 | 6626 | 4607 | 6273 | 6464 | 6680 | 6626 | 6680 | 4622 | 4621 |
| Mean | 7.50 | 8.86 | -0.94 | 1.31 | 1.45 | 4.68 | 3.48 | 3.91 | 378.59 | 43.98 |
| Median | 6.25 | 7.08 | -0.09 | 1.24 | 1.41 | 4.58 | 3.13 | 3.45 | 73.90 | 8.03 |
| Maximum | 47.25 | 47.08 | 28.67 | 3.82 | 7.51 | 28.57 | 28.83 | 38.00 | 28679.40 | 3383.10 |
| Minimum | 0.08 | 0.08 | -237.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 |
| Std. Dev. | 5.77 | 7.52 | 5.94 | 0.59 | 0.69 | 3.78 | 2.88 | 3.48 | 1160.90 | 145.08 |
| Skewness | 2.18 | 1.92 | -21.73 | 0.40 | 0.49 | 0.88 | 1.62 | 1.84 | 10.03 | 11.30 |
| Kurtosis | 10.99 | 7.93 | 689.04 | 2.55 | 4.09 | 4.28 | 8.54 | 9.07 | 156.79 | 193.03 |

## Table 3.11. Determinants of successful fund M&As

The table reports the outcome of logistic regressions where dependent variable is the probability of M&A success. The independent variables are: $Age_T$ stands for target age (in years); $Age_P$ stands for bidder fund age at the M&A deal date (in years); $SIZE_B$ stands for asset size of the acquiring fund at the M&A deal date; $Size_T$ stands for the asset size of the target at the M&A deal date; $MER_B$ stands for the average expense ratio of the acquiring fund post-M&A; $MER_T$ stands for the average expense ratio of the target pre -M&A ; $\sigma_B$ stands for the risk of the post- M&A bidder; $\sigma_P$ stands for the risk of the pre- M&A bidder; $\sigma_T$ stands for the risk of the target; $Alpha_T$ stands for the past performance of the target fund over its lifetime; $Flow_T$ is the average net asset flow of the target for the one year (or the corresponding term over which abnormal performance is estimated) prior to the M&A deal; $IS_T$ stands for the investment style of the target; and *Market* stands for the state of the market at the time of the M&A deal conclusion. *Family* stands for the nature of the merger&A: 1 if within-family and zero otherwise. $^{*}$, $^{**}$ and $^{***}$ signify statistical significance based on the p-values at the 0.10, 0.05 and 0.01 levels, respectively.

| Independent Variables | Lifetime | 1-year | 2-year | 3-year | 5-year | 7-year |
|---|---|---|---|---|---|---|
| *C* | 0.51$^{***}$ | 0.14 | -0.72$^{***}$ | -0.76$^{**}$ | -0.72 | -4.92$^{***}$ |
| $Age_T$ | 0.01 | 0.02$^{**}$ | 0.04$^{***}$ | 0.04$^{*}$ | 0.05 | 0.19 |
| $Age_P$ | -0.01 | 0.00 | 0.00 | 0.01 | -0.02 | 0.11 |
| $Alpha_T$ | 0.23$^{***}$ | 0.94$^{***}$ | 0.58$^{***}$ | 0.47$^{***}$ | -0.01 | 1.44$^{**}$ |
| $Flow_T$ | -0.01 | -0.01 | 0.00 | -0.01 | 0.00 | 1.52* |
| $IS_T$ | -0.23$^{***}$ | -0.12$^{**}$ | -0.14$^{**}$ | -0.18$^{**}$ | -0.02 | -0.77 |
| $Risk_T$ | -0.04$^{**}$ | 0.15$^{***}$ | 0.03 | 0.02 | 0.44$^{**}$ | 0.85 |
| $Risk_B$ | -0.07$^{***}$ | -0.86$^{***}$ | -0.58$^{***}$ | -0.94$^{***}$ | -0.31 | 1.07 |
| $Risk_P$ | -0.05$^{*}$ | 0.24$^{***}$ | 0.25$^{***}$ | 0.36$^{***}$ | -0.03 | -0.19 |
| $MER_T$ | 33.89$^{***}$ | 30.75$^{***}$ | 41.52$^{***}$ | 20.22 | 35.28 | 75.83 |
| $MER_B$ | -33.87$^{***}$ | -26.69$^{*}$ | -37.42$^{**}$ | 13.89 | -47.15 | -73.47 |
| $SIZE_T$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | -0.01 |
| $SIZE_B$ | 0.00 | 0.00$^{*}$ | 0.00 | 0.00 | 0.00 | 0.00 |
| *Market* | 0.03 | -0.45$^{***}$ | 0.43$^{***}$ | 0.40$^{***}$ | 0.14 | -1.23 |
| *Family* | 0.05 | 0.23$^{***}$ | 0.06 | -0.22$^{*}$ | 0.14 | 0.42 |
| Probability(LR stat) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Sample adjusted | 6672 | 5559 | 3920 | 2310 | 746 | 218 |
| Included observations | 2929 | 2504 | 1713 | 986 | 320 | 95 |
| Number of failures | 1588 | 1347 | 949 | 549 | 170 | 49 |
| Number of successes | 1341 | 1157 | 764 | 437 | 150 | 46 |

**Table 3.12. Determinants of successful fund M&As for the seven-year subsample**

This table reports summary results for the logistic regressions when the dependent variable is the probability of merger success based on objective-adjusted returns post-M&A. The independent variables are: $Age_T$ stands for target age (in years); $Age_P$ stands for bidder fund age at the M&A deal date (in years); $SIZE_B$ stands for asset size of the acquiring fund at the M&A deal date; $Size_T$ stands for the asset size of the target at the M&A deal date; $MER_B$ stands for the average expense ratio of the acquiring fund post-M&A; $MER_T$ stands for the average expense ratio of the target pre -M&A ; $\sigma_B$ stands for the risk of the post- M&A bidder; $\sigma_P$ stands for the risk of the pre- M&A bidder; $\sigma_T$ stands for the risk of the target; $Alpha_T$ stands for the past performance of the target fund over its lifetime; $Flow_T$ is the average net asset flow of the target for the one year (or the corresponding term over which abnormal performance is estimated) prior to the M&A deal; $IS_T$ stands for the investment style of the target; and *Market* stands for the state of the market at the time of the M&A deal conclusion. *Family* stands for the nature of the merger: 1 if within-family and zero otherwise. $^{*}$, $^{**}$ and $^{***}$ signify statistical significance based on the p-values at the 0.10, 0.05 and 0.01 levels, respectively.

| Independent Variables | Lifetime | 1-year | 2-years | 3-years | 5-years | 7-years |
|---|---|---|---|---|---|---|
| C | -3.08 | -1.60 | -3.79$^{*}$ | -10.49$^{***}$ | -8.24$^{**}$ | -4.92$^{***}$ |
| $Age_T$ | -0.12 | 0.23 | 0.19 | 0.30 | 0.32 | 0.19 |
| $Age_P$ | 0.35$^{***}$ | 0.09 | 0.05 | 0.15 | 0.18 | 0.11 |
| $Alpha_T$ | 0.74 | 1.23$^{**}$ | -0.38 | 0.60 | -0.80 | 1.44$^{**}$ |
| $Flow_T$ | 0.16 | 0.15 | -0.51 | 1.36$^{***}$ | 1.76$^{***}$ | 1.52$^{*}$ |
| $IS_T$ | -1.15 | -1.58 | -1.21$^{**}$ | -1.22$^{**}$ | -2.22$^{***}$ | -0.77 |
| $Risk_T$ | 3.23$^{***}$ | 0.83$^{*}$ | 1.23 | 2.04$^{*}$ | 0.40 | 0.85 |
| $Risk_B$ | -2.95$^{**}$ | -4.26$^{***}$ | -0.66 | -1.97$^{*}$ | -2.29$^{**}$ | 1.07 |
| $Risk_P$ | -1.94 | 0.48 | -0.58 | -0.99 | 1.97$^{***}$ | -0.19 |
| $MER_T$ | 320.71$^{**}$ | 352.29$^{**}$ | 220.08$^{*}$ | 525.98$^{***}$ | -45.40 | 75.83 |
| $MER_B$ | -216.29$^{*}$ | -150.06 | -68.75 | -161.62 | 268.94 | -73.47 |
| $SIZE_T$ | 0.00 | 0.01 | 0.00 | 0.00 | -0.02$^{***}$ | -0.01 |
| $SIZE_B$ | 0.00$^{**}$ | 0.00$^{**}$ | 0.00$^{**}$ | 0.01$^{***}$ | 0.01$^{***}$ | 0.00 |
| *Market* | 0.20 | -1.12 | 0.45 | 1.35$^{*}$ | 1.47 | -1.23 |
| *Family* | 1.34$^{**}$ | 1.85$^{***}$ | 0.32 | 2.00$^{***}$ | 0.86 | 0.42 |
| Probability(LR stat) | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 |
| Sample adjusted | 218 | 218 | 218 | 218 | 218 | 218 |
| Included observations | 102 | 102 | 102 | 102 | 102 | 95 |
| Number of failures | 49 | 40 | 61 | 64 | 63 | 49 |
| Number of successes | 53 | 62 | 41 | 38 | 39 | 46 |

## Table 3.13. Determinants of success using an alternative dependent variable

The table reports the outcome of logistic regressions where dependent variable is the probability of merger success based on the SDF alphas post-M&A. The independent variables are: $Age_T$ stands for target age (in years); $Age_P$ stands for bidder fund age at the M&A deal date (in years); $SIZE_B$ stands for asset size of the acquiring fund at the M&A deal date; $Size_T$ stands for the asset size of the target at the M&A deal date; $MER_B$ stands for the average expense ratio of the acquiring fund post-M&A; $MER_T$ stands for the average expense ratio of the target pre -M&A ; $\sigma_B$ stands for the risk of the post- M&A bidder; $\sigma_P$ stands for the risk of the pre- M&A bidder; $\sigma_T$ stands for the risk of the target; $Alpha_T$ stands for the past performance of the target fund over its lifetime; $Flow_T$ is the average net asset flow of the target for the one year (or the corresponding term over which abnormal performance is estimated) prior to the M&A deal; $IS_T$ stands for the investment style of the target; and *Market* stands for the state of the market at the time of the M&A deal conclusion. *Family* stands for the nature of the merger&A: 1 if within-family and zero otherwise. $^{*}$, $^{**}$ and $^{***}$ signify statistical significance based on the p-values at the 0.10, 0.05 and 0.01 levels, respectively.

| Independent Variables | Lifetime | 1-year | 2-years | 3-years | 5-years | 7-years |
|---|---|---|---|---|---|---|
| *C* | -1.75 | -0.11 | -4.80* | 11.485*** | -1.46 | 2.17 |
| $Age_T$ | 0.53 | 0.25 | 0.02 | -0.14* | 0.48** | -0.05 |
| $Age_P$ | 0.23* | 0.02 | 0.03 | -0.12 | 0.07 | -0.06 |
| $Alpha_T$ | 0.56 | -0.92* | 3.66*** | 4.50* | -0.89 | 1.12 |
| $Flow_T$ | 1.32* | -0.16 | -1.72** | -0.04 | 1.52** | 0.02 |
| $IS_T$ | -2.91* | -1.13** | -0.57 | -5.01*** | -3.81** | -0.62* |
| $Risk_T$ | 1.38 | 0.48* | 2.89*** | -1.35** | -1.17 | -0.34 |
| $Risk_B$ | -2.91*** | -1.31*** | -0.47 | -0.08 | -1.80** | -0.05 |
| $Risk_P$ | 1.77 | 0.62* | -3.24*** | -1.14* | 2.11 | -0.02 |
| $MER_T$ | 35.08 | 266.32 | -45.28 | -550.35*** | -38.72 | -214.43** |
| $MER_B$ | 1.04 | -197.13 | 398.02*** | 651.34*** | 246.73 | 272.19** |
| $SIZE_T$ | 0.00 | 0.01 | -0.01* | -0.01 | -0.01 | 0.00 |
| $SIZE_B$ | 0.00* | 0.00 | 0.00 | 0.00 | 0.01*** | 0.00 |
| *Market* | -0.01 | -0.37 | 1.01 | 2.48* | 0.18 | 1.76*** |
| *Family* | 2.42*** | -0.24 | 2.71*** | -† | 1.51 | -‡ |
| Probability(LR stat) | 0 | 0.00 | 0.00 | 0.00 | 0.00 | 0 |
| Sample adjusted | 218 | 218 | 218 | 218 | 218 | 218 |
| Included observations | 102 | 102 | 102 | 125 | 102 | 114 |
| Number of failures | 17 | 39 | 31 | 30 | 31 | 28 |
| Number of successes | 85 | 63 | 71 | 95 | 71 | 86 |

† When the dummy variable *Family* is included in the regression, the triangular matrix is too small, making the estimation of the coefficients inaccurate.

‡ When the dummy variable *Family* is included, it (quasi) perfectly predicts binary response success if it takes a value of 1 (within-family M&A).

## Table 4.1. Summary statistics for the monthly returns and net fund flows for the sample of U.S. equity mutual funds

The table reports the 1st, 5th, 50th, 95th and 99th percentiles of monthly returns and net fund flows, and the standard deviation, skewness and kurtosis of each distribution. All returns statistics are in percentages, and fund flows are in millions of U.S. dollars. The pre- and post-event statistics are calculated over the same number of months as the corresponding event for the sake of comparability. Peer-adjusted variables refer to fund returns or fund flows minus the corresponding returns or fund flows for a size-weighted portfolio of the funds with the same investment objective. "Early 2000 Recession" stands for the economic recession starting March 2001 and ending November 2001. "Great Recession" stands for the economic recession starting December 2007 and ending in June 2009. All the p-values for Jarque-Bera tests for the normality of the return and fund-flow series are close to zero (<0.001).

| | | 1% | 5% | 50% | 95% | 99% | Std Dev | Skew | Kurtosis |
|---|---|---|---|---|---|---|---|---|---|
| **Absolute Monthly returns** | Pre-Early 2000 Recession | -9.36 | -4.67 | -0.78 | 2.33 | 3.31 | 2.37 | -1.34 | 8.36 |
| | Pre-Great Recession | -2.26 | -0.63 | 0.66 | 1.55 | 2.25 | 0.74 | -1.64 | 11.11 |
| | During-Early 2000 Recession | -3.24 | -2.21 | -0.66 | 0.94 | 1.71 | 1.01 | -0.76 | 9.58 |
| | During-Great Recession | -5.08 | -3.32 | -2.00 | -1.22 | -0.62 | 0.73 | -1.63 | 10.54 |
| | Post-Early 2000 Recession | -5.67 | -3.98 | -1.98 | 0.31 | 1.88 | 1.44 | 0.36 | 7.53 |
| | Post-Great Recession | 0.44 | 0.86 | 2.01 | 4.85 | 6.83 | 1.37 | 1.13 | 6.84 |
| **Absolute Monthly Fund Flows** | Pre-Early 2000 Recession | -188.71 | -34.09 | -0.04 | 16.68 | 57.14 | 42.18 | -7.67 | 91.49 |
| | Pre-Great Recession | -179.97 | -43.49 | -0.24 | 20.99 | 112.86 | 47.03 | -6.60 | 99.53 |
| | During-Early 2000 Recession | -10.43 | -1.19 | 0.95 | 47.91 | 177.25 | 35.30 | 6.64 | 62.46 |
| | During-Great Recession | -115.83 | -33.97 | -0.21 | 30.83 | 151.24 | 44.34 | 3.56 | 81.15 |
| | Post-Early 2000 Recession | -184.64 | -42.08 | -0.31 | 10.80 | 62.07 | 41.07 | -6.39 | 83.12 |
| | Post-Great Recession | -221.88 | -84.70 | -1.78 | 13.05 | 54.89 | 44.50 | -2.92 | 32.38 |
| **Peer-adjusted Monthly Returns** | Pre-Early 2000 Recession | -4.27 | -2.32 | 0.03 | 2.53 | 4.16 | 1.54 | -0.22 | 7.70 |
| | Pre-Great Recession | -1.86 | -0.80 | -0.02 | 0.66 | 1.42 | 0.51 | -0.85 | 9.21 |
| | During-Early 2000 Recession | -2.41 | -1.29 | -0.01 | 1.28 | 2.17 | 0.83 | -0.93 | 10.55 |
| | During-Great Recession | -1.86 | -0.88 | -0.02 | 0.68 | 1.15 | 0.57 | -2.29 | 21.65 |
| | Post-Early 2000 Recession | -3.64 | -2.14 | -0.14 | 1.43 | 2.21 | 1.09 | -0.79 | 9.06 |
| | Post-Great Recession | -1.50 | -0.79 | -0.07 | 0.75 | 1.46 | 0.54 | 0.51 | 17.56 |
| **Peer-adjusted Monthly Fund Flows** | Pre-Early 2000 Recession | -71.73 | -9.53 | 82.89 | 281.98 | 1940.00 | 263.69 | 6.96 | 61.10 |
| | Pre-Great Recession | -104.67 | -4.14 | 61.64 | 232.46 | 438.77 | 152.30 | 8.42 | 117.68 |
| | During-Early 2000 Recession | -167.08 | -166.60 | -74.90 | -8.88 | 82.09 | 55.18 | 0.97 | 8.50 |
| | During-Great Recession | -413.13 | -389.36 | 2.37 | 96.71 | 193.56 | 138.29 | -1.56 | 5.79 |
| | Post-Early 2000 Recession | -148.35 | -84.59 | 50.71 | 219.85 | 407.07 | 118.65 | 1.72 | 13.27 |
| | Post-Great Recession | -1053.47 | -1037.57 | 4.93 | 157.05 | 210.74 | 339.40 | -1.81 | 5.29 |

**Table 4.2. Non- and parametric correlation measures between within-recessionary period returns and post-recessionary period fund flows**

| | Early 2000 Recession | | | | | | Great Recession | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Pearson | *p* | Spearman | *p* | Kendall | *p* | Pearson | *p* | Spearman | *p* | Kendall | *p* |
| Absolute Variables | | | | | | | | | | | | |
| All | 0.09 | 0.00 | 0.22 | 0.00 | 0.14 | 0.00 | 0.01 | 0.81 | 0.06 | 0.03 | 0.04 | 0.04 |
| Small-Growth | 0.12 | 0.05 | 0.19 | 0.00 | 0.12 | 0.00 | -0.09 | 0.26 | -0.13 | 0.11 | -0.09 | 0.08 |
| Small-Core | 0.02 | 0.74 | 0.09 | 0.14 | 0.06 | 0.00 | -0.07 | 0.33 | -0.16 | 0.03 | -0.11 | 0.03 |
| Small-Value | 0.03 | 0.77 | 0.12 | 0.16 | 0.09 | 0.00 | -0.09 | 0.45 | 0.02 | 0.84 | 0.01 | 0.88 |
| Mid-Growth | 0.18 | 0.00 | 0.24 | 0.00 | 0.16 | 0.00 | 0.05 | 0.60 | 0.12 | 0.20 | 0.08 | 0.23 |
| Mid-Core | -0.05 | 0.50 | 0.19 | 0.02 | 0.12 | 0.00 | -0.07 | 0.50 | 0.11 | 0.26 | 0.07 | 0.28 |
| Mid-Value | -0.13 | 0.25 | 0.13 | 0.25 | 0.09 | 0.00 | 0.36 | 0.01 | 0.38 | 0.00 | 0.28 | 0.00 |
| Large-Growth | 0.04 | 0.44 | 0.10 | 0.04 | 0.06 | 0.01 | 0.03 | 0.66 | 0.15 | 0.05 | 0.09 | 0.07 |
| Large-Core | -0.04 | 0.41 | 0.09 | 0.04 | 0.06 | 0.00 | -0.03 | 0.63 | -0.06 | 0.37 | -0.04 | 0.37 |
| Large-Value | 0.09 | 0.15 | 0.10 | 0.12 | 0.07 | 0.00 | -0.01 | 0.92 | -0.02 | 0.81 | -0.01 | 0.79 |
| Multi-Growth | 0.00 | 0.97 | 0.18 | 0.00 | 0.12 | 0.00 | 0.05 | 0.60 | 0.25 | 0.01 | 0.18 | 0.00 |
| Multi-Core | 0.08 | 0.28 | 0.13 | 0.07 | 0.09 | 0.00 | -0.02 | 0.84 | 0.04 | 0.71 | 0.02 | 0.71 |
| Multi-Value | 0.16 | 0.01 | 0.20 | 0.00 | 0.13 | 0.00 | 0.03 | 0.77 | 0.20 | 0.07 | 0.12 | 0.11 |
| Objective-Adjusted Variables | | | | | | | | | | | | |
| All | -0.12 | 0.00 | -0.05 | 0.01 | -0.03 | 0.01 | 0.04 | 0.11 | 0.11 | 0.00 | 0.07 | 0.00 |
| Small-Growth | -0.01 | 0.91 | -0.01 | 0.87 | 0.00 | 0.91 | -0.14 | 0.08 | -0.10 | 0.22 | -0.06 | 0.23 |
| Small-Core | -0.17 | 0.01 | -0.15 | 0.01 | -0.10 | 0.02 | -0.03 | 0.65 | -0.10 | 0.17 | -0.07 | 0.16 |
| Small-Value | -0.01 | 0.94 | -0.03 | 0.76 | -0.02 | 0.79 | -0.03 | 0.83 | 0.11 | 0.35 | 0.08 | 0.30 |
| Mid-Growth | -0.02 | 0.75 | -0.07 | 0.28 | -0.05 | 0.27 | 0.10 | 0.29 | 0.12 | 0.20 | 0.09 | 0.17 |
| Mid-Core | 0.00 | 1.00 | 0.04 | 0.59 | 0.03 | 0.57 | 0.06 | 0.55 | 0.12 | 0.21 | 0.08 | 0.24 |
| Mid-Value | 0.05 | 0.65 | 0.09 | 0.42 | 0.06 | 0.45 | -0.29 | 0.03 | -0.22 | 0.10 | -0.15 | 0.12 |
| Large-Growth | -0.10 | 0.03 | -0.16 | 0.00 | -0.11 | 0.00 | -0.35 | 0.00 | 0.03 | 0.64 | 0.03 | 0.59 |
| Large-Core | -0.04 | 0.37 | -0.10 | 0.03 | -0.06 | 0.03 | -0.18 | 0.01 | -0.05 | 0.44 | -0.04 | 0.41 |
| Large-Value | 0.00 | 0.99 | 0.02 | 0.80 | 0.01 | 0.82 | -0.13 | 0.11 | -0.10 | 0.23 | -0.06 | 0.26 |
| Multi-Growth | -0.37 | 0.00 | -0.21 | 0.00 | -0.13 | 0.00 | 0.32 | 0.00 | 0.25 | 0.01 | 0.18 | 0.01 |
| Multi-Core | -0.08 | 0.27 | 0.02 | 0.80 | 0.01 | 0.81 | -0.17 | 0.08 | 0.09 | 0.37 | 0.06 | 0.38 |
| Multi-Value | 0.14 | 0.02 | 0.16 | 0.01 | 0.11 | 0.01 | -0.11 | 0.34 | -0.02 | 0.88 | -0.02 | 0.77 |

### Table 4.3. Bootstrapped Gaussian copulas for during-recessionary period returns and post-recessionary period fund flows

In this table, '1% Left-tail' stands for the first percentile of the distribution of returns.

| | 1% Left-tail | 5% Left-tail | 10% Left-tail | 10% Right-tail | 5% Right-tail | 1% Right-tail |
|---|---|---|---|---|---|---|
| Absolute Variables | | | | | | |
| Early 2000 Recession (March 2001-Novembre 2001) | | | | | | |
| min | -0.30 | -0.14 | -0.10 | -0.13 | -0.08 | -0.72 |
| 1st Qrtl | -0.10 | -0.06 | -0.05 | -0.08 | -0.02 | -0.40 |
| median | 0.15 | 0.01 | 0.00 | -0.06 | 0.00 | -0.28 |
| 3rd Qrtl | 0.40 | 0.06 | 0.02 | -0.04 | 0.03 | -0.13 |
| max | 0.74 | 0.34 | 0.17 | 0.04 | 0.15 | 0.17 |
| Great Recession (December 2007-June 2009) | | | | | | |
| min | -0.49 | -0.09 | -0.15 | -0.21 | -0.24 | -0.61 |
| 1st Qrtl | 0.05 | -0.01 | -0.07 | 0.06 | 0.09 | -0.11 |
| median | 0.14 | 0.02 | -0.05 | 0.11 | 0.14 | 0.02 |
| 3rd Qrtl | 0.31 | 0.07 | -0.03 | 0.14 | 0.18 | 0.23 |
| max | 0.81 | 0.24 | 0.04 | 0.39 | 0.42 | 0.95 |
| Objective-adjusted Variables | | | | | | |
| Early 2000 Recession (March 2001-Novembre 2001) | | | | | | |
| min | -0.62 | -0.43 | -0.28 | -0.13 | -0.22 | -0.56 |
| 1st Qrtl | -0.28 | -0.23 | -0.14 | -0.05 | -0.08 | -0.11 |
| median | -0.16 | -0.17 | -0.09 | -0.02 | -0.05 | -0.02 |
| 3rd Qrtl | -0.09 | -0.11 | -0.05 | 0.00 | -0.02 | 0.05 |
| max | 0.26 | 0.14 | 0.08 | 0.10 | 0.09 | 0.37 |
| Great Recession (December 2007-June 2009) | | | | | | |
| min | -0.97 | -0.20 | -0.13 | -0.36 | -0.54 | -0.81 |
| 1st Qrtl | -0.61 | -0.11 | -0.06 | -0.13 | -0.28 | -0.38 |
| median | -0.01 | -0.08 | -0.03 | -0.08 | -0.21 | -0.23 |
| 3rd Qrtl | 0.10 | -0.03 | 0.00 | -0.03 | -0.13 | -0.07 |
| max | 0.79 | 0.18 | 0.17 | 0.11 | 0.07 | 0.31 |

**Table 4.4. Dependence between within-recessionary period fund returns and post-recessionary period fund flows**

This table is a recap of the signs (+ or -) of the relationship between the variables, if any, or independence (Ø), for the whole sample as well as fund categories, assessed at the 1% level of significance for the copulas and survival copulas analyses.

| | Early 2000 Recession | | Great Recession | |
|---|---|---|---|---|
| | Absolute variables | Objective-adjusted variables | Absolute variables | Objective-adjusted variables |
| COPULAS: 1% level | | | | |
| All | + | + | Ø | Ø |
| Small-Growth | + | + | - | - |
| Small-Core | + | + | - | - |
| Small-Value | Ø | Ø | Ø | Ø |
| Mid-Growth | + | + | - | Ø |
| Mid-Core | + | + | - | Ø |
| Mid-Value | + | Ø | Ø | - |
| Large-Growth | Ø | Ø | Ø | + |
| Large-Core | Ø | Ø | Ø | - |
| Large-Value | + | + | Ø | - |
| Multi-Growth | - | - | Ø | Ø |
| Multi-Core | + | + | Ø | + |
| Multi-Value | + | Ø | Ø | Ø |
| SURVIVAL COPULAS: 1% level | | | | |
| All | + | - | + | Ø |
| Small-Growth | + | + | + | + |
| Small-Core | + | + | + | Ø |
| Small-Value | - | - | Ø | Ø |
| Mid-Growth | + | Ø | + | Ø |
| Mid-Core | + | + | Ø | Ø |
| Mid-Value | Ø | Ø | Ø | - |
| Large-Growth | + | - | + | - |
| Large-Core | + | + | + | Ø |
| Large-Value | + | + | + | Ø |
| Multi-Growth | + | - | Ø | Ø |
| Multi-Core | + | + | Ø | - |
| Multi-Value | + | + | + | Ø |

## FIGURES

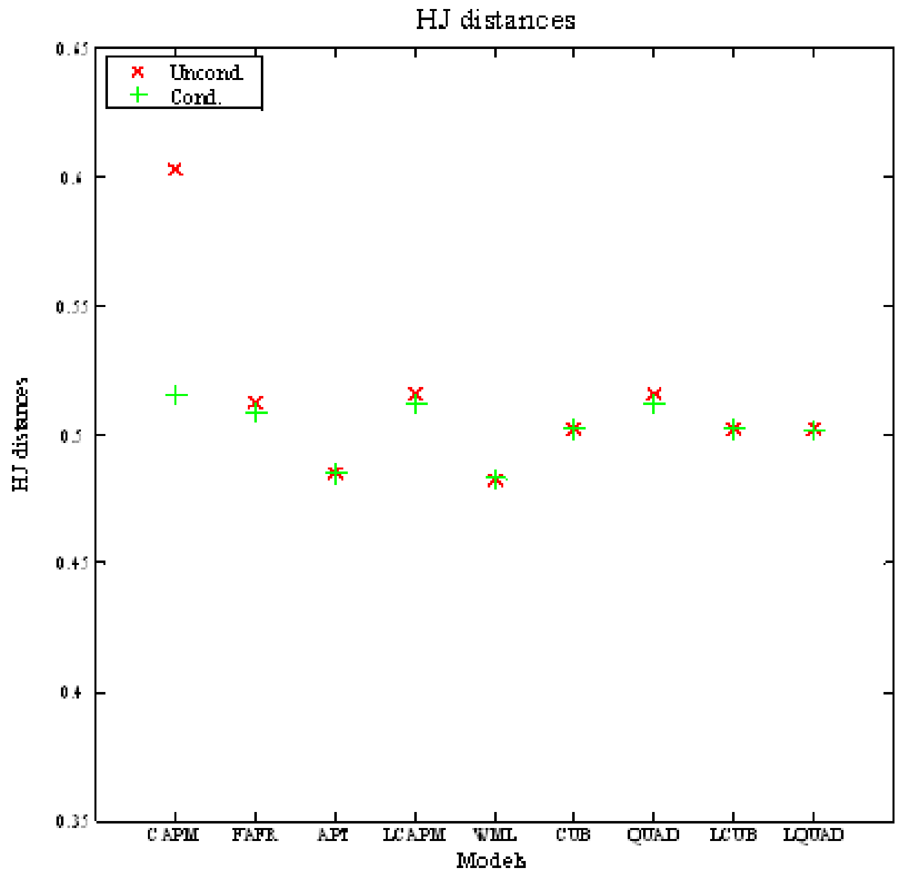



**Figure 2.1. Hansen-Jagannathan distances under (un)conditional setting**

Hansen-Jagannathan distances have been calculated as in Hansen-Jagannathan (1997). **Uncond** stands for Unconditional setting and **Cond** stands for conditional setting. CAPM stands for the single-factor linear pricing kernel. FAFR stands for the three-factor Fama-French model. APT stands for the arbitrage pricing theory-based model. LCAPM stands for the Jagannathan and Wang (1996) labor-CAPM. WML stands for the four-factor Carhart model. CUB stands for the non linear cokurtosis-based model as proposed by Dittmar (2002). QUAD stands for the non-linear coskewness-based model as proposed by Harvey and Siddique (2000). LCUB and LQUAD represent labor-cubic and labor-quadratic models respectively, as proposed by Fletcher and Forbes (2004).

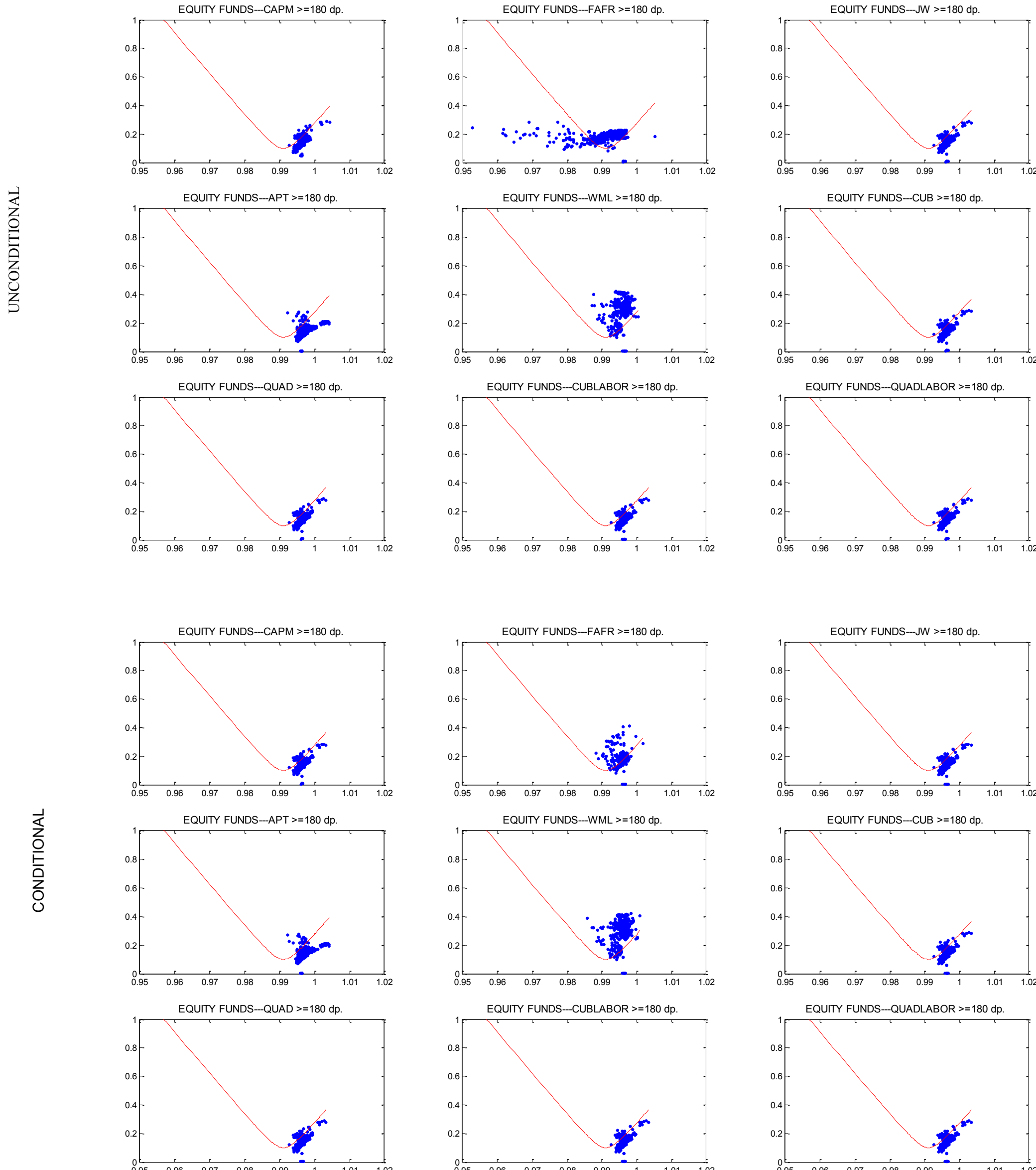



**Figure 2.2. Hansen-Jagannathan boundaries and empirical stochastic discount factors for the nine candidate models under (un)conditional settings**

The sample consists of equity funds that reported at least 180 monthly returns. CAPM stands for the single-factor linear pricing kernel. FAFR stands for the three-factor Fama-French model. APT stands for the arbitrage pricing theory-based model. JW stands for the Jagannathan and Wang (1996) labor-CAPM. WML stands for the four-factor Carhart model. CUB stands for the non linear cokurtosis-based model as proposed by Dittmar (2002). QUAD stands for the non-linear coskewness-based model as proposed by Harvey and Siddique (2000). CUBLABOR and QUADLABOR represent labor-cubic and labor-quadratic models respectively, as proposed by Fletcher and Forbes (2004).

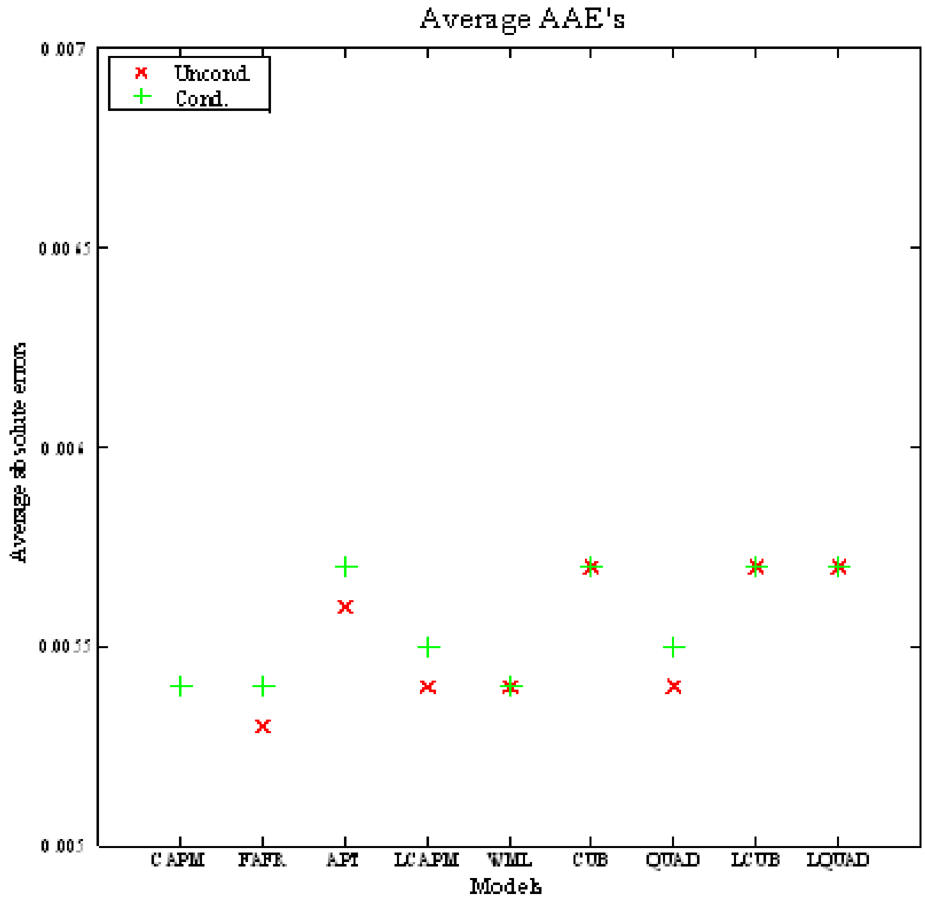



**Figure 2.3. Average absolute pricing errors**

Averge absolute pricing error is the second ranking criterion of the candidate models. The scatter plots represent the cross-section mean of the average absolute errors or AAEs for all equity and bond funds. **Uncond** stands for Unconditional setting and **Cond** stands for conditional setting. CAPM stands for the single-factor linear pricing kernel. FAFR stands for the three-factor Fama-French model. APT stands for the arbitrage pricing theory-based model. LCAPM stands for the Jagannathan and Wang (1996) labor-CAPM. WML stands for the four-factor Carhart model. CUB stands for the non linear cokurtosis-based model as proposed by Dittmar (2002). QUAD stands for the non-linear coskewness-based model as proposed by Harvey and Siddique (2000). LCUB and LQUAD represent labor-cubic and labor-quadratic models respectively, as proposed by Fletcher and Forbes (2004).

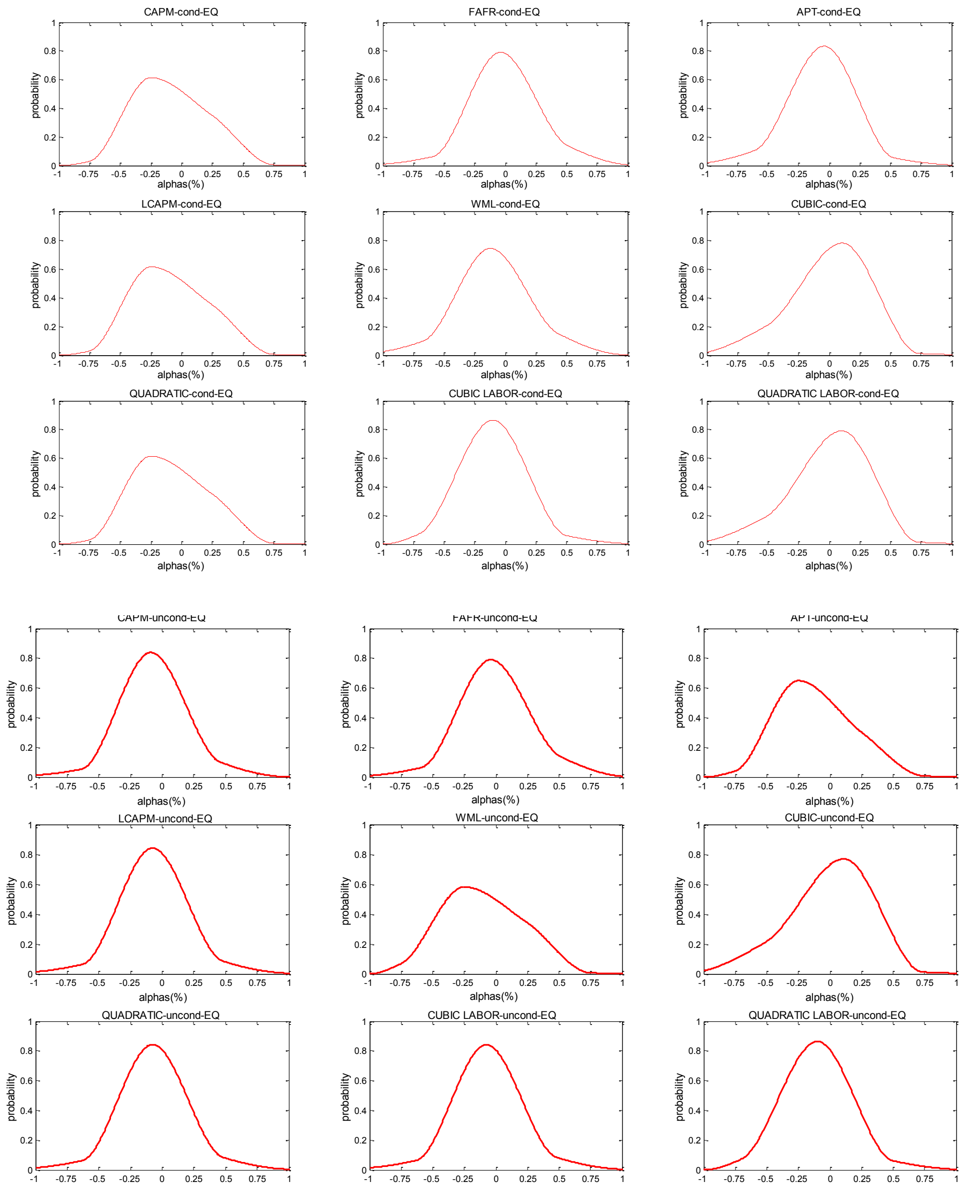



**Figure 2.4. Empirical density functions of the average abnormal performances for the nine candidate models for equity funds under the (un)conditional settings.**

The sample consists of equity funds that reported at least 180 monthly returns. CAPM stands for the single-factor linear pricing kernel. FAFR stands for the three-factor Fama-French model. APT stands for the arbitrage pricing theory-based model. LCAPM stands for the Jagannathan and Wang (1996) labor-CAPM. WML stands for the four-factor Carhart model. CUBIC stands for the non linear cokurtosis-based model as proposed by Dittmar (2002). QUADRATIC stands for the non-linear coskewness-based model as proposed by Harvey and Siddique (2000). CUBIC LABOR and QUADRATIC LABOR represent labor-cubic and labor-quadratic models respectively, as proposed by Fletcher and Forbes (2004).

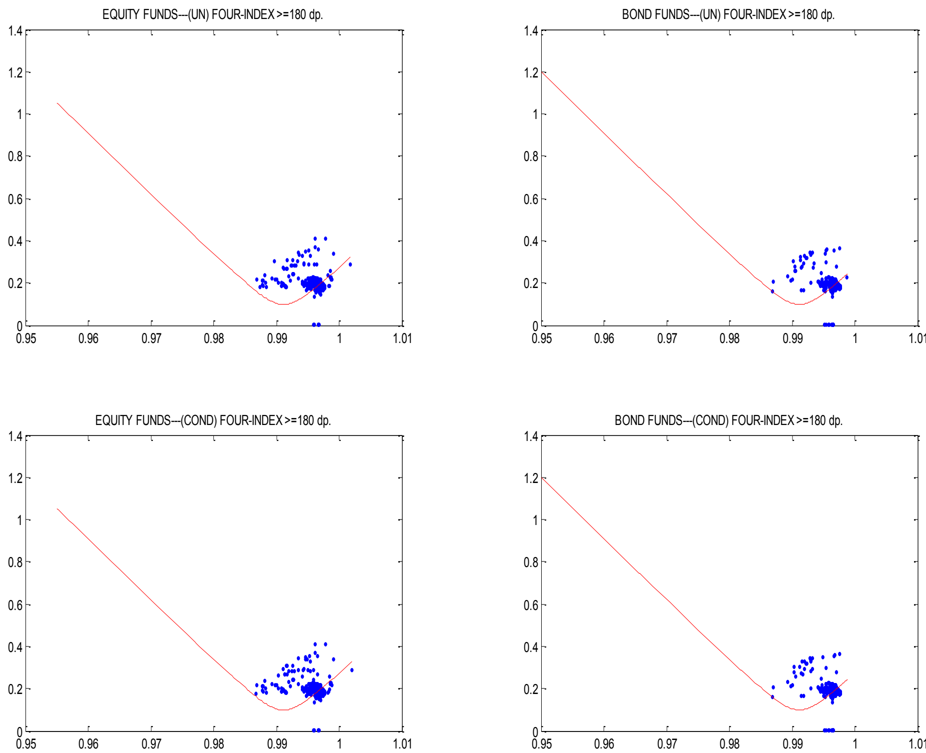



**Figure 2.5. Hansen-Jagannathan boundaries and empirical stochastic discount factors for bond funds for the four-index candidate model under (un)conditional settings.**

The samples consist of equity and bond funds that reported at least 180 monthly returns. FOUR-INDEX stands for the four-index model. The four factors in this model are: the stock market portfolio, the size portfolio, the value portfolio and the broad-based bond market portfolio. (UN) stands for unconditional version, whereas (COND) stands for conditional setting. The covered period spans about 30 years, from January 1976 to June 2006.

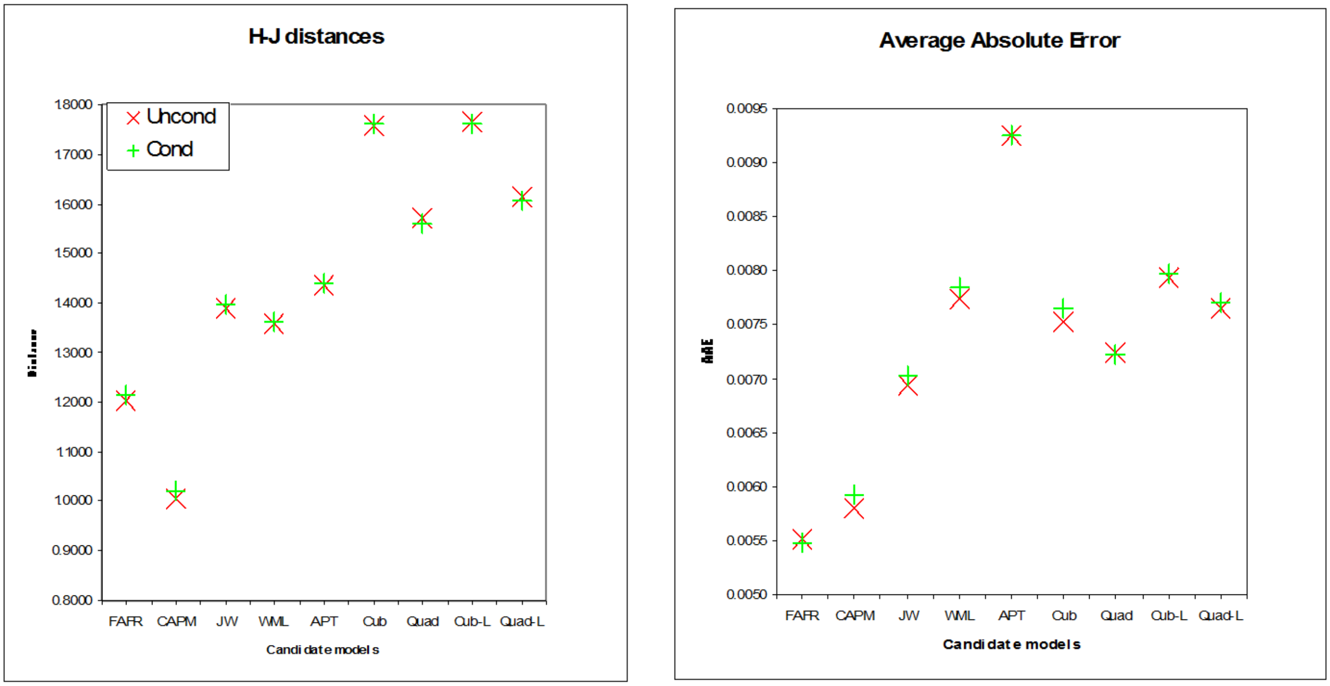



**Figure 2.6. Average Absolute Error and Hansen-Jagannathan distances for equity funds using an alternative Investment Opportunity set**

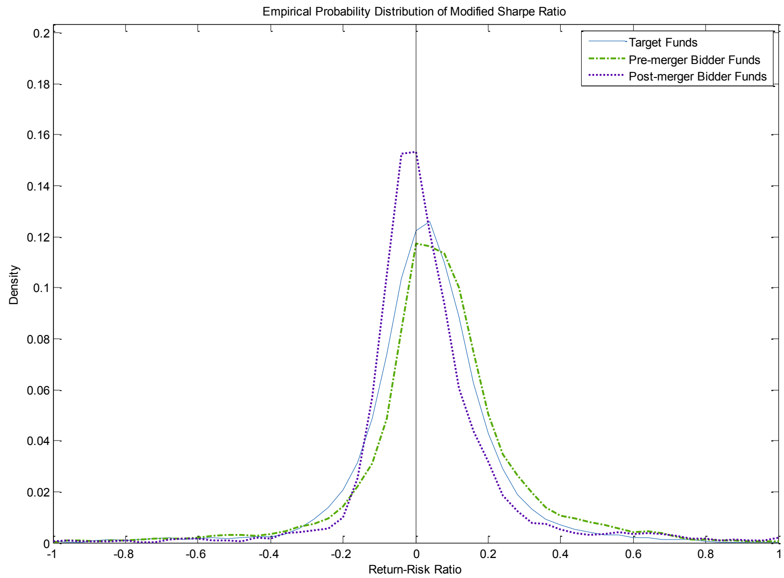



**Figure 3.1. Probability distribution of Sharpe-like ratios**

The figure represents the probability distribution of the ratios of SDF alphas over the lifetime of the funds and the square root of semi-variances of monthly returns for target, pre- and post-M&A bidders.

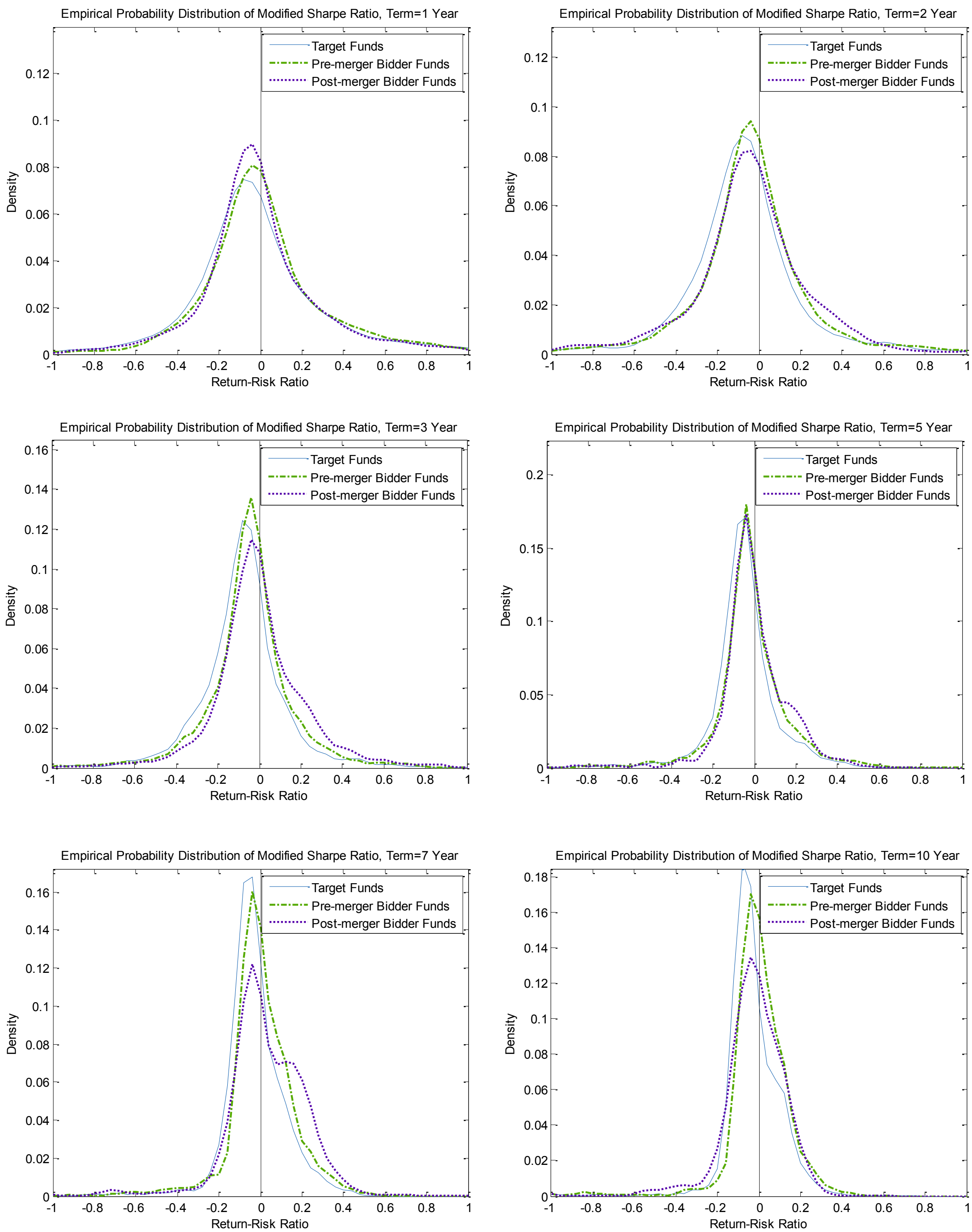



**Figure 3.2. Distributions of Sharpe-like ratios over various periods post-M&A**

Each figure represents the probability distribution of the ratios of SDF alphas and the square root of semi-variances of monthly returns for target, pre- and post-M&A bidders for terms from 1 year to 10 years.

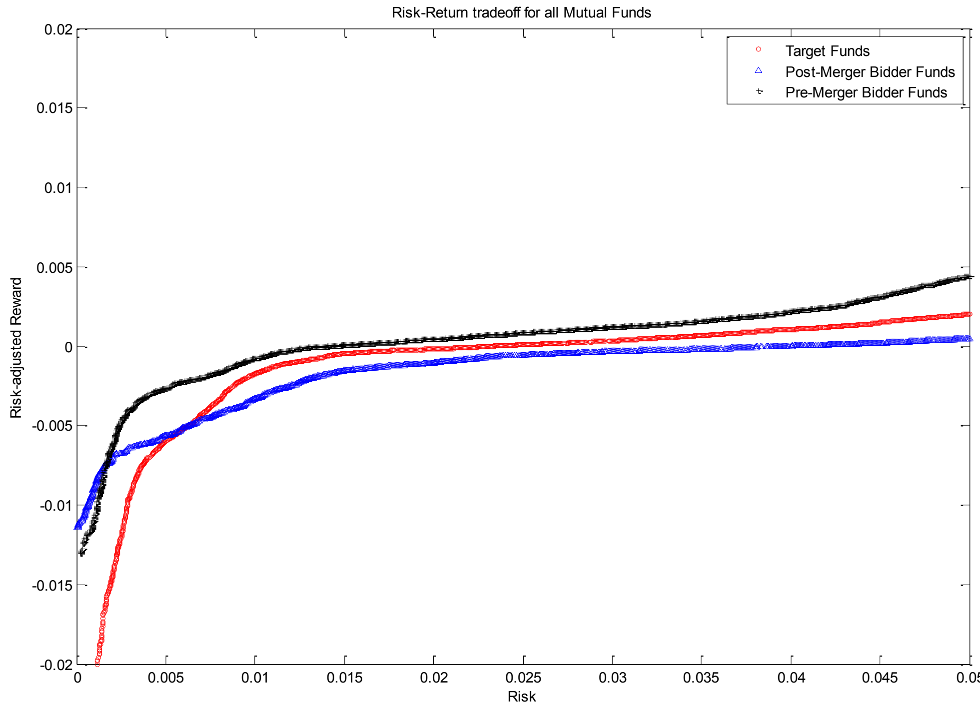



**Figure 3.3. Risk-Return tradeoffs based on second-order stochastic dominance**

The figure represents the portfolio frontiers formed by the targets, pre- and post-M&A bidder firms. The x-axis represents the square root of the semi-variances (risk) and the y-axis represents the SDF alphas (risk-adjusted reward). All SDF alphas are considered regardless of their statistical significance.

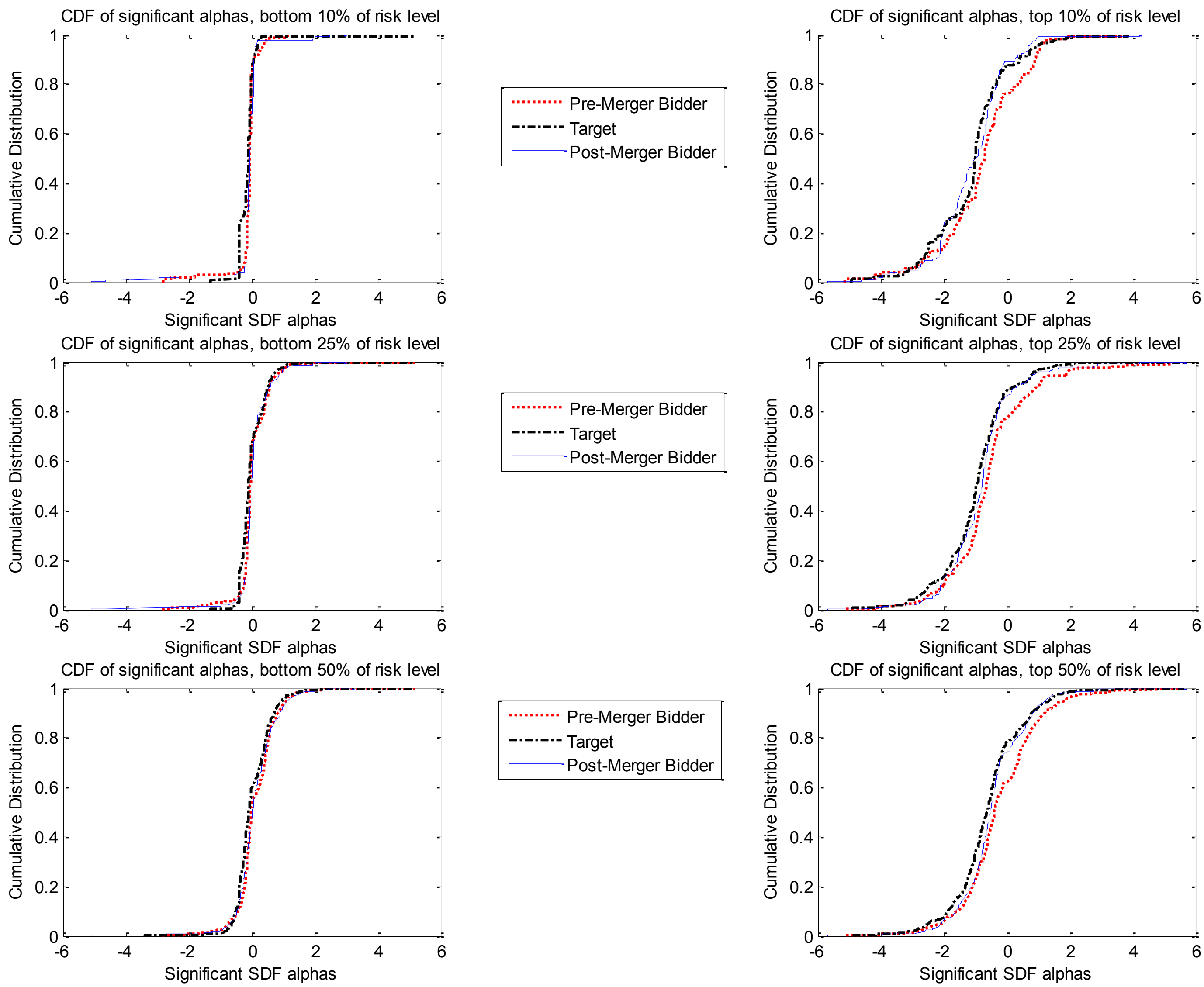



**Figure 3.4. Risk-return tradeoffs based on first-order stochastic dominance**

Each figure represents superposed cumulative distribution functions of significant alphas by levels of risk. Included in the bottom 10% are all cases of significant alphas for target and acquiring funds with levels of risks lower than the 10th percentile of the downside risk distribution.

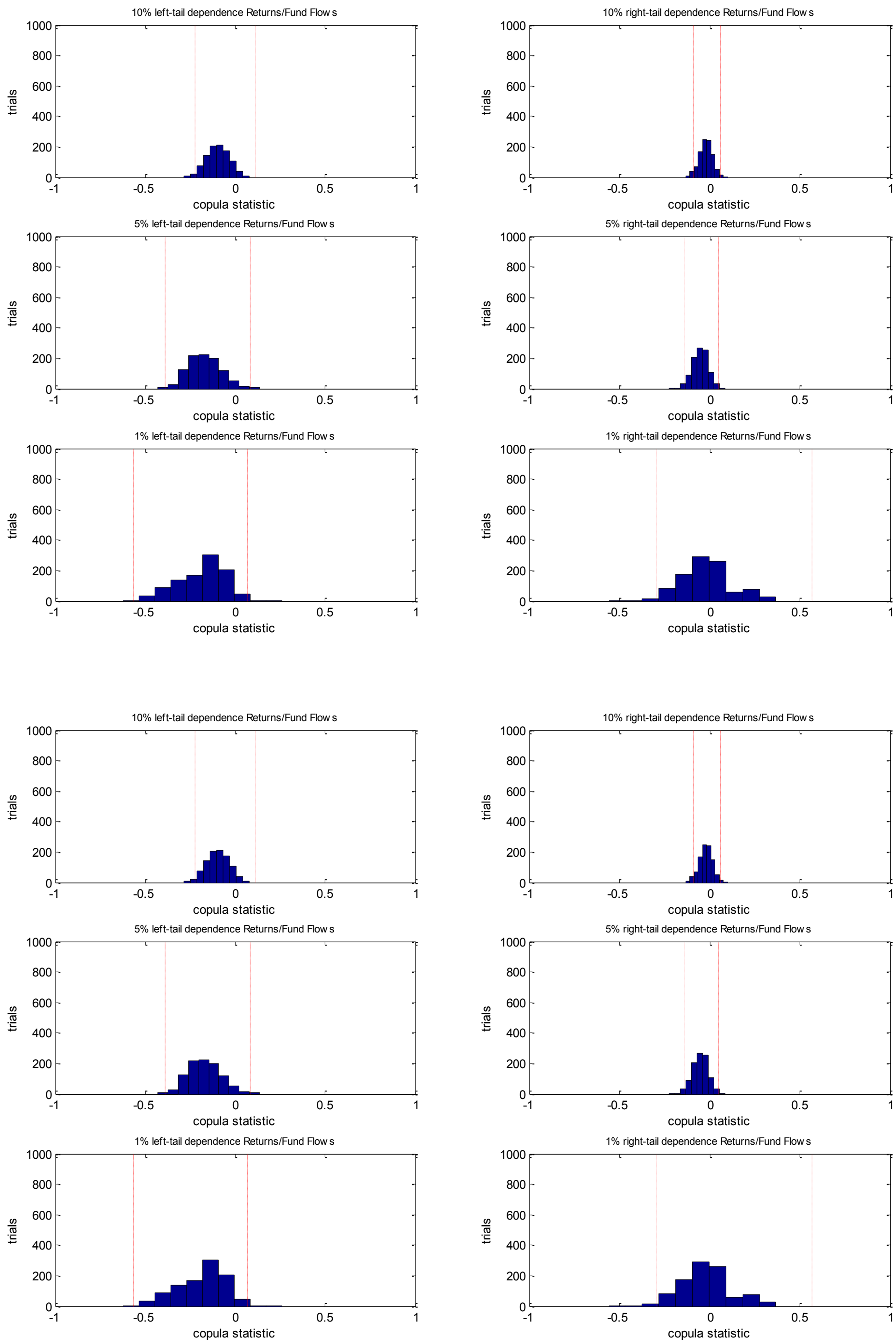



**Figure 4.1. The distribution of copulas around the Early 2000 Recession**

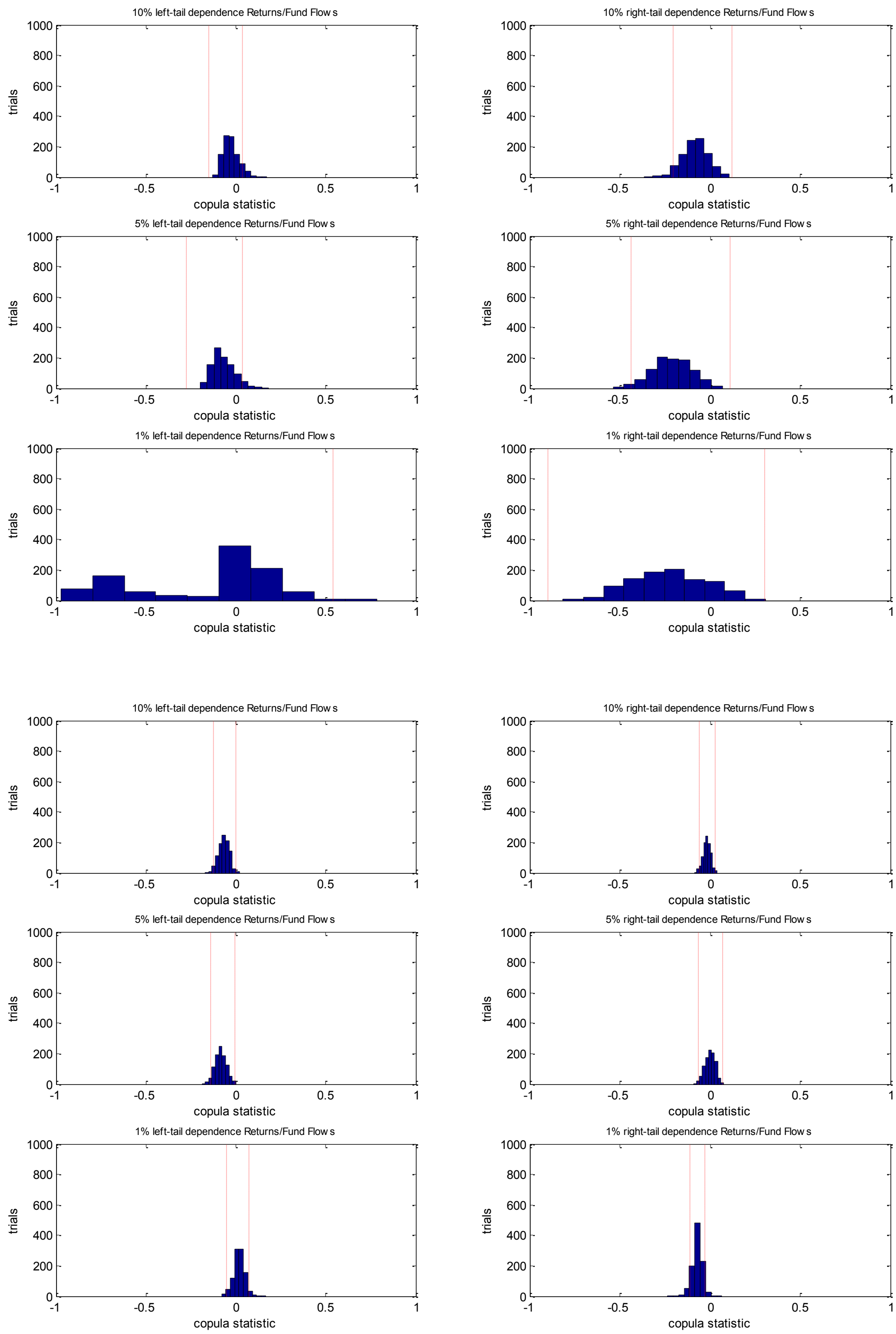
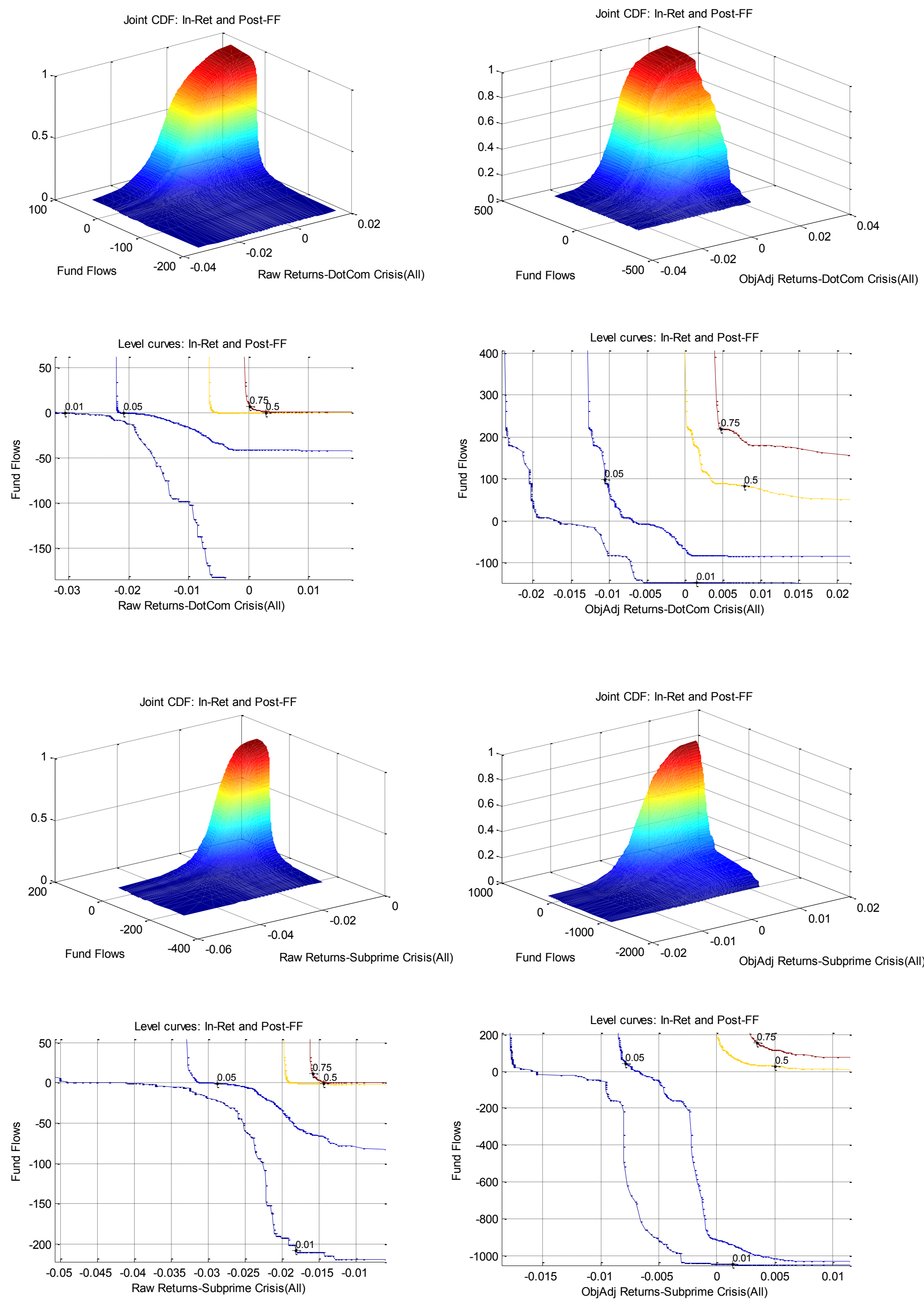
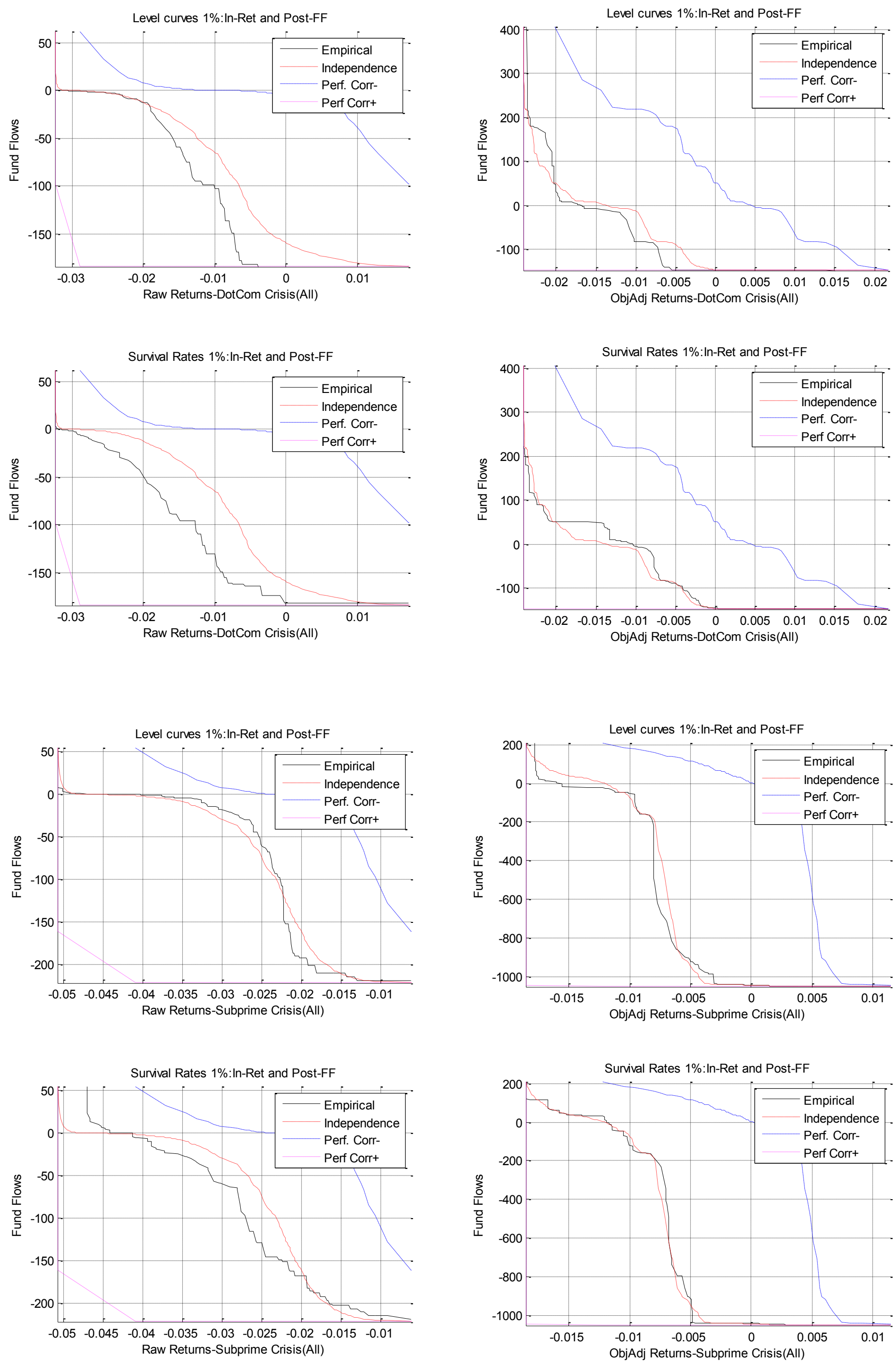



**Figure 4.2. The distribution of copulas around the Great Recession**




## Figure 4.3. Joint cumulative distribution functions

This set of figures shows the cumulative distribution functions of absolute and objective-adjusted monthly returns and fund flows around the Early 2000 Recession (Dot-Com Crisis) and Great Recession (Subprime Crisis) as well as the associated level curves at the 1%, 5%, 50% and 75% levels, for the whole sample of U.S. equity mutual funds. "In-Ret" refers to within-recessionary period returns and "Post-FF" refers to post-recessionary period fund flows.




# Figure 4.4. Level curves for the copulas and survival copulas

This set of figures shows level curves at 1% for copulas and survival copulas of absolute and objective-adjusted variables around the Early 2000 Recession (Dot-Com Crisis) and Great Recession (Subprime Crisis). Each quadrant shows Fréchet bounds as well as the empirical curves at the 1% level for the whole sample of U.S. equity mutual funds.