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Prior Performance and Risk-Taking of Mutual Fund Managers: A Dynamic Bayesian Network Approach

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We analyze the behavior of mutual fund managers with a special focus on the impact of prior performance. In contrast to previous studies, we do not focus solely on volatility as a risk measure, but also consider alternative definitions of risk and style. Using a dynamic Bayesian network, we are able to capture non-linear effects and to assign exact probabilities to the mutual fund managers' adjustment of behavior. In contrast to theoretical predictions and some existing studies, we find that prior performance has a positive impact on the choice of risk level, i.e., successful fund managers take on more risk in the following calendar year. In particular, they increase volatility, beta, and tracking error, and assign a higher proportion of their portfolio to value stocks, small firms, and momentum stocks. Overall, poor-performing fund managers switch to passive strategies.

Introduction

The behavior of mutual fund managers has been subject to considerable academic research. As rational agents, they are supposed to adjust their behavior in accordance with the incentives they face. We divide these incentives into two categories: the structure of their compensation schemes, and investor behavior.

Most compensation schemes are constructed like a call option, i.e., fund managers have a higher upside than downside potential. In a multiperiod context, a positive relationship between past performance and new fund flows has been observed. Thus a high-performing fund manager is rewarded with new capital, but a poor-performing manager does not suffer the same amount of cash outflows. If compensation is linked to fund size, this provides an incentive for managers to increase a portfolio's riskiness to a suboptimal point from an investor's perspective. In short, in so-called mutual fund tournaments, portfolio managers compete for better performance, greater fund inflows, and higher compensation.

Many authors have focused on the theoretical basis of agency conflicts in the mutual fund industry, i.e., on asymmetric information, hidden activity between mutual fund managers and their investors, and on the call option-like function of compensation schemes. Fund managers may unnecessarily shift a fund's risk in response to its relative performance. This behavior is linked to compensation and investor reactions.

Carpenter [2000] solves the dynamic investment problem of a risk-averse manager compensated using a call option on the assets he controls, i.e., a convex compensation scheme. She shows that under the manager's optimal policy, the option is likely to end up deep in or deep out of the money, because managers generally take on more risk than the investors would choose.

Berk and Green [2004] propose a model that incorporates two important points: Performance is not persistent, and fund flows respond rationally to past performance. In particular, they assume investors behave as Bayesians would, i.e., they update their beliefs about a fund manager's skill based on observed returns and prior beliefs. They show that a rational model for active portfolio management can explain many empirical observations without relying on investor irrationality and asymmetric information.

Similar models relying on Bayesian updating have also been proposed (see Schmidt [2003] and Dangl, Wu, and Zechner [2004]). Lynch and Musto [2003] focus on how fund managers change their strategy over time. In their model, strategy changes occur only after periods of poor performance.

From an empirical point of view, different authors have analyzed the actual behavior of mutual fund managers. Deli [2002] investigates marginal compensation rates in mutual fund advisory contracts. He finds that marginal compensation depends positively on turnover and fund type (e.g., equity, closed-end), and is negatively related to fund size and size of the fund family.

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Therefore, incentives to take risk may differ across fund managers.

Chevalier and Ellison [1997] estimate the shape of the relationship between performance and new fund flows because it creates incentives for fund managers to increase or decrease fund riskiness. They find that funds tend to change their volatility depending on their relative performance by the end of September.

Similarly, Brown, Harlow, and Starks [1996] focus on mid-year effects. In particular, they test the hypothesis that mutual managers showing an underperformance by mid-year change the fund's risk differently than those showing an outperformance at the same time. Their empirical analysis shows that mid-year losers tend to increase fund volatility to a greater extent than their successful counterparts.

Busse [2001], however, has suggested that some prior findings may be spurious. Using daily data as well as Brown, Harlow, and Starks's [1996] methodology, he finds no mid-year effect.

In sum, existing empirical analyses have failed to deliver clear evidence about the behavior of mutual fund managers, and there are doubts about the robustness of many findings.

In this paper, we contribute to the literature in a number of ways. In contrast to existing studies, we do not focus solely on volatility as a risk measure. We consider other measures as well, such as beta, tracking error, and style measures like the high-minus-low (HML) factor, the small-minus-big (SMB) factor, and the momentum (UMD) factor. Furthermore, in contrast to previous studies, we use a robust, non-parametric approach. Because we do not impose any distributional assumptions, we are able to capture a wide range of non-linear and asymmetric patterns. Moreover, rather than using a subgroup of mutual funds, we use a complete set of all U.S. equity funds to obtain a more lengthy time frame of data.

We compute conditional transition matrices, and compare whether they differ for successful and unsuccessful mutual funds. For the empirical analysis, we use a Bayesian network, a model for representing conditional dependencies between a set of random variables. Until now, research on Bayesian networks (BN) has mainly concentrated in statistics and computer science, especially artificial intelligence (Korb and Nicholson [2004], Neapolitan [2004]), pattern recognition (Duda, Hart, and Stork [2001]), and expert systems (Jensen [2001], Cowell et al. [2003]). The term "Bayesian network" is not yet widespread, but special cases of Bayesian networks are already widely used in economics and finance. Many state space models such as the Kalman filter and hidden Markov models are Bayesian networks with a simple dependency structure. Moreover, many classical econometric approaches such as discrete choice models and regressions are so-called naive Bayesian networks because of their mono-causal dependency structure (Jordan, Ghahramani, and Saul [1997]).

Bayesian networks work as follows. Suppose there are three variables, the tracking error in period T, the return in period T, and the tracking error in period $T + 1$. Suppose next that all variables are conditionally dependent, i.e., the tracking error in period T affects the return in period T and the tracking error in period $T + 1$, and the return in period T affects the tracking error in $T + 1$. In classical econometrics, this problem is referred to as multicollinearity, and can lead to identification problems. Bayesian networks can deal with such complex settings and help overcome identification problems. For a discussion of a wide range of different settings of Bayesian networks, see Pearl [2000].

Besides being a modern tool for identifying the impact and magnitude of different causal sources, Bayesian networks have many advantages over standard econometric methods. For example, they allow the computation of exact conditional probabilities to assess a factor's magnitude. Thus we can analyze whether probabilities change from 50:50 to 60:40 or to 90:10. Moreover, Bayesian networks capture non-linear and asymmetric patterns.

Using Bayesian networks on a set of U.S. equity funds over about twenty years of data, we find that prior performance has a positive impact on the choice of risk level (in other words, successful fund managers take on more risk in the following time period). In particular, they increase volatility, beta, and tracking error, and assign a higher proportion of their portfolio to value stocks, small firms, and momentum stocks.

This article is structured as follows: In the second section, we outline the econometric approach. The third section presents our empirical results. The final section is the conclusion.

Model

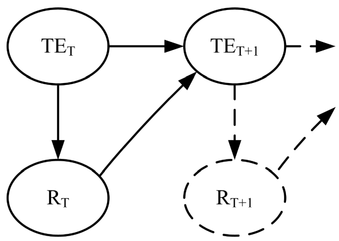
Introduction to Bayesian Networks

A Bayesian network (BN) is a graphical model for representing conditional dependencies between a set of random variables. This includes learning about conditional distributions and updating beliefs about probability distributions for a target node given some observation for at least one variable.

Figure 1 shows a dynamic Bayesian network. The structure is similar to those proposed by Pearl [2000] for causal discovery. The circles denote the nodes, i.e., the variables, and the arcs denote the conditional dependencies between two nodes, which can be of any type. The most common conditional probability distributions (CPD) are Gaussian distributions and

FIGURE 1
Illustration of a Dynamic Bayesian Network

Step 1: Representation



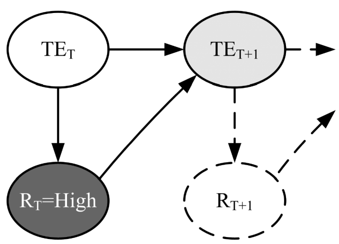
TE_T	
TE_T=Low	TE_T=High
0.5	0.5

Step 3: Learning about Probability Distributions

TE_T	R_T	
	R_T=Low	R_T=High
TE_T=Low	0.5	0.5
TE_T=High	0.9	0.1

TE_T	R_T	TE_{T+1}	
		TE_{T+1}=Low	TE_{T+1}=High
TE_T=Low	R_T=Low	1	0
	R_T=High	0.1	0.9
TE_T=High	R_T=Low	0.1	0.9
	R_T=High	0.01	0.99

Step 2 : Inference



TE_T		R_T		TE_{T+1}		P
Low	0.5	Low	0.5	Low	1	0.25
				High	0	0
		High	0.5	Low	0.1	0.025
				High	0.9	0.225
High	0.5	Low	0.9	Low	0.1	0.045
				High	0.9	0.405
		High	0.1	Low	0.01	0.0005
				High	0.99	0.0495
$P(R_T)$						0.3
$P(TE_{T+1}=High \mid R_T=High)$						0.2745/0.3 = 0.9150
$P(TE_{T+1}=Low \mid R_T=High)$						0.0255/0.3 = 0.0850

The three main issues for Bayesian networks are 1) representation, i.e., what is a Bayesian network, 2) probabilistic inference, i.e., the updating of probability distributions for a query node given evidence for a particular node, and 3) the estimation of parameters for conditional probability distributions for a Bayesian network based on sample data.
Representation: A Bayesian network consists of a set of variables, usually denoted as nodes (illustrated as circles). The arcs represent conditional dependencies in the network between nodes.
Inference: Probabilistic inference denotes the updating of probability distributions for a query node given some evidence (posterior distribution). The graph illustrates the probability updating for the query node TR_{T}, i.e., the tracking error in period $T+1$, conditional on the evidence that R_T, return in period T, was high.
Learning: Maximum likelihood methods are appropriate to learn the parameters for conditional probability distributions in a Bayesian network.

multinomial (or tabular) distributions. Figure 1 shows a binomial distribution.

We use a dynamic Bayesian network to analyze the revision of behavior in the mutual fund industry. We analyze how past performance affects a set of variables describing the risk-taking behavior of mutual fund managers. For example, suppose a fund manager can to some degree choose the tracking error of his portfolio, i.e., how close he mimics the relevant index or whether he chooses a more active investing style. By assumption, there is a fifty-fifty chance he will choose a high or low tracking error. Suppose next that the choice of magnitude of the tracking error affects the subsequent return. Thus a low tracking error leads to a 50% chance of a high return and a 50% chance of a low return. In contrast, we assume that a high tracking error leads to a 90% chance of a low return and a 10% chance of a high return.

The tracking error in period $T+1$ is the result of two variables, the tracking error and the return in period T. These conditional dependencies have a straightforward interpretation. On the one hand, there may be some degree of persistency in the behavior, i.e., a fund manager who has had a high tracking error in period T will tend to maintain a high tracking error. On the other hand, there may be some degree of learning or revision of behavior.

Figure 1 shows how the dynamic Bayesian network can be used to update beliefs about probability distributions. Suppose the investor knows a fund had superior performance in period T. The question is how this knowledge affects the belief about the distribution of the tracking error in period $T + 1$. As shown in Figure 1, the straightforward application of Bayes's theorem leads to a probability of 91.50% for a high tracking error and 8.5% for a low tracking error.

Bayesian networks are also frequently referred to as probabilistic networks (Cowell et al. [2003]), Bayesian artificial intelligence (Korb and Nicholson [2004]), and Bayesian belief networks (Duda, Hart, and Stork [2001]). As noted by Borgelt and Kruse [2002], Bayesian networks rely on the achievements of many other concepts, especially classification and regression trees, naive Bayes classifiers, artificial neural networks, and graph theory.

As mentioned earlier, other econometric approaches, such as the Kalman filter, hidden Markov models, and state space models, can be regarded as special cases of Bayesian networks and particularly of dynamic Bayesian networks (DBN) (Jordan, Ghahramani, and Saul [1997]). Even regressions and discrete choice models can be incorporated into a Bayesian network structure in what are called naive Bayes nets.

BNs are very powerful tools for dealing with uncertainty, incomplete information, and complex probabilistic structures. They enable the extraction of probabilistic structures from data, as well as decision making in these structures. BNs are thus well-suited for financial applications.

This section addresses the three main issues associated with BNs: 1) the question of representation, or what is a Bayesian network? 2) the question of learning, or how can the parameters of a BN be estimated? and 3) the question of inference, or how can BNs be used to answer probabilistic questions? For extended coverage of this topic and of decision making within BNs, we refer to Jensen [2001], Cowell et al. [2003], Korb and Nicholson [2004], and Neapolitan [2004].

Representation

As defined by Jensen [2001], a Bayesian network consists of a set of variables with directed arcs between them. These variables form a directed acyclic graph (DAG), and, for each arc that connects two variables, a potential table (i.e., a conditional distribution) is defined.

Suppose there are four random variables, A, B, C, and D. Applying the chain rule, the joint probability can be written as a product of conditional probabilities $P(A, B, C, D) = P(D|A, B, C) \cdot P(C|A, B) \cdot P(B|A) \cdot P(A)$. Suppose next that A and D are conditionally independent, i.e., $P(A, D|B, C) = P(A|B, C) \cdot P(D|B, C)$, and B and C are conditionally independent. Using Bayes's theorem and the previous factorization, we show that:

$$P(A, D|B, C) = \frac{P(A, B, C, D)}{P(B, C)}$$
$$= \frac{P(A) \cdot P(B) \cdot P(C|A) \cdot P(D|B, C)}{\int\int P(A) \cdot P(B) \cdot P(C|A) \cdot P(D|B, C) dA dD}.$$

Basically, there are three elementary theorems of probability, the building blocks for BN: Bayes's theorem, the chain rule, and conditional dependency.

Learning

In the previous subsection, we assumed that the parameters or conditional probability distributions were known. However, in most cases, it is necessary to learn about the parameters of a BN based on a data set. For parameter learning, maximum likelihood (ML) can be used. As noted by Ghahramani [2001], the likelihood decouples into local terms involving each node and its parents. This simplifies the maximum likelihood estimation by reducing it to a number of local maximization problems.

Suppose a data set consists of M cases for each n node. Let $d^{(h)} = (d_1^{(h)}, \ldots, d_n^{(h)})'$ denote the vector of observations for a single case for all nodes in the network. Therefore, the training data set d is given by $d = \{d^{(1)}, d^{(2)}, \ldots, d^{(M)}\}$. Neapolitan [2004] shows that the likelihood function is given by

$$L(d \mid \theta) = \prod_{i=1}^{n} \prod_{h=1}^{M} P(d_i^{(h)} \mid pa_i^{(h)}, \theta_i)$$

where $pa_i^{(h)}$ contains the values of the parents of node X_i in the hth case, and θ is the parameter set.

For this paper, we use a multinomial distribution. Thus the maximization problem simplifies to a closed-form solution if the data are complete. The likelihood function is given by

$$L(d) = \prod_{i=1}^{n} \prod_{j=1}^{q_i} E\left(\prod_{k=1}^{r_{ij}} F_{ijk}^{s_{ijk}}\right),$$

where q_i denotes the parents of node X_i, and r_i is the number of different classes of the multinomial distribution. F_{ijk} denotes the distribution of node i conditional on the parent node j where the value of node x_i is equal to k. The exponent s_{ijk} denotes the number of cases in which x_i is equal to k. See Neapolitan [2004] for the proof of these results.

Suppose next that the conditional distributions F_{ijk} have a Dirichlet distribution, i.e., a generalized beta distribution with (prior) parameters $a_{ij1}, a_{ij2}, \ldots, a_{ijr_i}$, $N_{ij} = \sum_k a_{ijk}$, and $M_{ij} = \sum_k s_{ijk}$

The likelihood is given by

$$L(d) = \prod_{i=1}^{n} \prod_{j=1}^{q_i} \frac{\Gamma(N_{ij})}{\Gamma(N_{ij} + M_{ij})} \prod_{k=1}^{r_i} \frac{\Gamma(a_{ijk} + s_{ijk})}{\Gamma(a_{ijk})}$$

where $\Gamma(.)$ denotes the gamma function. The use of Dirichlet distributions as conditional distributions has many advantages and is not restrictive. The Dirichlet distribution is the natural conjugate prior for the multinomial distribution. In other words, an application of Bayes's theorem, with the Dirichlet distribution as the prior distribution and the multinomial distribution as the likelihood, leads to a closed-form solution for the posterior distribution with the same functional form as the prior, i.e., a Dirichlet distribution.

Therefore, the Dirichlet distribution is useful for Bayesian sequential analysis and for Bayesian updating. It has upper and lower bounds and can be used to model probabilities that cannot become greater than 1 or lower than 0. We can incorporate prior information about conditional dependencies or assign almost uninformative priors by setting all a_{ijk} to 1.

Inference

Suppose the structure of a BN and all conditional probability distributions (CPD) are known, and a researcher has evidence about at least one node for a new case. The goal of probabilistic inference (also referred to as belief updating, belief propagation, or marginalization) is to update the marginal probabilities in the network to incorporate this new evidence (Ghahramani [2001]). Formally, the task of inference is to find the posterior distribution $P(X = x \mid E = e)$, where X denotes the query node and E is the set of evidence nodes.

By using the local structure of a BN, we show that belief updating can be divided into the predictive support for X from evidence nodes connected to X through its parents, $U_1, \ldots, U_m$, and the diagnostic support for X from evidence nodes connected to X through its children, $Y_1, \ldots, Y_m$ (Korb and Nicholson [2004]).

Pearl's [1982] message-passing algorithm shows how to update the posterior distribution *Bel(X)*. The derivation involves the repeated application of Bayes's theorem and the use of the conditional independencies encoded in the network structure. The basic idea is that $Bel(X)$ is updated locally at each iteration of the algorithm using three parameters, $\lambda(X)$, $\pi(X)$, and the conditional probability table (CPT), where $\lambda(X)$ and $\pi(X)$ are computed using the messages received from the parents π and the children λ of node X(Korb and Nicholson [2004]). In Bayes's theorem, π plays the role of the prior and λ plays the role of the likelihood.

The algorithm requires that three types of parameters be maintained:

1) The current strength of the predictive support π contributed by each incoming link $U_i \rightarrow X$, i.e., $\pi_X(U_i) = P(U_i \mid E_{U_i \backslash X})$, where $E_{U_i \backslash X}$ is all evidence connected to U_i except via X.
2) The current strength of the diagnostic support λ contributed by each outgoing link $X \rightarrow Y_j : \lambda_{Y_j}(X) = P(E_{Y_j \backslash X} \mid X)$, where $E_{Y_j \backslash X}$ is all evidence connected to Y_j through its parents except via X.
3) The fixed CPD $P(X \mid U_i, \ldots, U_n)$, i.e., the conditional distribution of node X is only dependent on its parents.

Pearl's [1982] message-passing algorithm consists of two steps. In the first, belief updating, messages arrive from the parents or the children of an activated node X and lead to changes in belief parameters. In the second, bottom-up and top-down propagation, the activated node computes new messages for the parents λ and the children λ to send it in the appropriate direction.

In the first step, the posterior distribution of each activated node X, proportional to the messages from the parents $\pi_X(U_i)$ and the messages from its children $\lambda_{Y_j}(X)$, is determined as follows:

$$Bel(x_i) = \alpha \lambda(x_i) \pi(x_i)$$

where $\pi(x_i) = \sum_{u_1, \ldots, u_n} P(x_i \mid u_1, \ldots, u_n) \prod_i \pi_X(u_i)$

and

$$\lambda(x_i) = \begin{cases} 1 \text{ if evidence is } X = x_i \\ 0 \text{ if evidence is for another } x_j \\ \prod_j \lambda_{Y_j}(x_i) \text{ otherwise} \end{cases}$$

and where α is a normalizing constant, rendering $\sum_{x_i} Bel(X = x_i) = 1$

In the second step, node X sends new λ messages to its parents

$$\lambda_X(u_i) = \sum_{x_i} \lambda(x_i) \sum_{u_k : k \neq i} P(x_i \mid u_i, \ldots, u_n) \prod_{k \neq i} \pi_X(u_k)$$

and new π messages to its children

$$\pi_{Y_j}(x_i) = \begin{cases} 1 \text{ if evidence value } x_i \text{ is entered} \\ 0 \text{ if evidence is for another value } x_j \\ \alpha Bel(x_i)/\lambda_{Y_j}(x_i) \text{ otherwise} \end{cases}$$

This procedure is repeated until a node has received all messages.

We divide the inference methods into two categories, exact inference and approximate inference algorithms. The latter have been developed because probabilistic inference can be computationally difficult for complex networks because the required computational power increases exponentially with the number of parent nodes. Well-known algorithms for exact inference include variable elimination, Pearl's message-passing algorithm, the noisy-or-gate algorithm, and the junction tree algorithm. For approximate inference, standard algorithms include likelihood weighting, logic sampling, and Markov chain Monte Carlo (MCMC) (for an overview, see Korb and Nicholson [2004] or Neapolitan [2004]).

Data

For our analysis, we use a complete sample of all U.S. open-end equity funds, containing a total of 1,923 funds. The data set comes from Reuters Lipper. For each fund, we have information about launch date, sector (equity, international, large-cap, mid-cap, and small-cap), style (income, core, growth, value), annual fee, and total assets as of April 30, 2004. We also have monthly price information over nineteen years, December 1984 to December 2003. We exclude international mutual funds from our analysis, as well as funds with less than two years of data.

For benchmarking purposes, we use the excess return on the S&P 500 index as the market portfolio, and the three-month Treasury bill rate as the risk-free rate. These data come from Datastream. As a second benchmark, we use the Carhart [1997] four-factor model. The data for the market risk premium, the size premium, the value premium, and the momentum premium come from the Fama and French data library.

Table 1 gives the descriptive statistics for the data we use here. The number of funds increased from 191 in 1985 to 1,478 in 2003. The average return across all funds fluctuated substantially during that time, from a minimum of -26.35% in 2002 to a maximum of 28.26% in 2003. Similarly, the performance of single funds shows a high degree of dispersion.

Performance Measurement

A number of approaches have been suggested to measure fund performance (see, e.g., Kothari and Warner [2001], Wermers [2000], and Daniel et al. [1997]). To estimate the exposure toward the Fama and French [1993] risk factors and the Carhart [1997] momentum factor, we run the following regression for each fund i and each calendar year t:

$$\begin{aligned} r_{i,t} - r_{f,t} = {} & \alpha_{Carhart,\,i,\,t} + MRP_{Carhart,\,i,\,t} \cdot r_{Carhart} \\ & + HML_{i,\,t} \cdot r_{HML} + SMB_{i,\,t} \cdot r_{SMB} \\ & + UMD_{i,\,t} \cdot r_{UMD} + \varepsilon_{Carhart,\,i,\,t} \end{aligned}$$

where $r_{i,t}$ denotes the return of fund i, $r_{f,t}$ is the risk-free rate, and $\varepsilon_{Carhart,i,t}$ is the regression residual. The coefficients to be estimated are denoted by $MRP_{Carhart,i,t}$, $HML_{i,t}$, $SMB_{i,t}$, and $UMD_{i,t}$, and the risk premia by $r_{Carhart}$, r_{HML}, r_{SMB}, and r_{UMD}. We use an analogous approach for the risk exposure with respect to the S&P 500:

$$\begin{aligned} r_{i,\,t} - r_{f,t} = {} & \alpha_{SP500,\,i,\,t} + MRP_{SP500,\,i,\,t} \cdot r_{SP500} \\ & + \varepsilon_{SP500,\,i,\,t}. \end{aligned}$$

In the analysis following, $R_{Raw,\,i,\,t} = r_{i,\,t}$ is the unadjusted return of a fund, $R_{SP500,\,i,\,t} = \alpha_{SP500,\,i,\,t}$ is the

Table 1. *Descriptive Statistics for Annual Continuously Compounded Returns*

Year	Funds	Mean	Std.	Skew	Kurt	Min	25%	50%	75%	Max
1985	191	18.87	7.37	−0.01	3.67	−3.23	14.18	19.43	23.23	43.56
1986	216	0.49	10.80	−0.20	5.28	−48.43	−5.64	0.55	8.00	45.38
1987	243	−13.49	12.46	−0.23	5.87	−60.19	−19.86	−13.13	−5.38	42.81
1988	284	9.46	8.12	0.08	4.52	−15.31	4.27	9.58	14.36	46.10
1989	305	15.31	8.38	0.01	3.44	−9.40	10.36	14.95	20.95	41.45
1990	326	−11.70	8.79	−0.63	3.76	−41.48	−16.63	−10.80	−5.52	11.51
1991	350	26.28	12.08	−1.29	16.97	−75.62	18.99	25.39	32.88	63.08
1992	387	3.52	8.02	−0.72	7.93	−48.47	−0.39	3.59	7.29	30.10
1993	452	5.34	8.53	−1.14	10.06	−51.79	0.49	5.73	10.44	36.90
1994	539	−6.52	7.30	−0.54	5.32	−41.25	−10.34	−5.95	−2.41	21.08
1995	622	20.44	8.72	−0.36	5.07	−22.82	15.67	21.01	25.75	48.42
1996	701	9.39	9.09	−1.07	9.59	−61.24	4.93	9.56	14.72	44.06
1997	822	11.36	11.24	−1.18	7.27	−56.69	5.48	12.89	18.44	49.91
1998	977	6.57	15.34	−0.12	3.58	−48.04	−3.24	6.84	16.87	58.22
1999	1114	17.05	22.76	1.07	5.02	−53.06	1.48	13.49	27.79	136.39
2000	1233	−12.14	22.51	−1.52	9.89	−188.63	−23.45	−10.09	2.68	40.86
2001	1369	−11.83	16.82	−0.30	4.28	−90.89	−21.35	−12.61	−1.30	45.78
2002	1478	−26.35	11.34	−0.66	5.64	−103.74	−32.59	−26.08	−19.18	14.08
2003	1478	28.26	8.98	0.42	12.28	−58.39	22.29	26.70	33.06	97.56

The table gives descriptive statistics for annual continuously compounded returns for all funds existing in one particular year. The data set is from Reuters Lipper.

risk-adjusted return using the S&P 500 as a benchmark, and $R_{Carhart,\,i,\,t} = \alpha_{Carhart,\,i,\,t}$ is the risk-adjusted return using the Carhart model as a benchmark.

The tracking error measures a fund's deviation from a passive index. We define tracking error TE as the volatility σ of the residuals of the regressions on the index, i.e.,

$$TE_{Carhart,\,i,\,t} = \sigma(\varepsilon_{Carhart,\,i,\,t}) \text{ and } TE_{SP500,\,i,\,t} = \sigma(\varepsilon_{SP500,\,i,\,t}).$$

Implementation

Figure 2 shows the corresponding dynamic Bayesian network. For each fund, we estimate eight different factors describing mutual fund behavior for each year: the standard deviation of returns, the beta against the S&P 500 and the Fama and French market portfolio, the loading on the value versus growth factor, the loading on the size factor, the loading on the momentum factor, and the tracking error against the S&P 500 and the Fama and French market portfolio.

We performed a likelihood ratio test, and found that all arcs in the BN are highly significant. To get robust results that are independent of restrictive distributional assumptions and to incorporate non-linear behavior, we use a multinomial distribution with four classes where variables are grouped into quartiles for each year.

The implementation of the Bayesian network has been carried out using the "Bayes's Net Toolbox for MatLab." For testing, we created a large number of different artificial data sets and re-extracted the underlying probability distributions. In all instances, the underlying probability distributions were recovered accurately.

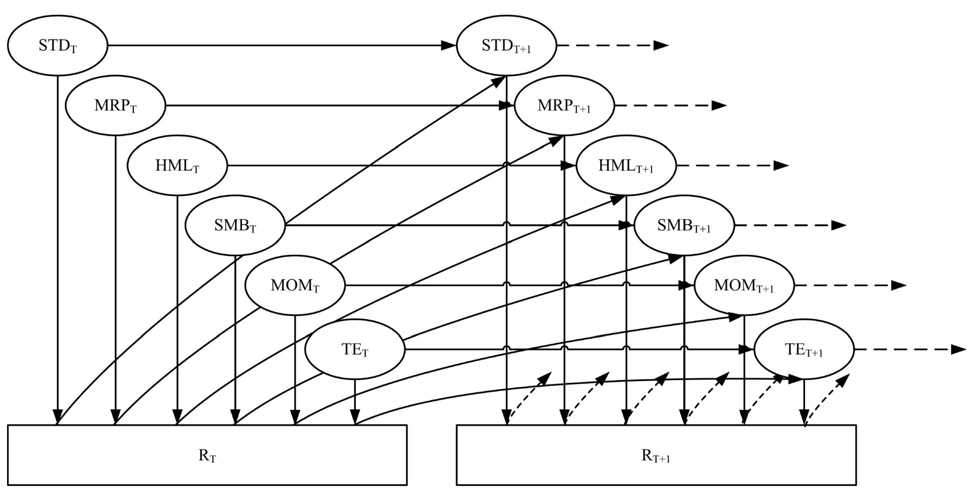
We initialized the BN by setting all a_{ijk} to 1, thus ensuring the analysis incorporates no material prior information. The BN is used primarily as an econometric tool.

Empirical Results

The analysis is structured as follows. We focus first on the marginal distributions within the time period of the relationship between risk and return. We then focus on intertemporal relationships of different measures of risk and style. Finally, we turn to the marginal distributions of risk and style conditional on past performance.

Due to the large amount of data, we focus on the empirical part of risk-adjusted returns using the S&P 500 as a benchmark in a one-factor model. Unless otherwise stated, results for unadjusted returns and returns adjusted with the Carhart four-factor model are very similar.

FIGURE 2
Dynamic Bayesian Network Used in the Empirical Analysis



We analyze the joint effect of the risk level in T and the risk-adjusted return in T on the choice of the risk level in $T + 1$ for a number of different measures of risk, w. The data set was provided by Reuters Lipper and consists of 1,923 funds with return data from 1984 to 2004. We used the following as risk measures: volatility (*STD*), beta with respect to the market portfolio (*MRP*), factor loading on the value premium (*HML*), factor loading on the size premium (*SMB*), factor loading on the momentum premium (*UMD*), and tracking error (*TE*). A return is denoted by R. Tracking error and beta are computed with respect to the S&P 500 and the CRSP market portfolio using one-factor and four-factor models, respectively (denoted as TE_{SP500}, TE_{Carhart}, MRP_{SP500}, and MRP_{Carhart}). Similarly, return R is computed on a raw basis (without risk adjustment), risk-adjusted in a one-factor model with respect to the S&P 500 and the Carhart [1997] four-factor model (denoted as R_{Raw}, RS_{P500}, and $R_{Carhart}$).

Table 2. *Transition Probabilities between Risk and Return*

		$R_{SP500,T}$			
From	**To**	**Q1**	**Q2**	**Q3**	**Q4**
STD_T	Q1	11.8%*	28.9%**	28.3%**	30.8%**
	Q2	15.5%*	25.1%	30.6%**	28.6%**
	Q3	17.9%*	21.7%*	25.0%	34.4%**
	Q4	22.8%*	16.6%*	19.0%*	41.4%**
$MRP_{SP500,T}$	Q1	16.0%*	18.6%*	22.6%*	42.6%**
	Q2	15.1%*	22.4%*	27.8%*	34.5%**
	Q3	16.5%*	25.7%	27.4%**	30.2%**
	Q4	21.1%*	21.8%*	23.9%	33.0%**
HML_T	Q1	24.0%	23.0%*	19.4%*	32.6%**
	Q2	15.7%*	28.0%**	30.0%**	26.2%
	Q3	13.1%*	24.7%	30.3%**	31.8%**
	Q4	17.8%*	15.6%*	22.2%*	44.2%**
SMB_T	Q1	21.7%*	28.2%**	25.7%	24.2%
	Q2	14.5%*	30.4%**	29.9%**	25.0%
	Q3	13.3%*	24.2%	29.6%**	32.7%**
	Q4	19.5%*	14.8%*	21.1%*	44.4%**
UMD_T	Q1	33.7%**	30.7%**	18.4%*	17.0%*
	Q2	20.3%*	32.1%**	26.5%**	21.0%*
	Q3	12.9%*	22.0%*	32.0%**	33.0%**
	Q4	12.9%*	14.3%*	23.2%*	49.4%**
$TE_{SP500,T}$	Q1	14.3%*	29.2%**	30.8%**	25.5%
	Q2	18.1%*	25.1%	27.7%**	29.0%**
	Q3	18.0%*	19.0%*	22.5%*	40.3%**
	Q4	20.7%*	13.9%*	19.4%*	45.8%**

The table gives the transition probabilities between different measures of risk and the subsequent return. *denotes a value statistically different from 0.25 on a 95% level, and ** denotes a 99% level. Standard errors have been computed by bootstrapping.
The table is interpreted as follows. Say in one particular year a fund has a volatility in the lowest quartile among all other funds. The fund would have a probability of 11.8% (first row, first column) of achieving a risk-adjusted return in the lowest quartile among all other funds. Analogously, the chance is 30.8% (first row, fourth column) of obtaining a risk-adjusted return in the highest quartile among all other funds.

Risk and Return

Table 2 shows the relationship between the set of variables describing the risk exposure of mutual funds and the performance measured on a risk-adjusted basis. We test for significance against a null hypothesis of a no-probabilistic relationship, i.e., the null hypothesis for a multinomial distribution with four classes is that the probability for each class is 25%.

We interpret Table 2 as follows. Suppose one year a fund experiences volatility in the lowest quartile. The fund would then have an 11.8% probability (first row, first column) of achieving a risk-adjusted return in the lowest quartile among all funds. Analogously, the chance is 30.8% (first row, fourth column) of obtaining a risk-adjusted return in the highest quartile.

We find that the higher the volatility, the more likely a fund will have an extreme return in quartiles 1 (Q1) and 4 (Q4). The transition probability of ending in the first quartile of returns is only 11.8% for funds with a volatility in Q1, and 22.8% for funds with a volatility in Q4. Similarly, funds with a low standard deviation in Q1 have a 30.8% chance of reaching a high return in Q4, while funds with a high standard deviation in Q4 have a 41.4% chance. Funds with a low risk level have a higher chance of reaching a return centered around the mean. For example, a fund with a volatility in Q1 has a 28.9% chance of a return in Q2; a fund with a high volatility has a 16.6% chance.

For the exposure to market risk, or beta, the findings are reversed. Funds with a low beta in Q1 have a 42.6% chance of achieving a risk-adjusted return in Q4. High-beta funds have only a 33.0% transition probability of a return in Q4. The data show that the higher a fund's beta, the lower its relative risk-adjusted return.

The style factors in the Carhart [1997] four-factor model, i.e., the value premium, size premium, and momentum premium (UMD), show the expected results. As documented by Fama and French [1993], trading strategies based on size factors and valuation ratios have historically earned superior returns. Value-oriented funds, i.e., those with a high loading on the value premium (HMLT in Q4), have a 44.2% chance of a return in Q4. In contrast, growth funds (HMLT in Q1) have a 32.6% chance of a return in Q4, and small-cap funds (SMBT in Q4) have a 44.4% chance. Large-cap stocks have only a 24.2% chance.

The findings for momentum funds are even more striking. Funds with a high exposure to momentum stocks (Q4) had a 49.4% chance for a return in the highest quartile. For funds avoiding momentum stocks (Q1), this chance is reduced to 17.0%.

The tracking error indicates the magnitude of active portfolio management of a fund manager. The transition matrix shows that fund managers with a high tracking error (Q4) are 45.8% more likely to have a return in the highest quartile than fund managers with a low tracking error (Q1) (25.0%). The data indicate that active portfolio management has had some value.

Persistence in Risk Levels

In this section, we analyze the persistence in the choice of risk levels. Table 3 shows the relationship between standard deviation in period T and the successive period $T + 1$. The diagonal elements of the transition matrix are especially interesting, because they represent the degree of persistence in the choice of risk levels.

For the standard deviation, the probabilities of staying in the same quartile (the diagonal elements of the transition matrix) are 50.4%, 37.8%, 41.2%, and 70.1%, respectively. This means that a fund with a low return volatility has a 50.4% chance of staying in the lowest quartile, a fund with a volatility in the second quartile has a 37.8% chance of staying in the same quartile, and so on.

Table 3. *Transition Probabilities between Risk in T and T + 1*

From	To	XXX_T M: $R_{SP500,T}$ Q1	Q2	Q3	Q4
STD_T	Q1	50.4%**	32.9%**	14.0%*	2.6%*
	Q2	24.4%	37.8%**	29.7%**	7.9%*
	Q3	8.4%*	22.8%	41.2%**	27.4%
	Q4	1.2%*	6.3%*	22.2%*	70.1%**
$MRP_{SP500,T}$	Q1	46.0%**	28.7%**	17.6%*	7.5%*
	Q2	25.4%	31.0%**	27.9%**	15.5%*
	Q3	11.8%*	25.5%	36.4%**	26.1%
	Q4	4.7%*	13.8%*	27.0%	54.1%**
HML_T	Q1	49.7%**	24.6%	15.5%*	9.9%*
	Q2	26.4%	34.3%**	25.0%	13.3%*
	Q3	14.9%*	27.7%**	32.4%**	24.8%
	Q4	11.5%*	15.4%*	28.5%**	44.4%**
SMB_T	Q1	49.3%**	29.5%**	14.7%*	6.4%*
	Q2	37.8%**	33.1%**	18.9%*	10.0%*
	Q3	15.4%*	17.7%*	35.1%**	31.7%**
	Q4	4.2%*	5.8%*	21.1%*	68.7%**
UMD_T	Q1	42.9%**	25.2%	18.0%*	13.7%*
	Q2	26.0%	32.7%**	24.5%	16.1%*
	Q3	16.1%*	27.8%**	31.3%**	24.6%
	Q4	11.4%*	15.2%*	26.3%	46.9%**
$TE_{SP500,T}$	Q1	61.9%**	25.5%	9.1%*	3.4%*
	Q2	22.5%	36.8%**	25.4%	15.2%*
	Q3	7.4%*	23.9%	32.5%**	36.0%**
	Q4	1.7%*	9.8%*	26.0%	62.4%**

The table gives the transition probabilities between different measures of risk in T and $T + 1$. XXX means that the target (column) variable is the same as in the appropriate row. The table gives the results for the model with risk adjustment using the S&P 500. *denotes a value statistically different from 0.25 on a 95% level, and **on a 99% level. Standard errors have been computed by bootstrapping.

The table is interpreted as follows. Suppose a fund has in one particular year a volatility in the lowest quartile among all other funds. The fund manager would have selected with a probability of 50.4% (first row, first column) a return volatility in the lowest quartile among all funds in the next calendar year. Analogously, the chance is 2.6% (first row, fourth column) to select a volatility on the highest quartile among all other funds in the next calendar year.

In contrast, for the exposure toward market risk, the data show a lower degree of behavior persistence. For the beta against the S&P 500, the percentages of staying in the same class are 46.0%, 31.0%, 36.4%, and 54.1%, respectively. Therefore, we conclude that fund managers are more likely to adjust their market risk than their portfolio volatility. In general, the degree of persistence is larger for funds with a very low or very high exposure to a risk factor.

Our findings are similar for the style factors in the Carhart [1997] four-factor model. For the HML factor, the transition probabilities for staying in the same class are 49.7%, 34.4%, 32.4%, and 44.4%; for the SMB factor, they are 49.03%, 33.1%, 35.1%, and 68.7%. For the momentum (UMD) factor, the percentages are 42.9%, 32.7%, 31.3%, and 46.9%. Therefore, over the whole sample, the persistence in choice of risk levels is particularly high for funds with a high concentration of investment in small-caps (high SMB factor). However, this finding is consistent with prior expectations, because the choice of risk level and its persistence are at least partially a result of a fund's investment policy.

For the tracking error against the S&P 500, the diagonal transition probabilities are 61.9%, 36.8%, 32.5%, and 62.4%. Therefore, we find that the persistence of active and passive portfolio management measured as the deviation from the index is substantial.

Overall, we find strong evidence for persistence in the choice of risk levels. In particular, funds with very high and very low exposure to specific risk factors show a high degree of persistence. However, these results are not surprising because a number of factors, especially institutional restrictions, tend to lead to persistent behavior.

Impact of Prior Performance

We next examine how the impact of prior performance influences the risk-taking behavior of mutual fund managers. The complete empirical results are included in the appendix (Tables A1 and A2). Due to the large amount of empirical data, we focus on the results shown in Tables 4 and 5.

Table 4 shows the difference in transition probabilities for top- and poor-performing mutual funds for risk-adjusted returns using the S&P 500 as the benchmark. For volatility, we find that poor-performing fund managers tend to strongly decrease their portfolio volatility in the following calendar year. For example, the difference in transition probabilities for funds with a volatility in the highest quartile is 18.9%. Only successful funds with low volatility (in Q1) increase their volatility the following calendar year.

For beta, the results are mixed. Funds with exposure to market risk above the median (Q3 and Q4) take on more market risk the following calendar year (e.g., the difference in transition probabilities for Q4 to Q4 is 9.8%). This indicates successful fund managers are 9.8% more likely to maintain their risk level than unsuccessful managers.

In contrast, unsuccessful managers, with a beta in Q1, increase their market risk exposure significantly. For example, the difference in transition probabilities from Q1 to Q2 is −8.4%. This indicates poor-performing funds are 8.4% more likely to increase their market risk exposure.

We interpret the style factors as follows. A high loading (in Q4) on the value factor (HML) indicates a fund invests in value stocks; a low factor loading on the value factor (Q1) is interpreted as an investment in growth stocks. A fund investing in small-caps shows high exposure to the size factor (SMB), and a large-cap fund shows an exposure in the first quartile. Funds investing in momentum stocks have a high loading on

Table 4. *Impact of Prior Performance on the Choice of Risk Level (returns adjusted with the S&P 500)*

		XXX_{T+1} Difference			
From	**To**	**Q1**	**Q2**	**Q3**	**Q4**
STD_T	Q1	6.3%	−1.5%	−1.1%	−3.6%**
	Q2	−10.3%**	−0.9%	7.4%*	3.8%*
	Q3	−8.5%**	−9.0%**	0.0%	17.0%**
	Q4	−2.1%**	−6.0%**	−10.7%**	18.9%**
$MRP_{SP500,T}$	Q1	13.3%**	−8.4%**	−1.8%	−3.0%**
	Q2	3.3%	−6.8%**	3.3%	0.0%
	Q3	−5.8%**	−4.7%**	1.7%	8.8%**
	Q4	−5.0%**	−1.8%	−3.0%	9.8%**
HML_T	Q1	−8.5%**	−3.6%	5.4%**	6.7%**
	Q2	−8.4%**	−0.5%	2.3%	6.6%**
	Q3	−7.1%**	−4.1%	5.8%*	5.4%*
	Q4	−9.8%**	−0.5%	3.2%*	7.1%**
SMB_T	Q1	−6.7%*	−3.1%	3.0%	6.8%**
	Q2	−11.4%**	−1.8%	5.5%*	7.7%**
	Q3	−13.1%**	−7.9%**	5.0%*	16.0%**
	Q4	−6.5%**	−5.8%**	−1.2%	13.6%**
UMD_T	Q1	−13.0%**	−5.2%*	8.7%**	9.5%**
	Q2	−3.4%	−1.4%	2.0%	2.7%
	Q3	−8.7%**	1.5%	9.5%**	−2.2%
	Q4	−6.6%**	−1.9%	5.3%**	3.2%
$TE_{SP500,T}$	Q1	13.0%**	−11.5%**	−4.1%	2.7%*
	Q2	−5.8%*	−4.3%	1.7%	8.4%**
	Q3	−6.6%**	−5.0%*	0.9%	10.6%**
	Q4	−3.1%**	−9.3%**	−4.5%*	17.0%**

The table gives the difference in transition probabilities between different measures of risk in T and $T+1$ for funds with a performance in the highest quarter in T and for funds with a performance in the lowest quarter in T. XXX denotes that the target (column) variable is the same variable as in the appropriate row. The table gives the results for returns adjusted with the S&P 500. *denotes a value statistically different from 0 on a 95% level, and **on a 99% level. Standard errors have been computed by bootstrapping. The results in this table are based on a risk-adjusted return using a one-factor model and the S&P 500 as the market portfolio.
The results in the table have been computed as follows. Top-performing funds have a return in the fourth quartile in one calendar year, poor-performing funds have a return in the first quartile in one calendar year. Both groups have different transition matrices for the risk level in the next year. We show the difference of element-by-element subtraction of the transition matrices. The transition matrix of poor-performing funds has been subtracted from the matrix of top-performing funds. Therefore, positive elements indicate that the transition probability for top-performing funds was higher than for poor-performing funds, and vice versa.

Table 5. *Impact of Prior Performance on the Choice of Risk Level (returns adjusted with the Carhart Model)*

		XXX_{T+1} Difference			
From	**To**	**Q1**	**Q2**	**Q3**	**Q4**
STD_T	Q1	7.0%	1.6%	−5.8%	−2.8%**
	Q2	2.1%	−3.8%	2.6%	−1.0%
	Q3	1.0%	1.7%	−0.1%	−2.6%
	Q4	0.0%	0.0%	−1.2%	1.4%
$MRP_{SP500,T}$	Q1	−0.2%	−2.1%	4.0%*	−1.6%
	Q2	−6.8%**	−3.7%	7.6%**	2.8%
	Q3	−3.9%*	−7.5%**	2.7%	8.6%*
	Q4	−2.3%**	−1.2%	0.0%	2.9%
HML_T	Q1	−3.4%	−1.5%	2.4%*	2.5%*
	Q2	−5.9%**	7.1%**	2.1%	−3.3%
	Q3	−4.6%*	2.4%	0.4%	1.7%
	Q4	0.0%	−0.3%	0.0%	−0.1%
SMB_T	Q1	15.5%**	1.4%	−10.3%**	−6.6%**
	Q2	7.4%**	−0.3%	−3.2%	−3.7%*
	Q3	−3.9%*	0.0%	−0.1%	4.1%
	Q4	−0.5%	−0.2%	4.1%*	−3.4%*
UMD_T	Q1	1.7%	1.2%	1.9%	−4.9%**
	Q2	−2.0%	8.1%**	−0.4%	−5.5%**
	Q3	−7.2%**	0.6%	11.2%**	−4.0%
	Q4	−2.6%*	−0.5%	5.9%**	−2.6%
$TE_{SP500,T}$	Q1	30.4%**	−6.9%**	−18.9%**	−4.4%**
	Q2	3.6%	3.6%	−3.2%	−4.0%
	Q3	−1.8%*	5.9%*	−2.6%	−1.4%
	Q4	−0.1%	0.0%	1.6%	−1.5%

The table shows the difference in transition probabilities between different measures of risk in T and $T+1$ for funds with performances in the highest and lowest quarters in T. XXX means that the target (column) variable is the same as in the appropriate row. The table shows the results for returns adjusted with the Carhart model. *denotes a value statistically different from 0 on a 95% level, and **on a 99% level. Standard errors have been computed by bootstrapping.
The results in the table have been computed as follows. Top-performing funds have a return in the fourth quartile in one calendar year, poor-performing funds have a return in the first quartile in one calendar year. Both groups have different transition matrices for the risk level in the next year. We show the difference of element-by-element subtraction of the transition matrices. The transition matrix of poor-performing funds has been subtracted from the matrix of top-performing funds. Therefore, positive elements indicate that the transition probability for top-performing funds was higher than for poor-performing funds, and vice versa.

the UMD factor (Q4), and contrarian funds have a low loading on UMD.

For the HML, SMB, and UMD factors, there is overwhelming evidence of increased risk-taking by successful fund managers. They tend to invest heavily in the future in value stocks, small-caps, and momentum stocks.

For the loading on the value premium (HML), all differences in transition probabilities ending in Q1 are negative; those ending in Q4 are positive. For example, successful funds that invested in growth stocks are 6.7% more likely to switch to a substantial value investment (transition element Q1 to Q4), and poor-performing funds are 8.5% more likely to continue the unsuccessful growth stock investments (transition element Q1 to Q1).

For the size exposure, the change in behavior is even stronger. All successful managers, regardless of their prior size exposure, invest substantially in small-caps. Successful managers who have previously invested primarily in large-caps are 6.8% more likely to invest substantially in small-caps than their unsuccessful counterparts (transition probability Q1 to Q4).

For the momentum exposure, we again see increased risk-taking by successful managers, but it is less evident. We observe material changes for fund managers who previously neglected momentum stocks (Q1). If these fund managers achieved good performance, they were 9.5% more likely to invest heavily in momentum stocks in the future than poor-performing managers (transition probability Q1 to Q4).

Tracking error as a measure of active portfolio management validates the findings for other variables. Successful managers generally increase tracking error; poor-performing fund managers tend to decrease it. Successful fund managers are 17.0% more likely to maintain a tracking error in the highest quartile (Q4), compared to unsuccessful ones.

We next analyze how portfolio managers respond to prior performance measured with the Carhart [1997] four-factor model, which explains a high proportion of the cross-sectional variance of mutual fund performance. After accounting for a fund's exposure against value and growth stocks, large- and small-caps, and momentum stocks, Carhart finds little evidence for persistence in the performance of mutual funds.

Overall, the results for returns risk-adjusted with the Carhart model and with a one-factor model, the S&P 500, indicate differences (see Table 5). Table 4 indicates substantial and significant changes in behavior, especially for the first and fourth quartiles. But the results for the Carhart model are less apparent.

For volatility in general, we find no change in behavior. However, there is little evidence for increased risk-taking by low-performing funds. For beta, the data confirm our previous findings. A good performance induces increased risk-taking the following period. However, most findings are statistically insignificant.

For the HML, SMB, and UMD factors, the results are mixed and differ somewhat from previous findings. For HML, we find a clear, statistically significant pattern. For SMB, the findings are reversed. For UMD, the results are ambiguous. For the Carhart model, we find strong evidence that successful fund managers abstain from small-caps (the transition probability from Q4 to Q4 is −3.4%). This indicates successful fund managers tend to reduce their exposure to small-caps compared to poor-performing fund managers.

After controlling for a fund's style, we find that unsuccessful funds tend to change their momentum strategy, but in different directions. The transition probability from Q2 to Q2 is significantly positive at 8.1%, indicating successful funds are 8.1% more likely to choose a comparable momentum level. Unsuccessful funds change their strategy in both directions: some choose a contrarian strategy, others opt for a stronger momentum strategy.

For tracking error, superior performance tends to lead to a more passive investment style after controlling for a fund's style. However, this finding is only significant for the first quartile transition probabilities.

Discussion

Existing literature on the behavior of mutual fund managers has focused on incentives (Brown, Harlow, and Starks [1996], Chevalier and Ellison [1997], Carpenter [2000], Busse [2001], and Carhart et al. [2002]). Incentives in the mutual fund industry are primarily driven by two factors, compensation schemes and investor behavior. Standard compensation schemes in the mutual fund industry are convex, i.e., fund managers take part in the positive performance of their funds by receiving bonuses, but they do not usually take part in the negative performance. Portfolio managers have a call option on the portfolio they are managing.

Moreover, intertemporal investor behavior increases the effect of convex compensation schemes. Investors tend to allocate a large proportion of new capital to funds that performed well in the previous period, but they do not tend to withdraw capital from poorly performing funds. Therefore, if a manager's salary depends on assets under management, investor behavior induces a convex relationship between fund performance and fund size. Overall, theoretically, both patterns lead to excessive risk-taking by mutual fund managers.

However, in our empirical analysis, we were unable to find evidence of such behavior. Our findings are probably attributable to the different setting in this study compared to others. We used a large sample of funds over a longer time period and different measures of risk and return. We also imposed less restrictive assumptions for the empirical analysis (we do not assume any linear relationships or normal distributions).

Brown, Harlow, and Starks [1996] focus solely on volatility as a risk measure, and use only a small sample of funds focusing on growth stocks over a fifteen-year time period. Their analysis focuses on mid-year effects, and they find that funds performing poorly by mid-year tend to increase their volatility over the rest of the year.

Busse [2001] uses a very similar methodology and the same data set as in Brown, Harlow, and Starks [1996] but with a daily frequency. He finds that intra-year fund changes are attributable to changes in the volatility of common stocks and are not related to changing factor exposures or residual risk.

Similarly, Chevalier and Ellison [1997] analyze the impact of past performance on fund flows using a semi-parametric approach. Their results confirm prior expectations: The flow-performance relationship creates incentives for fund managers to adjust fund riskiness depending on mid-year performance.

How can we explain increased risk-taking after years of good performance, and decreased risk-taking after years of poor performance? Our explanation is two-sided. First, poor-performing managers follow a more passive strategy to minimize their future risks. Relative performance, not absolute performance, is relevant. Second, successful managers take on more risk because they have become more confident in their own skills. Success creates confidence. Basically, our analysis shows that the best explanation can be found in a combination of the models by Lynch and Musto [2003] for unsuccessful managers and Berk and Green [2004] for successful managers. Mutual fund manager behavior is more complex than assumed by theoretical models, which usually capture only one aspect of the actual behavior.

Lynch and Musto [2003] propose a model in which strategy changes occur only after periods of bad performance. However, a priori, their model does not explain how the strategy changes. Their empirical analysis finds evidence of a change in factor loadings: Poor performers seem to increase their UMD loading and decrease their HML loading. Neither market beta nor SMB loading is systematically affected by fund performance.

The different results by Lynch and Musto [2003] when compared to our analysis might be due to their shorter sample period and to our use of a non-linear model. Our analysis shows that, after a period of poor performance, managers choose a passive investment style (lower tracking error). They take less market risk, decrease their exposure to value, and increase their exposure to large-caps and stocks with a low momentum effect.

Berk and Green [2004] propose a model that incorporates two important features. First, performance is not persistent, i.e., active portfolio managers do not outperform passive benchmarks on average. Second, fund flows respond rationally to past performance. They assume investors behave as Bayesians, updating their beliefs about a fund manager's skill based on observed returns and prior beliefs.

Conclusion

How do mutual fund managers react to past performance? Theory suggests that high-performing mutual fund managers reduce their risk level, while poor-performing managers take on more risk because they do not bear the downside risk. However, this behavior might be unrealistic under real-world conditions due to such limitations as tracking error restrictions. And factors besides compensation maximization may be even more important. For example, if relative performance is more important than absolute performance, managers will tend to take on only small idiosyncratic risk compared to their relevant benchmark.

This paper has analyzed a large sample of U.S. investment funds over a period of twenty years. We compute different measures of style and risk for each year. Overall, our analysis extends the existing literature in a number of ways. In contrast to existing studies, we do not focus solely on volatility as a measure of risk. We use other measures such as beta, tracking error, and style measures such as the high-minus-low (HML) factor, the small-minus-big (SMB) factor, and the momentum (UMD) factor as well. Furthermore, we use a robust, non-parametric approach and are therefore able to capture a wide range of non-linear and asymmetric patterns because we do not impose any restrictive distributional assumptions. To combat a data bias, we use a complete set of all U.S. equity funds to ensure a long time period of data, rather than a subgroup of mutual funds.

Our analysis does not lend any support to the hypothesis that poor-performing fund managers increase their risk level. We find that prior performance has a positive impact on the choice of risk level, i.e., successful fund managers take on more risk in the following time period. In particular, they increase volatility, beta, and tracking error, and assign a higher proportion of their portfolio to value stocks, small firms, and momentum stocks. Overall, poor-performing fund managers switch to passive strategies. Unsuccessful managers decrease the level of idiosyncratic risk and follow the relevant benchmark more closely.

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Table A1. *Impact of Prior Performance on Choice of Risk Level (returns adjusted with the S&P 500)*

		XXX_{T+1} $R_{SP500,T}$=4Q				XXX_{T+1} $R_{SP500,T}$=1Q				XXX_{T+1} Difference			
from	**to**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
STD_T	Q1	50.6%**	31.1%**	15.5%*	2.7%*	44.2%**	32.7%*	16.6%*	6.3%*	6.3%	−1.5%	−1.1%	−3.6%**
	Q2	22.3%	35.4%**	29.8%*	12.3%*	32.7%*	36.3%**	22.4%	8.4%*	−10.3%**	−0.9%	7.4%*	3.8%*
	Q3	4.8%*	16.1%*	39.5%**	39.4%**	13.4%*	25.2%	38.9%**	22.3%	−8.5%**	−9.0%**	0.0%	17.0%**
	Q4	0.3%*	2.6%*	14.3%*	82.5%**	2.5%*	8.6%*	25.1%	63.6%**	−2.1%**	−6.0%**	−10.7%**	18.9%**
$MRP_{SP500,T}$	Q1	54.3%**	23.8%	14.8%*	6.9%*	40.9%**	32.2%**	16.7%*	10.0%*	13.3%**	−8.4%**	−1.8%	−3.0%**
	Q2	31.0%**	26.5%	26.0%	16.3%*	27.6%	33.3%**	22.6%	16.3%*	3.3%	−6.8%**	3.3%	0.0%
	Q3	13.8%*	23.3%	30.6%**	32.1%**	19.6%*	28.1%	28.8%	23.3%	−5.8%**	−4.7%**	1.7%	8.8%**
	Q4	3.9%*	11.3%*	22.1%*	62.5%**	8.9%*	13.2%*	25.1%	52.6%**	−5.0%**	−1.8%	−3.0%	9.8%**
HML_T	Q1	46.1%**	21.6%*	17.8%*	14.3%*	54.7%**	25.2%	12.4%*	7.5%*	−8.5%**	−3.6%	5.4%**	6.7%**
	Q2	26.0%	28.8%	24.5%	20.4%*	34.5%**	29.4%**	22.1%*	13.8%*	−8.4%**	−0.5%	2.3%	6.6%**
	Q3	14.3%*	18.7%*	31.9%**	34.9%**	21.4%	22.8%	26.1%	29.5%**	−7.1%**	−4.1%	5.8%*	5.4%*
	Q4	7.7%*	13.3%*	26.2%	52.5%**	17.6%*	13.9%*	2.0%	45.4%**	−9.8%**	−0.5%	3.2%*	7.1%**
SMB_T	Q1	38.7%**	24.7%	22.2%*	14.2%*	45.5%**	27.9%	19.2%*	7.3%*	−6.7%*	−3.1%	3.0%	6.8%**
	Q2	24.0%	29.2%**	25.3%	21.3%*	35.5%**	31.1%**	19.7%*	13.6%*	−11.4%**	−1.8%	5.5%*	7.7%**
	Q3	7.2%*	10.7%*	36.0%**	45.9%**	20.3%*	18.7%*	30.9%**	29.9%**	−13.1%**	−7.9%**	5.0%*	16.0%**
	Q4	0.8%*	2.3%*	19.1%*	77.6%**	7.4%*	8.1%*	20.4%*	63.9%**	−6.5%**	−5.8%**	−1.2%	13.6%**
UMD_T	Q1	33.2%**	17.6%*	24.9%	24.1%	46.3%**	22.8%*	16.2%*	14.6%*	−13.0%**	−5.2%*	8.7%**	9.5%**
	Q2	25.3%	24.6%	25.3%	24.5%	28.8%*	26.1%	23.1%	21.8%*	−3.4%	−1.4%	2.0%	2.7%
	Q3	13.3%*	23.8%	32.2%**	30.6%**	22.1%	22.2%	22.6%	32.8%**	−8.7%**	1.5%	9.5%**	−2.2%
	Q4	8.3%*	11.4%*	25.1%	55.0%**	14.9%*	13.3%*	19.8%*	51.8%**	−6.6%**	−1.9%	5.3%**	3.2%
$TE_{SP500,T}$	Q1	55.0%**	27.1%	11.4%*	6.3%*	42.0%**	38.7%**	15.5%*	3.6%*	13.0%**	−11.5%**	−4.1%	2.7%*
	Q2	13.1%*	35.0%**	27.3%	24.3%	19.0%*	39.4%**	25.0%	15.8%*	−5.8%*	−4.3%	1.7%	8.4%**
	Q3	2.1%*	19.7%*	33.4%**	44.5%**	8.8%*	24.8%	32.5%**	33.8%**	−6.6%**	−5.0%*	0.9%	10.6%**
	Q4	0.3%*	4.7%*	20.8%*	74.0%**	3.5%*	14.0%*	25.4%	56.9%**	−3.1%**	−9.3%**	−4.5%*	17.0%**

The table shows the transition probabilities between different measures of risk in T and $T + 1$ for funds with a performance in the highest quarter in T (first four columns), those with a performance in the lowest quarter in T (middle four columns), and the difference between these transition probabilities. XXX means that the target (column) variable is the same as in the appropriate row. This table gives the results for returns adjusted with the S&P 500. For the left and middle set of columns,*denotes a value statistically different from 0.25 on a 95% level, and **on a 99% level. For the difference between transition probabilities in the right set of columns, the null hypothesis is 0.00, i.e., we test whether this difference is statistically different from 0. Standard errors have been computed by bootstrapping.

Table A2. *Impact of Prior Performance on Choice of Risk Level (returns adjusted with the Carhart model)*

		XXX_{T+1} $R_{Carhart,T}$=4Q				XXX_{T+1} $R_{Carhart,T}$=1Q				XXX_{T+1} Difference			
from	**to**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
STD_T	Q1	47.3%**	32.2%*	17.5%*	2.9%*	40.2%**	30.5%*	23.4%	5.8%*	7.0%	1.6%	−5.8%	−2.8%**
	Q2	23.6%	32.5%**	33.4%**	10.4%*	21.4%	36.3%**	30.7%*	11.4%*	2.1%	−3.8%	2.6%	−1.0%
	Q3	8.1%*	22.2%	38.4%**	31.1%**	7.0%*	20.5%*	38.5%**	33.8%**	1.0%	1.7%	−0.1%	−2.6%
	Q4	1.3%*	6.4%*	20.7%*	71.5%**	1.5%*	6.4%*	21.9%*	70.0%**	0.0%	0.0%	−1.2%	1.4%
$MRP_{SP500,T}$	Q1	42.3%**	26.8%	21.1%*	9.5%*	42.6%**	29.0%*	17.0%*	11.2%*	−0.2%	−2.1%	4.0%*	−1.6%
	Q2	19.0%*	28.2%	31.3%**	21.3%	25.8%	31.9%**	23.6%	18.5%*	−6.8%**	−3.7%	7.6%**	2.8%
	Q3	12.0%*	20.5%*	32.9%**	34.5%**	15.9%*	28.0%	30.1%**	25.8%	−3.9%*	−7.5%**	2.7%	8.6%*
	Q4	4.8%*	12.3%*	23.4%	59.3%**	7.1%*	13.5%*	22.8%	56.4%**	−2.3%**	−1.2%	0.0%	2.9%
HML_T	Q1	50.9%**	24.1%	14.4%*	10.4%*	54.3%**	25.6%	12.0%*	7.9%*	−3.4%	−1.5%	2.4%*	2.5%*
	Q2	29.1%*	32.9%**	24.6%	13.2%*	35.0%**	25.8%	22.4%*	16.5%*	−5.9%**	7.1%**	2.1%	−3.3%
	Q3	16.4%*	25.1%	31.4%**	26.9%	21.0%	22.7%	30.9%**	25.1%	−4.6%*	2.4%	0.4%	1.7%
	Q4	16.2%*	14.8%*	26.0%	42.8%**	16.1%*	15.1%*	25.5%	43.0%**	0.0%	−0.3%	0.0%	−0.1%
SMB_T	Q1	55.9%**	26.4%	11.1%*	6.4%*	40.3%**	24.9%	21.5%*	13.1%*	15.5%**	1.4%	−10.3%**	−6.6%**
	Q2	37.3%**	29.9%**	19.3%*	13.3%*	29.9%**	30.3%**	22.5%	17.1%*	7.4%**	−0.3%	−3.2%	−3.7%*
	Q3	10.6%*	14.8%*	34.2%**	40.2%**	14.6%*	14.8%*	34.4%**	36.0%**	−3.9%*	0.0%	−0.1%	4.1%
	Q4	4.1%*	6.0%*	23.4%	66.3%**	4.6%*	6.2%*	19.2%*	69.8%**	−0.5%	−0.2%	4.1%*	−3.4%*
UMD_T	Q1	46.4%**	22.4%	17.8%*	13.2%*	44.6%**	21.2%*	15.9%*	18.1%*	1.7%	1.2%	1.9%	−4.9%**
	Q2	26.5%	35.0%**	22.4%	15.9%*	28.7%	26.9%	22.8%	21.5%*	−2.0%	8.1%**	−0.4%	−5.5%**
	Q3	16.1%*	25.3%	32.9%**	25.5%	23.3%	24.7%	21.6%	30.2%*	−7.2%**	0.6%	11.2%**	−4.0%
	Q4	12.7%*	14.3%*	27.8%*	45.0%**	15.3%*	14.9%*	21.9%*	47.7%**	−2.6%*	−0.5%	5.9%**	−2.6%
$TE_{SP500,T}$	Q1	67.1%**	24.0%	5.3%*	3.4%*	36.7%**	31.0%*	24.3%	7.9%*	30.4%**	−6.9%**	−18.9%**	−4.4%**
	Q2	18.7%*	37.8%**	25.5%	17.8%*	15.0%*	34.2%**	28.8%	21.9%	3.6%	3.6%	−3.2%	−4.0%
	Q3	4.2%*	24.9%	31.9%**	38.7%**	6.1%*	19.0%*	34.6%**	40.2%**	−1.8%*	5.9%*	−2.6%	−1.4%
	Q4	1.6%*	10.0%*	26.7%	61.5%**	1.8%*	9.9%*	25.1%	63.0%**	−0.1%	0.0%	1.6%	−1.5%

This table gives the transition probabilities between different measures of risk in T and $T+1$ for funds with a performance in the highest quarter in T (first four columns), those with a performance in the lowest quarter in T (middle four columns), and the difference between these transition probabilities. XXX means that the target (column) variable is the same as in the appropriate row. This table gives the results for returns adjusted with the Carhart model. For the left and middle set of columns, *denotes a value statistically different from 0.25 on a 95% level, and **on a 99% level. For the difference between transition probabilities in the right set of columns, the null hypothesis is 0.00, i.e., we test whether this difference is statistically different from 0. Standard errors have been computed by bootstrapping.