Market timing: A decomposition of mutual fund returns

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Market timing: A decomposition of mutual fund returns*

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Abstract

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Keywords: Market timing, Mutual funds, Performance evaluation

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1 Introduction

The investment performance of mutual funds is often measured by their average return over a certain holding period. Although these average returns can be quite disperse, it is not always clear what causes these return differences. The dispersion in the average fund return is frequently attributed to the management's selectivity skill (alpha) or the exposure to the stock market (beta). Whereas the alpha is the additional return provided by the fund management, the return differences caused by beta are interpreted as a compensation for bearing undiversifiable risk instead of management skill. Each private investor can decide for himself whether to hedge this market risk and be exposed to the fund's residual return, provided that he has an accurate estimate of the fund's future market exposure. Obtaining an accurate estimate is in general not an easy task, especially when funds exhibit time-varying market exposures.

There is ample empirical evidence that the market exposures of mutual funds change over time; see e.g. Alexander, Benson & Eger (1982). While this time-variation might be due to beta changes in the fund's underlying stocks, the management might also actively decide to alter the exposure to the market. These active decisions motivated by the suggested ability to predict the direction of the market are often referred to as timing decisions. While investors may benefit from active allocation towards rising and away from declining markets, most of the empirical evidence suggests that mutual fund managers are not capable to adjust their exposures accordingly; see, e.g., Ferson & Schadt (1996).[1]

Funds most prone to actively change their market exposures are the so-called asset allo-

[1] Other references supporting their findings are, for example, Treynor & Mazuy (1966), Henriksson & Merton (1981), Veit & Cheney (1982), Lockwood & Kadiyala (1988), and Chan & Chen (1992). A notable exception is Bollen & Busse (2001), who find empirical evidence supporting daily timing ability of fund managers. In addition, Wermers (2000) finds timing ability using a holdings-based performance analysis.

cation mutual funds. These funds claim in one way or another that they move in and out of the stock market when they deem it necessary.[2] The fund's prospectus is often opaque concerning the level of variability in the stock market exposure and the past success of the management in picking bull or bear markets. For a prospective investor's optimal portfolio choice, both the amount of undiversifiable market risk as well as the fund specific component are important ingredients. Knowledge about the dynamics of the fund's market exposure and the associated additional expected return are important for the investor's risk-return trade-off. Conditioning on the current state of the economy and the fund's past behavior may help the investor in deciding whether a mutual fund improves the risk-return trade-off with respect to his existing portfolio.

The mutual fund manager may change the fund's market exposure for a variety of reasons. For example, there is a large literature on the predictability of market returns using publicly available information such as the aggregate dividend yield and measures of the term structure of interest rates. The manager might change his market exposure depending on this publicly available market forecast or on his own interpretation of economic variables. Further, market exposure is adjusted due to the manager's personal expectation about future market movements. We specify a dynamic model for beta to allow for the possibility that fund managers slowly adjust their exposure (e.g. to reduce transactions costs) or have a long-run target beta from which they do no want to deviate too much. Finally, betas may fluctuate randomly, not related to any of the previous components. The skill of the manager can be divided in a selectivity and timing component. If the manager possesses timing ability, the expected conditional return of the mutual fund is larger in periods when the conditional volatility

[2] Consider for example the prospectus of the Caldwell and Orkin Market Opportunity Fund, *"The fund normally invests between 90% and 100% in equities; management may modify this allocation range when market conditions warrant."* or the Gabelli Mathers Fund, *"The fund usually invests a substantial portion in common stocks; it may, however, invest all or any portion of assets in fixed income securities."*

of the stock market is high. Selectivity or alpha captures the systematic fund returns that cannot be explained by the dynamic exposure to the stock market.

The main contribution of this paper is the decomposition of the mutual fund's conditional expected return in five components; the fund's long-run average market exposure, its reaction on the current macro economic situation, the fund's market exposure in the recent past, market timing, and selectivity (or alpha). This decomposition follows from our specification how a mutual fund changes its market exposure over time. We determine the magnitudes of the components by investigating a representative sample of 78 mutual funds that classify themselves as having an asset allocation perspective. The results of this empirical analysis shed light on the driving factors behind the conditional and unconditional expected fund return. In order to decompose the fund's conditional expected return, we estimate a dynamic performance evaluation model that generalizes the stochastic market exposure model by Lockwood & Kadiyala (1988) and the conditional performance evaluation model by Ferson & Schadt (1996). The results from our generalized model indicate that for several funds the findings reported in the previous literature might be biased because of a too restricted model specification.

Our empirical results indicate that managers are changing their market exposure substantially over time. The empirical decomposition suggests that management skill, selectivity and expert timing, explain part of the dispersion in cross-sectional fund returns. Our evidence suggests that several funds have significant selectivity and timing skills. We also find that selectivity and timing are negatively correlated, so that investors who pick a fund with high selectivity are likely to end up with negative timing skill. This is important for the portfolio choice problem of individual investors.

We further investigate the relation of turnover and expense ratios with fund performance.

The relation with turnover allows us to examine whether heavy trading is associated with higher performance. Our results indicate that the 10 funds with highest and lowest turnover outperform the average fund. Our results suggest that both managers with heavy trading, as well as managers with little trading outperform the average fund. In addition, we find that funds with both high and low expense ratios have managers with better skills than the average fund.

The remainder of this paper is organized as follows. In Section 2 we explain the decomposition of the conditional expected fund return in five factors. In Section 3 we describe our sample and how the public market forecast is determined. Section 4 analyzes the empirical return decomposition, and is divided in four parts. First, we investigate management selectivity and timing skill. Second and third, we examine the dynamic market exposure and the variability in the fund returns. Fourth and last, we relate our estimation results to other well-known performance evaluation models. In Section 5 we investigate the relation between turnover and expense ratios to managerial skill. Section 6 concludes the paper.

2 Factors driving the expected fund return

In this section, we decompose the conditional expected market return into five components. This decomposition builds on the large body of literature on return-based performance evaluation.[3] Estimation of these components provides new insights in the importance of the dynamics of a fund's stock market exposure on its average return. The return of a mutual

[3] When the exact portfolio holdings of a mutual fund are known, holdings-based decompositions might be used. See, e.g., Wermers (2000) for a decomposition of mutual fund returns in stock picking talent, style, transactions costs, and expenses.

fund is represented by a single factor model, where the (excess) market return is the factor,

$$R^e_{i,t} = \alpha_i + \beta_{i,t} R^e_{m,t} + \varepsilon_{i,t}, \tag{1}$$

where $R^e_{i,t}$ denotes the return of the mutual fund i in excess of the risk-free rate in period t, and $R^e_{m,t}$ denotes the excess return of the market over the risk-free rate in the same period. We define . The parameter

$$\beta_{i,t} = \frac{\mathrm{Cov}_{t-1}\{R^e_{i,t}, R^e_{m,t}\}}{\mathrm{Var}_{t-1}\{R^e_{m,t}\}}$$

measures the sensitivity of the fund return to the stock market movement in period t, and $\mu_{i,t} = \alpha_i + \varepsilon_{i,t}$ denotes the unexplained part of the fund's period t return. We assume that the conditional expectation of this unexplained part is time invariant, that is

$$\mathrm{E}_{t-1}\{\mu_{i,t}\} = \alpha_i. \tag{2}$$

The intuition behind this restriction is that an asset allocation mutual fund is assumed to have a constant level of selectivity, regardless of the economic situation.[4]

Time variation in the exposure to the stock market is allowed, since asset allocation funds are explicitly aiming to achieve superior returns by increasing (decreasing) their exposure to the stock market when the excess market returns are expected to be positive (negative). The dynamic process for the market exposure is described by

$$\beta_{i,t+1} = \overline{\beta}_i + \rho_i \left(\beta_{i,t} - \overline{\beta}_i\right) + \delta_i' X_t + \tau_i \left(R^e_{m,t+1} - \mathrm{E}_t\{R^e_{m,t+1}\}\right) + \eta_{i,t+1}, \tag{3}$$

[4]See, e.g., Christopherson, Ferson & Glasmann (1998) and Christopherson, Ferson & Turner (1999) for a model in which selectivity depends on the recent macro economic developments. Our methodology can be extended in a straightforward way to incorporate this as well.

where $\overline{\beta}_i$ is the long-run average market exposure of fund i, ρ_i is the strength of the delayed reaction (mean-reversion) in the market exposure, $\delta_i' X_t$ captures the manager's reaction to recent macro economic news, τ_i is the market timing coefficient, and $\eta_{i,t+1}$ is the idiosyncratic component not captured by the previous components. Note that for the long-run average to be well-defined the mean-reversion coefficient ρ_i is required to be smaller than one in absolute value. The macro economic series X_t are assumed to be stationary as well (which can be obtained by differencing the non-stationary macro variables, if necessary).

The expected excess return conditional on public information is denoted by $\mathrm{E}_t\{R^e_{i,t+1}\}$, and equals

$$\mathrm{E}_t\{R^e_{i,t+1}\} = \mathrm{E}_t\{\mu_{i,t+1}\} + \mathrm{E}_t\{\beta_{i,t+1}\} \cdot \mathrm{E}_t\{R^e_{m,t+1}\} + \mathrm{Cov}_t\{\beta_{i,t+1}, R^e_{m,t+1}\}. \tag{4}$$

Our aim is to find the driving factors behind the conditional expected return of mutual funds. In order to achieve this goal, the decomposition from equation (4) is analyzed using the dynamic process for the market exposure from equation (3). The first term, capturing selectivity of the management, is assumed to be constant over time. In order to analyze the second term in the decomposition, the conditional expected market exposure is required. Conditioning on macro economic information and past market exposure we obtain the conditional market exposure for fund i for period $t+1$,

$$\mathrm{E}_t\{\beta_{i,t+1}\} = \overline{\beta}_i + \rho_i \left(\beta_{i,t} - \overline{\beta}_i\right) + \delta_i' X_t. \tag{5}$$

This enables us to predict the market exposure in the next period, given the information at the end of this period. The timing component vanishes from equation (5), because conditional on the current macro information the market surprise return equals zero. In other words, private investors are assumed to have no market timing ability, so they cannot foresee how the manager is going to change his beta using his private information about future market movements.

The last term from the decomposition in equation (4) measures the conditional covariance between the future market exposure of the fund and the future market return. Using (3), this component can be straightforwardly rewritten as

$$\mathrm{Cov}_t\{\beta_{i,t+1}, R^e_{m,t+1}\} = \tau_i \mathrm{Var}_t\{R^e_{m,t+1}\}. \tag{6}$$

The only fund specific component in this last term is the timing coefficient τ_i. Given τ_i, the conditional variance of the market return determines the conditional expected return from the timing ability of the fund manager. Hence, in tranquil stock markets, the expected return due to timing ability is smaller than in volatile markets. This is consistent with the findings of Pesaran & Timmermann (1995), who conclude that aggregate stock return predictability is lower in calm stock markets.

Over the past decades, many papers have been published on the predictability of the direction of the stock market as a whole.[5] While the evidence in favor of economic predictability is limited, there is some agreement on the predictive power of certain macro economic indicators. The model for the dynamics in the market exposure in (3) investigates the ability of the fund manager to predict the direction of the market in excess of the predicted market return based on publicly available information. In order to separate this notion from usual timing, we use "expert" timing ability to refer to our definition. The intuition behind this expert timing is that private investors may be able to react themselves on the publicly availably

[5]See, e.g., Breen, Glosten & Jagannathan (1989) and Pesaran & Timmermann (1995).

macro data in order to time the market by the means of trading a stock index and money market fund. One might expect an asset allocation mutual fund to provide additional value for the private investor on top of the (publicly) anticipated market return. The conditional forecast of the stock market return in excess of the risk-free rate is assumed to be given by

$$\mathrm{E}_t\{R^e_{m,t+1}\} = \gamma' X_t, \tag{7}$$

where $R^e_{m,t+1}$ is the return on the relevant stock market index in excess of the risk-free rate in period $t+1$ and X_t is a vector of publicly available information (including a constant) at the end of period t such as (functions of) the dividend yield or measures of the term or credit spread.

The model for the market exposure presented in equation (3) reduces to two well-established mutual fund performance evaluation models when appropriate restrictions are imposed. The conditional model by Ferson & Schadt (1996) is obtained when $\rho_i = 0$ and $\eta_{i,t} = 0$ for each t. The stochastic components model by Lockwood & Kadiyala (1988) requires restrictions $\rho_i = 0$ and $\delta_i = 0$. Both models specify the timing component as the cash-versus-stocks decision, instead of relative to the predicted stock market return as in our model. Evidently, when the historical average is used as a predictor in our model, and the necessary restrictions are imposed, our model produces the same results as the models by Ferson & Schadt (1996) and Lockwood & Kadiyala (1988).

Substituting equations (2), (5), (6), and (7) into equation (3), we obtain the conditional expected mutual fund return,

$$\mathrm{E}_t\{R^e_{i,t+1}\} = \alpha_i + \left(\overline{\beta}_i + \rho_i \left(\beta_{i,t} - \overline{\beta}_i\right) + \delta_i' X_t\right) \cdot \gamma' X_t + \tau_i \mathrm{Var}_t\{R^e_{m,t+1}\}, \tag{8}$$

which consists of five different components. Before moving to the empirical implementation, let us consider a stylized example to illustrate the potential magnitudes of the components distinguished above. Suppose that the fund specific parameters are $\alpha_i = 0.05\%$ per month, $\overline{\beta}_i = 0.50, \rho_i = 0, \delta_i = 0$, and $\tau_i = 0.10$. Suppose further that the conditional expected market return for next month is 1.0 percent and the conditional variance is 0.0030 (which corresponds to standard deviation of about 5.5 percent per month). The conditional expected return of this fund now equals

$$\begin{aligned} \mathrm{E}_t\{R^e_{i,t+1}\} &= 0.05\% + 0.50 * 1\% + 0.10 * 0.30\% \\ &= 0.05\% + 0.50\% + 0.03\% = 0.58\%. \end{aligned}$$

In this example, the most important factor in the expected return is the average market exposure. The manager skills cumulate to an annual return of 96 basis points (bp). Thus, the private investor (without these skills) would earn almost one percent per year less on his portfolio with the same average beta. Now suppose that the market exposure in the previous period was 0.70, for the mean-reversion parameter we assume $\rho_i = 0.30$, and the macro factors account for $\delta_i' X_t = 0.10$. In this case the return of the fund can be split up in five parts,

$$\begin{aligned} \mathrm{E}_t\{R^e_{i,t+1}\} &= 0.05\% + (0.50 + 0.30 \cdot 0.20 + 0.10) * 1\% + 0.10 * 0.30\% \\ &= 0.05\% + (0.50\% + 0.06\% + 0.10\%) + 0.03\% = 0.74\%. \end{aligned}$$

In this second example, the conditional expected return of the fund has increased by 16 bp per month, and we are able to separate how much of the conditional market exposure is due to the long-run average, mean-reversion, and the macro economic situation. Although the conditional expected return increased, the manager skill is the same. Omitting these two additional terms in empirical analyses might bias the estimates found for selectivity and timing. In the next section we estimate the parameters of this model for a sample of asset allocation mutual funds.

3 Data

Our focus lies on the performance measurement of mutual funds that try to time the market. Because of their investment philosophy, this group of funds is expected to actively change their market exposure. We analyze the group of funds that classify themselves to the Morningstar database as having an asset allocation perspective.[6] It is required that the fund's inception date is prior to March 1995 in order to have sufficient data available. We excluded 9 funds that are categorized by Morningstar as bond funds, and do not allow multiple share classes of the same fund to be in the sample (so our sample consists of distinct portfolios only). This results in a sample of 78 mutual funds with monthly total return data from June 1972 to May 2002 for the funds that exist over this entire 30-year period. The data for the risk factors and conditioning information are from the data library of Kenneth French and the Federal Reserve Bank of St Louis.

In Table 1 we present the summary statistics of the 78 funds in our sample. The average returns from these funds vary between 0.12 and 1.35 percent per month over the period March 1995 to May 2002. The volatility, measured by the standard deviation of the returns over the same period, is between 0.011 and 0.104 percent per month. This large difference in volatility is an indication that some funds invest substantially more in fixed-income type

[6] This sample selection criterion is similar to Becker, Ferson, Myers & Schill (1999). We do not investigate the possibility of timing between bonds and cash, which might be an alternative way to provide value to the investor.

Table 1: **Descriptive statistics of asset allocation funds.** In this table the names of the funds from our sample are listed, together with some descriptive statistics. The column indicated with "Ave" contains the average monthly returns (in percentages) over the period 1995–2002. The column with "Std" contains the standard deviation over this period. The columns "Exp" and "Turn" contain the average expense ratio and turnover, over the fund's entire history. The columns "Alpha" and "Timing" contain the estimation results for the selectivity and timing return of these asset allocation funds.

Nr	Fund name	Average	StDev	Expense	Turnover	Alpha	Timing
1	Advantus Spectrum A	0.69	4.04	1.24	113.27	-0.111	0.000
2	Amer Funds Income Fund A	1.02	2.23	0.65	35.15	0.149	0.011
3	Aon Asset Allocation	0.95	3.29	0.68	70.17	-0.104	0.029
4	AXP Managed Allocation A	0.61	3.16	0.89	94.31	-0.105	0.000
5	Barclays Gbl Inv AA	0.93	3.11	0.76	40.71	-0.026	-0.004
6	Barclays Gbl Inv LP 2010	0.80	2.04	0.95	55.17	-0.113	0.073
7	Barclays Gbl Inv LP 2020	0.88	2.99	0.95	46.00	-0.107	0.046
8	Barclays Gbl Inv LP 2030	0.97	3.63	0.95	34.33	-0.076	0.026
9	Barclays Gbl Inv LP 2040	1.02	4.31	0.95	31.80	-0.058	-0.004
10	Barclays Gbl Inv LP Inc	0.63	1.11	0.95	70.40	-0.139	0.099
11	Berwyn Income	0.78	1.72	1.37	29.77	0.302	-0.082
12	Bruce	1.29	4.44	2.18	24.06	0.192	-0.207
13	Caldwell Orkin Mkt Opp	1.17	2.66	1.41	289.70	0.423	-0.087
14	Capital Val Inv	0.82	5.02	2.48	31.20	-0.162	0.417
15	Country Asset Allocation	0.87	2.56	1.41	30.88	-0.062	0.130
16	Deutsche Emerg Gr A	1.11	10.37	1.46	60.23	-0.289	-0.016
17	Deutsche Life Mid Invm	0.79	1.91	1.00	202.86	-0.121	0.110
18	Deutsche Life Shrt Invm	0.67	1.18	1.00	263.43	-0.152	0.136
19	Eclipse Asset Manager	1.01	2.84	0.71	84.20	0.071	0.029
20	Elfun Diversified	1.00	2.53	0.49	78.50	0.112	-0.001
21	Enterprise Managed A	0.81	4.02	1.57	50.50	-0.158	-0.100
22	EquiTrust Managed	0.71	2.37	1.95	65.50	0.333	-0.222
23	EquiTrust Value Growth	0.44	4.03	1.26	71.61	-0.278	0.000
24	Exeter Blended Asset I A	0.79	2.06	1.20	58.00	-0.057	0.076
25	Exeter Blended Asset IIA	1.03	3.04	1.17	74.40	-0.007	0.080
26	Federated Kaufmann K	1.35	6.43	2.27	116.25	0.657	-0.299
27	Federated Mgd Con Gr Ins	0.58	1.70	1.03	93.50	-0.158	0.043
28	Federated Mgd Gr Ins	0.64	3.51	1.09	100.71	-0.270	0.007
29	Federated Mgd Mod Gr Ins	0.65	2.64	1.04	95.57	-0.199	0.024
30	Fidelity Asset Mgr: Inc	0.63	1.23	0.70	125.33	0.014	0.035
31	Fidelity Value	1.18	4.72	1.00	171.43	0.278	-0.120
32	Fifth Third Str Inc Adv	0.71	1.41	1.94	103.60	0.083	-0.020
33	First Inv Total Return A	0.79	2.91	1.26	115.22	-0.354	0.169
34	Flex-funds Muirfield	0.71	3.84	1.33	286.67	-0.226	0.073
35	FMI AAM Palm Beach T/R	0.99	4.52	1.95	49.77	0.126	-0.029
36	Gabelli ABC	0.74	1.19	1.96	397.25	0.262	-0.023
37	Gabelli Mathers	0.12	1.53	0.89	207.50	0.079	-0.139
38	Galaxy Asset Alloc Ret A	0.80	2.70	1.30	59.88	-0.120	0.044
39	GE Strategic InvestmentA	0.95	2.55	0.85	102.13	0.067	-0.035
40	General Securities	0.71	5.36	1.46	44.27	-0.345	0.347

Table 1: **(continued):**

Nr	Fund name	Average	StDev	Expense	Turnover	Alpha	Timing
41	Guardian Asset Alloc A	0.91	3.39	0.95	95.00	-0.084	0.004
42	Hartford Advisers HLS IA	0.98	2.96	0.66	40.00	-0.018	0.035
43	ING Ascent I	0.77	3.50	1.30	165.83	0.034	-0.057
44	ING Crossroads I	0.69	2.74	1.29	160.00	0.059	-0.067
45	ING Legacy I	0.67	1.89	1.29	141.00	0.044	-0.024
46	INVESCO Growth Inv	0.63	9.16	0.85	125.64	-0.022	0.010
47	MegaTrends	0.81	4.56	1.83	104.50	-0.131	0.137
48	Montgomery Balanced R	0.70	2.92	0.78	97.14	-0.073	0.121
49	Morgan Stanley Strateg B	0.88	3.29	1.54	129.58	-0.008	-0.017
50	Nations Asset Alloc InvA	0.88	2.84	0.78	104.38	-0.053	0.061
51	One Group Balanced A	0.85	2.61	1.17	69.13	-0.108	0.067
52	Oppenheimer Discip Alc A	0.61	2.50	1.14	123.76	0.016	-0.088
53	Oppenheimer Quest Opp A	1.09	3.53	1.77	55.42	0.143	0.000
54	Phoenix-Oakhurst Str A	0.84	3.15	1.33	236.63	-0.091	0.061
55	Preferred Asset Alloc	0.97	2.78	1.03	25.33	0.047	-0.030
56	Sand Hill Portfolio Mgr	0.57	3.46	1.88	33.67	-0.258	0.060
57	Scudder Dynamic Growth A	0.61	9.66	0.89	89.12	-0.021	-0.023
58	Seligman Income A	0.41	2.18	0.87	68.96	-0.029	-0.034
59	Smith Barney Soc Aware B	0.83	3.29	2.04	65.62	-0.070	0.016
60	State St Res Str Gr A	0.96	3.12	1.27	113.83	0.068	-0.033
61	Strong Balanced	0.66	3.15	1.24	252.72	0.037	0.120
62	T. Rowe Price Pers Bal	0.92	2.43	1.03	44.86	0.114	-0.059
63	T. Rowe Price Pers Inc	0.82	1.79	0.93	47.86	0.084	-0.023
64	UBS Tactical Allocation C	1.11	4.23	1.80	40.00	-0.137	0.026
65	Valley Forge	0.61	2.31	1.69	43.29	0.046	0.012
66	Value Line Asset Alloc	1.28	4.31	1.14	152.25	0.554	-0.274
67	Vanguard Asset Alloc	1.09	3.04	0.48	35.33	0.135	-0.015
68	Vanguard LifeSt Cons Gr	0.83	1.91	0.00	5.00	0.035	0.035
69	Vanguard LifeSt Growth	0.94	3.55	0.00	3.00	-0.034	-0.009
70	Vanguard LifeSt Income	0.78	1.27	0.00	9.57	0.079	0.050
71	Vanguard LifeSt Mod Grth	0.90	2.73	0.00	6.00	-0.002	0.019
72	Wells Fargo Asset All A	0.93	3.11	0.94	52.85	-0.098	0.134
73	Wells Fargo Index All A	0.98	4.33	1.39	40.92	0.077	-0.002
74	Wells Fargo Outlook TdyA	0.59	1.11	1.24	59.00	-0.179	0.103
75	Wells Fargo Outlook2010A	0.77	2.04	1.24	47.00	-0.101	0.050
76	Wells Fargo Outlook2020A	0.86	2.98	1.24	43.00	-0.107	0.038
77	Wells Fargo Outlook2030A	0.94	3.64	1.24	29.75	-0.100	0.023
78	Wells Fargo Outlook2040A	0.98	4.32	1.24	28.00	-0.099	0.000
	Average	0.83	3.24	1.17	90.51	-0.012	0.013

securities than others.[7]

The time-series average of the fund's turnover and expense ratio can also be found in Table 1. This data is also extracted from the Morningstar database. We observe that the average turnover also varies substantially across funds. Some funds trade frequently, replacing each asset on average once per quarter. The average expense ratios range from zero to almost 2.5 percent per annum. Below, we relate both turnover and expenses to the fund's performance.

In order to identify expert timing, which is the ability of the manager to anticipate deviations of the market return from the forecast based on publicly available information, we specify a linear forecasting process for the latter. To keep in line with the conditional performance literature, we adopt the predictive variables from Ferson & Schadt (1996). These are (1) the one-month Treasury bill yield, (2) the dividend yield,[8] (3) the slope of the term structure, (4) the quality spread in the corporate bond market, and (5) a January dummy. The slope of the term structure is the constant maturity 10-year Treasury bond yield less the 3-month Treasury bill yield. The corporate bond spread is Moody's BAA-rated bond yield less the AAA-rated bond yield. The descriptive statistics of these variables can be found in Table 2, Panel A. We use a 60-month rolling window regression of the market return on the lagged variables and use these parameter estimates to predict next month's market return. The difference between the observed market return and its prediction is called the market surprise. In our terminology, fund managers who are to some extent able to predict this surprise are expert market timers. In Table 2, Panel B we display the summary statistics of our market return prediction model. As can be seen from this table, the correlation of 0.14 between the predicted market return and the actual market return is modest over the full

[7] We also plot the estimation results for selectivity and timing for each fund in Table 1. Summarized results are discussed in the remainder of this section.

[8] Ferson & Schadt (1996) use the dividend yield on the CRSP value weighted market return. We use the dividend yield on the S&P 500 instead, but expect this to have minor influence on the results.

sample period. In the most recent part of the sample, the correlation becomes even negative, with –0.16 over the last three years. It seems that the out-of-sample ability of this linear model to forecast movements in the stock market is low.[9]

4 Performance attribution of asset allocators

In order to obtain the estimated return components as derived in Section 2 of this paper, we estimate the following model for the conditional fund returns from equation (8)

$$R_{i,t}^e = \alpha_i + \beta_{i,t} R_{m,t}^e + \varepsilon_{i,t} \tag{9}$$

$$\beta_{i,t} = \overline{\beta}_i + \rho_i \left(\beta_{i,t-1} - \overline{\beta}_i\right) + \delta_i' X_{t-1} + \tau_i \left(R_{m,t}^e - \widehat{R}_{m,t}^e\right) + \eta_{i,t}, \tag{10}$$

where $\widehat{R}_{m,t}^e$ is the predicted market return based on publicly available information. We assume that the error terms $\varepsilon_{i,t}$ and $\eta_{i,t}$ are independently and normally distributed with variances σ_ε^2 and σ_η^2. The parameters of interest of the model, α_i, ρ_i, δ_i, τ_i, and the series of parameters $\beta_{i,t}$ follow from maximum likelihood estimation and the Kalman filter, respectively.[10] We define the mean-reversion term as $\beta_{i,t}^* = \rho_i \left(\beta_{i,t-1} - \overline{\beta}_i\right)$.

In state-space terminology, equation (9) is called the measurement equation, and equation (10) is called the transition equation. Under the normality assumption, the Kalman filter is the minimum mean square estimator for the parameters $\beta_{i,t}$. When the disturbances are not normally distributed, the Kalman filter is still the minimum mean square linear estimator.

[9] Unreported results indicate that our main conclusions do not materially change when no predictability in the market return is assumed. In that case, expert timing reduces to the usual notion of timing.

[10] Without the mean-reversion term in the market exposures, the model reduces to a linear regression model with heteroskedastic errors. We estimate the model with Ssfpack, described in Koopman, Shephard & Doornik (1999).

Table 2: **Descriptive statistics of the predicted market return.** In Panel A we present descriptive statistics of our prediction variables for several subsamples. We use a 60 month rolling OLS regression to estimate the predictive model parameters. In addition to the constant, five predictive variables are used: the level of short interest rate, the dividend yield, the term spread, the default spread, and the January dummy. For the prediction of the market return of June 1972, we estimate the regression parameters on the sample June 1967 – May 1972, and use these to predict the market return of June 1972. This is repeated by moving the estimation sample forward each month. The column labeled "Predict" in Panel B contains the average monthly predicted return, "Realized" contains the realized excess market return over the same period, "Correlation" denotes the correlation coefficient between the predicted and realized market returns, and "SigSurprise" contains the volatility of the surprise market return over the sample, which is defined as the realized market return less the predicted market return.

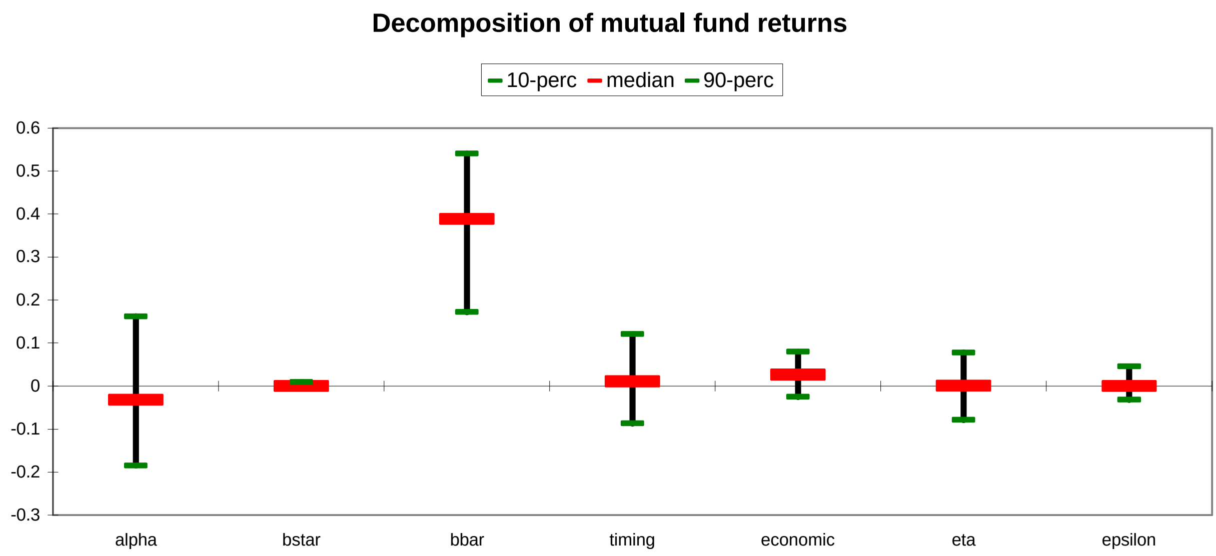
Panel A

Sample		T-Bill	Div. yield	Default	Term	January
1972:6-2002:5	average	6.58	3.45	1.10	0.90	0.08
	stdev	2.72	1.35	0.45	1.16	0.28
1972:6-1982:5	average	8.15	4.57	1.26	0.12	0.08
	stdev	3.26	0.96	0.50	1.22	0.28
1982:6-1992:5	average	7.19	3.83	1.28	1.39	0.08
	stdev	1.65	0.72	0.39	0.78	0.28
1992:6-2002:5	average	4.40	1.96	0.74	1.17	0.08
	stdev	1.15	0.67	0.17	1.00	0.28

Panel B

Sample		Predict	Realized	Correlation	SigSurprise
1972:6	2002:5	0.693	0.463	0.136	4.89
1972:6	1982:5	0.572	-0.094	0.171	5.22
1982:6	1992:5	0.702	0.851	0.233	4.73
1992:6	2002:5	0.805	0.631	-0.068	4.70
1992:6	1999:12	0.895	1.217	-0.071	4.22
2000:1	2002:5	0.521	-1.207	-0.164	5.76

Figure 1: Decomposition of conditional mutual fund returns. For the 7 factors in our decomposition, we display the median value (horizontal line) and the 40 percent of funds below and above the median (vertical line). The numbers on the y-axis are basis points per month. Bstar denotes the the mean-reversion component and Bbar the long-term target exposure.



Thus, the Kalman filter is optimal in this sense if we restrict our attention to estimators that are linear in the observations. The $\beta_{i,t}$-s follow from recursions based on the fit of the observed data $\left(R^e_{i,t}, R^e_{m,t}, X_{t-1}\right)$ with the specified measurement and transition equation, in combination with the assumptions about the error terms. For more details on the Kalman filter and its properties see, e.g., Harvey (1993).

We constrain the parameter ρ_i to be between zero and one. Economically, the exclusion of negative values of ρ_i means that we do not allow the exposure to oscillate monthly around its long-run average. In other words, an exposure below (above) the long-run average in this month is not allowed to imply an exposure above (below) the long-run average next month. The restriction that ρ_i is below one prevents an explosive market exposure, which would become unrestrictedly large as time goes by. The macro economic variables as well as the market surprise are demeaned, in order for the interpretation of $\overline{\beta}_i$ to be the funds average

Table 3: **Parameter estimates for model with dynamic exposures.** The parameter estimates from equation (9)– (10) are displayed. For each parameter, the cross- sectional average, the 10-percentile, the median, and the 90-percentile are tabulated. The standard deviations from the hyperparameters η and ε are also included, as well as the time-series minimum and maximum estimate for the market exposure β.

Parameter	Min.	Mean	Max.	10-perc	median	90-perc	sign +	sign -
alpha	-0.35	-0.01	0.66	-0.18	-0.03	0.16	4	4
long-run beta	0.12	0.60	1.53	0.26	0.61	0.88	78	0
timing * 100	-1.51	0.06	2.36	-0.44	0.05	0.54	6	1
dividend yield	-0.42	0.05	0.46	-0.08	0.06	0.16	25	6
term spread	-0.43	-0.02	0.33	-0.09	-0.02	0.07	3	5
default spread	-1.07	-0.16	0.45	-0.42	-0.17	0.14	1	13
interest rate	-3.31	-0.35	1.09	-0.90	-0.35	0.26	0	11
january dummy	-0.22	0.04	1.18	-0.09	0.01	0.19	3	12
rho	0.00	0.12	0.93	0.00	0.01	0.40	–	–
stdev eta	0.00	0.15	0.83	0.01	0.12	0.32	–	–
stdev epsilon	0.48	1.24	5.49	0.61	0.92	2.11	–	–

exposure. The inferences about timing or selectivity are not affected by this transformation.

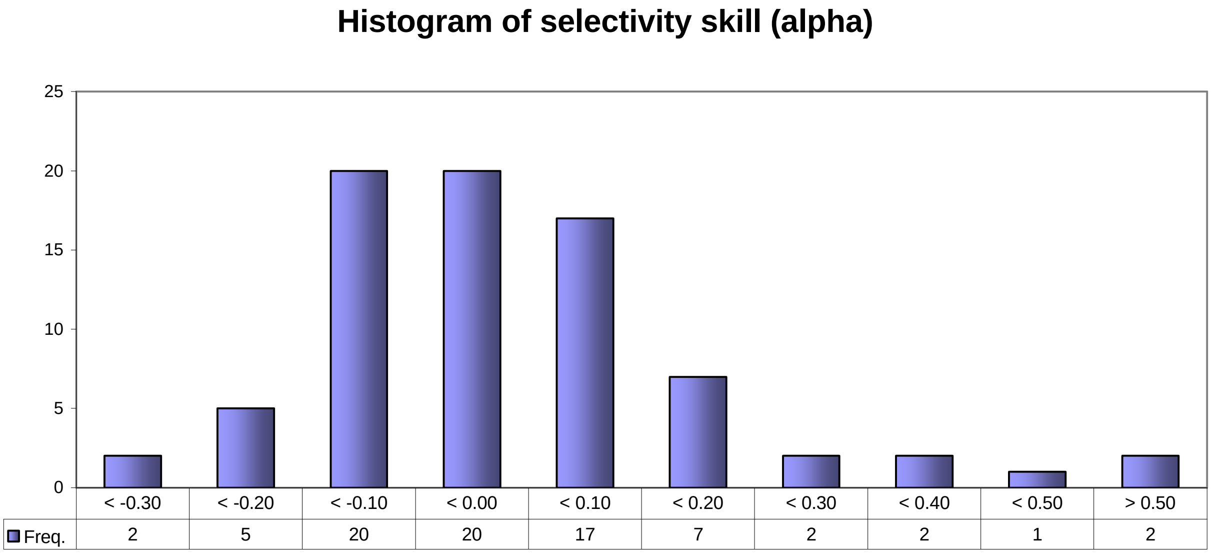
The model from (9)–(10) is estimated for each of the 78 funds from our sample of asset allocation funds. Summary statistics of the estimated coefficients can be found in Table 3. The estimated parameters are used to compute the conditional return decomposition from equation (4). In the remainder of this section, we analyze the importance of each of the factors of this decomposition. This provides insights in the economic magnitudes of time-variation in market exposures, timing ability, and selection ability of mutual funds with an asset allocation aim. A graphical overview of the importance of the factors we discriminate in our analysis is provided by Figure 1. The median value and the estimated return for the fund at the 10 and 90 percent interval are displayed. A long vertical bar for a component indicates that return dispersion attributed to that factor is high.

4.1 Manager skills: Selectivity and timing

First, consider the selectivity or micro-forecasting component, which is reflected by α_i in equation (9). Since the primary objective of the funds is asset allocation, we do not expect to find economically significant positive α-s. Figure 2 shows the distribution of the selectivity parameter of the funds in our sample. This figure indicates that the selectivity skill is spread around zero, with 47 out of 78 funds having a negative estimate for alpha. The distribution of alphas is somewhat skewed, with five funds exceeding 30 bp per month and only two funds falling below –30 bp. The estimation summary in Table 3 shows a negative alpha of –3 bp for the median asset allocation fund. The dispersion in manager selectivity indicates the risk for the investor from picking the right or wrong manager, all other things equal. The 80 percent interval of alphas around the median ranges from -18 bp to 16 bp per month. Thus, while the median alpha is close to zero, selection of one particular asset allocation fund might lead to a substantial variation in manager selectivity. There are only a few funds for which the α_i-s are statistically significant. We find four funds with a statistically significant positive, and four funds with a significantly negative selectivity coefficient. This is just over 10 percent of our sample, yet larger than the 5 percent we would expect if all managers in the sample have no selectivity.

The traditional timing skill of the fund manager is measured by the correlation of the fund's exposure to the market with the excess return on the market in the same month. Ferson & Schadt (1996) argue that the market is to a certain extent predictable, and timing related this public market forecast should not be attributed to manager ability. A private investor could, in principle, replicate such strategy himself at relatively low cost, because it is based on publicly available information. However, the return differential between the market and

Figure 2: Histogram of estimated selectivity skill.



the predicted component cannot be forecasted by the private investor, and this expert timing provides insight in the true skills of the manager. In Figure 3 we summarize the estimation results for the expert timing coefficient, represented by τ_i in equation (10). For 47 funds we find a positive estimate, which is somewhat higher than the 39 we would expect if managers have no timing skill. In Table 3 we see that the median timing coefficient is slightly positive with 0.0005. From equation (6) we know that the expected gains from expert market timing depend on the conditional variance in the surprise market return. The average return due the timing component is 1.2 bp per month.[11] The 80 percent interval for the timing return is -8.7 to 12.1 bp per month. In order to obtain an overview, Figure 1 displays the dispersion from each of the factors influencing the average return. The timing interval is only half the size of the interval of the selectivity return computed above. Note that the statistical significance of the timing parameter is limited. We find six statistically significant positive estimates, while

[11] Since not all funds from our sample exist over the entire 1972-2002 period, the reported gains from timing do not equal $0.0006 \cdot (4.88)^2 = 1.4$ bp. The somewhat lower volatility in the '90-s might cause the marginally lower reported average fund timing returns of our sample.

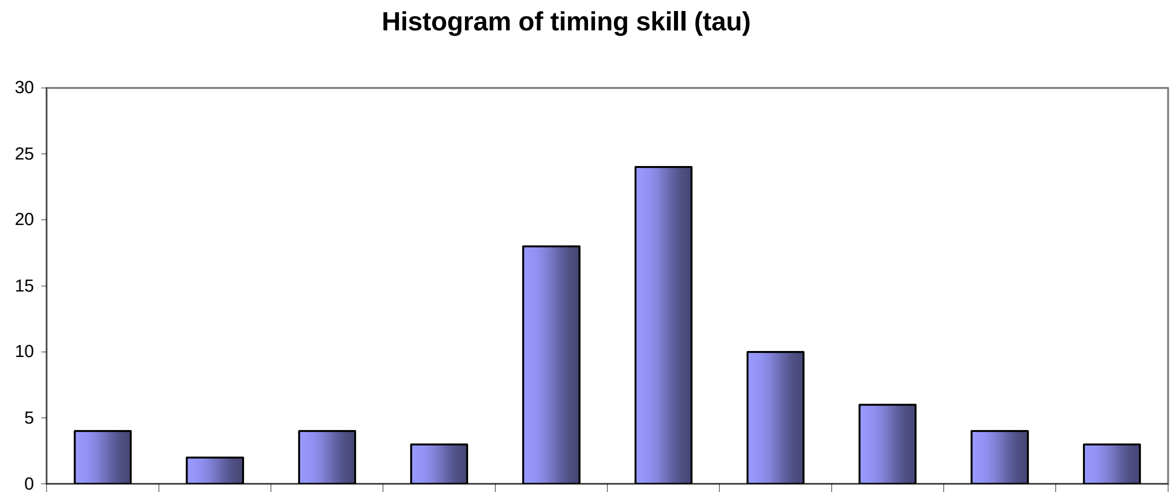
just one is significantly negative. If there would be no timing, we would expect two positive and two negative rejections. Hence, albeit not overwhelming, our results indicate that there is evidence supporting timing ability for some mutual fund managers. However, note that our sample consists only of surviving funds, which might bias our timing results in favor of timing.

The estimates for selectivity and timing at the individual fund level can be found in Table 1. The results on selectivity and timing suggest that an investor who is able to select the fund with both top decile alpha and timing might have an expected return of 55.5 bp per month over an investor selecting the bottom decile alpha and timing.[12] This is true if the decision about selectivity and timing can be separated from each other. However, the benefits of management skills for private investors are reduced if managers with positive (negative) timing ability at the same time have negative (positive) selectivity. Most empirical studies find that the correlation between selectivity and timing is negative, suggesting that high (low) timing corresponds to low (high) selectivity. Glosten & Jagannathan (1994), among others, indicate that there is an economic explanation for this result. Managers might purchase put options, which lead to reduced market exposures when stock returns are low, implying timing ability. Obviously, this type of timing is artificial and is unrelated to manager skill. The cost of buying put options is reflected in lower manager selectivity. We also examine the combination of returns due to selectivity and expert timing to gauge the potential expected return difference that investors in a fund can obtain due to good management.

The correlation between the returns due to selectivity and expert timing in our sample is –0.71, which is consistent with the hypothesis that the manager is buying options rather than being a true market timer. Another explanation is provided by Edelen (1999), who claims

[12] This follows from $55.5 = (16.2 + 12.1) + (18.5 + 8.7)$.

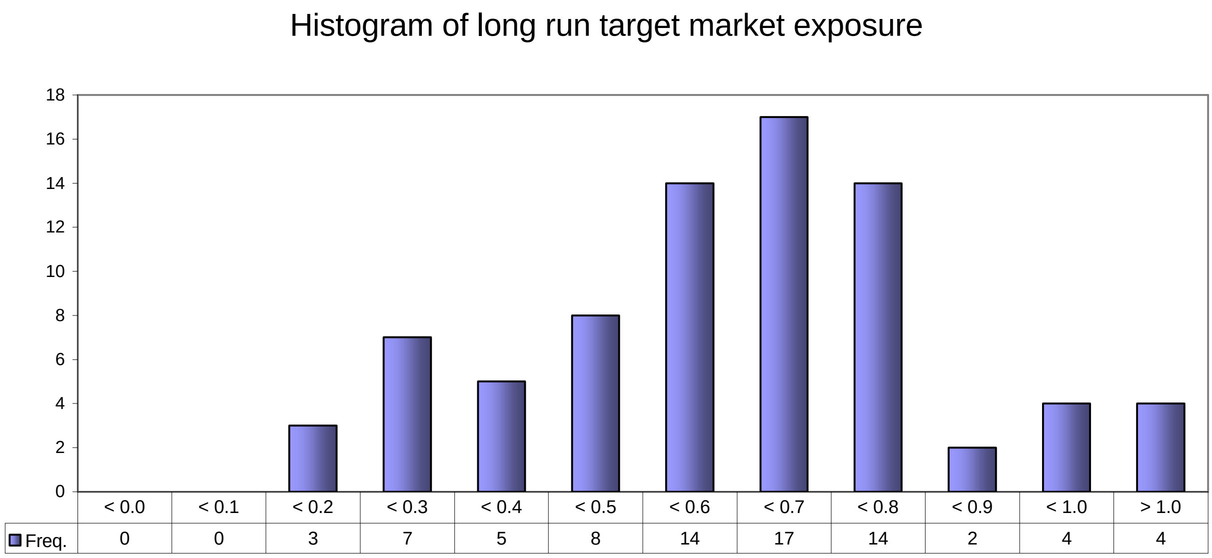
Figure 3: Histogram of estimated expert timing skill.



	< -0.8%	< -0.6%	< -0.4%	< -0.2%	< 0.0%	< 0.2%	< 0.4%	< 0.6%	< 0.8%	> 0.8%
Freq.	4	2	4	3	18	24	10	6	4	3

that providing liquidity to accommodate inflow and outflow of money affects timing measures. However, the results from Edelen suggest that using conditional performance measures such as Ferson & Schadt (1996) accounts for these liquidity effects. We find that for each of the eight funds with significant α-s, the corresponding τ-s are of the opposite sign, of which three are also statistically significant. The average return of the sum of selectivity and timing is close to zero, and the 80 percent spread of the sum is from –0.13 to 0.16 bp. The size of this spread in total manager skill (29 bp) is considerably lower than the sum of the spread in alpha (35 bp) and the timing return (21 bp). This indicates that private investors cannot exploit both selectivity and expert timing skill at the same time. An investor who picked a fund with adverse selectivity skill enjoys this negative relation, since most likely the expert timing skill of the fund manager partially compensates the losses on selectivity. Nevertheless, manager skill dispersion amounts to a return difference of 3.5 percent per annum, which indicates the importance of selecting the mutual fund with the best manager.

Figure 4: Histogram of estimated long-run market exposure.



4.2 Non-skill components of conditional expected return

We now turn to analyzing the components of expected return not related to manager skill. The three remaining components are the long-term market exposure, mean-reversion or delayed reaction, and macro economic sensitivities. These three components can also be found in the decomposition of conditional fund returns in equation (8).

A histogram of the estimates of the long-term market exposures is displayed in Figure 4. The median fund has a long-term exposure to the market of 0.61. The dispersion in these unconditional market exposures ranges from 0.26 to 0.88, excluding the top and bottom decile. The long-term market exposure is below one for all but 4 funds, indicating that most funds are on average only partially exposed to stock market risks. This can be achieved by investing in, for example, bonds or cash, but also by investing in low beta stocks. In the latter case, information about the holdings in asset classes, as provided by for example Morningstar, would not suffice to find a low market exposure. Edelen (1999) indicates that mutual funds are less exposed to the stock market because they need cash in their portfolio in order to accommodate the inflow and outflow of investor's money. The expected return that can be attributed to this component is the long-term exposure multiplied by the conditionally expected risk premium. The average fund return related to the long-term exposure is 34 bp per month.[13]

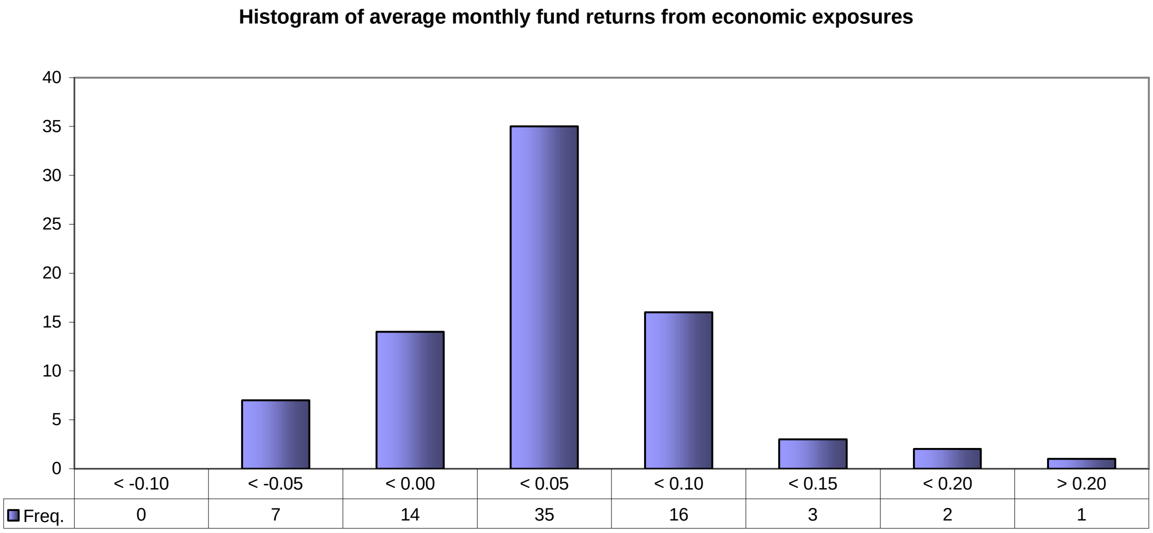
The component that captures delayed reaction to past signals to deviate from the long-run target exposure seems to be of minor importance for this particular empirical application. In total 51 funds have a mean-reversion coefficient below 0.05, indicating that most funds adapt their exposures quickly.[14] On the other hand, for eight funds this term is above 0.40, suggesting economic importance in certain cases. Leaving out this component might lead to biased estimates for the other parameters in the model. This mean-reversion component measures temporary deviations from the long-run average, and hence its total effect is expected to be around zero. The small impact of returns attributable to this factor is also found in the data. The fund with mean-reversion at the 90th percentile can attribute on average only 1 bp to this factor.

The sensitivities to economic variables are used both directly and indirectly in our estimation of the market exposure. In addition to the term $\delta_i' X_{t-1}$ in equation (9), the predicted market return is also a linear combination of the same macro variables. Thus $-\tau_i \widehat{R}_{m,t}$ can be rewritten as $\widehat{\phi}_i' X_{t-1}$, where $\widehat{\phi}_i$ is a linear function of the expert timing coefficient (τ_i) and the parameters from our predictive market return model ($\widehat{\gamma}$). The δ_i represents the macro sensitivities that are not explained by the expert timing behavior of the mutual fund man-

[13]Since the funds in our sample have different starting dates, the average return due to this component is a product of the long-term market exposure and a weighted average of the excess market returns. The lower average market return in the first 10 years is underweighted because only a couple of funds existed back then.

[14]See Alexander et al. (1982) for a discussion on the random walk specification of the market exposure of mutual funds engaged in market timing or variability in the beta of stocks in the mutual fund portfolio. The mean-reversion specification used here reduces to the random walk specification when the mean-reversion parameter ρ is equal to one.

Figure 5: Histogram of estimated average return due to macro exposures.



ager. The returns from the explicit part can be interpreted as macro sensitivities of the fund deviating from the optimal macro exposure for timing. Figure 5 shows that mutual fund returns from direct macro economic exposures are modest. About 75 percent of the funds achieve a positive average return from this component. This result suggests that managers are able to increase fund returns by using economic information deviating from the public forecast as specified in our model. The average contribution of this factor is small, with 2.8 bp per month. The interval after deleting the 10 percent highest and lowest returns reaches from -2.5 to 8.0 bp, and is about half the size of the timing component. Investigating the statistical significance of the sensitivities to the individual macro variables shows that more than 5 percent is rejected at the 95 percent level for each of the five variables separately. The estimated coefficient for the dividend yield is statistically significant at the 95 percent level for 40 percent of the funds. The lowest number of rejections are for the term spread, but with 10 percent this is still more than the 5 percent significance level of the test. See Table 3 for more details. These results indicate that mutual fund managers are able to use economic information to increase returns above the public forecast.

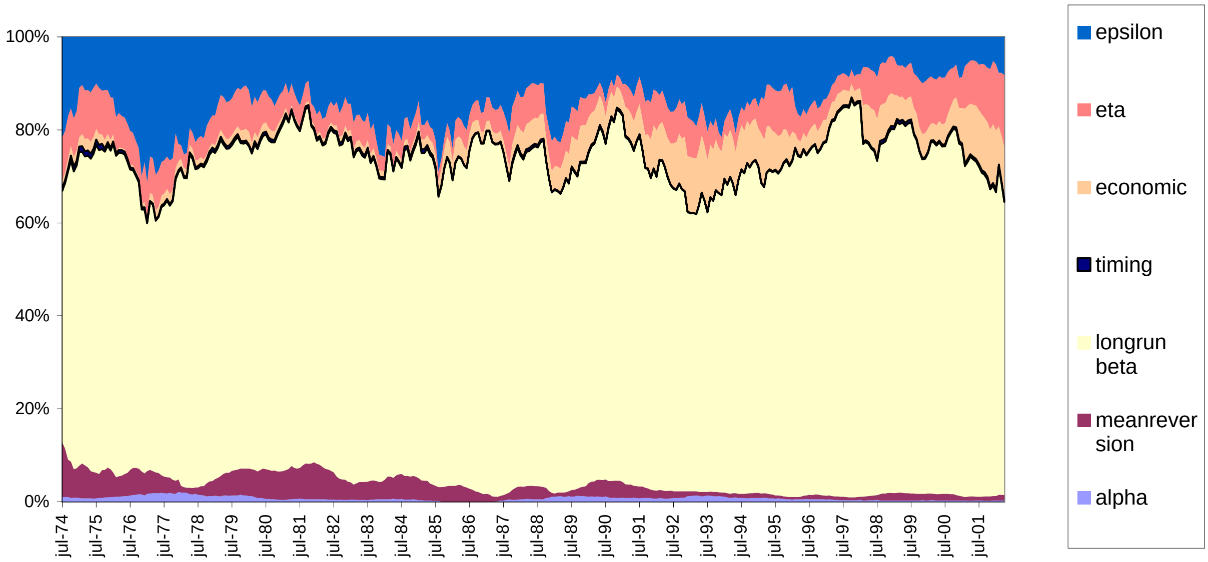
4.3 Time-series variability in the market exposures

The importance of allowing market exposures to change over time for performance evaluation depends on the variation employed by these managers. In order to motivate the use of a dynamic process for the market exposure, as in equation (10), we examine the minimum and maximum estimated exposure for each of the funds in our sample. The summary statistics of this analysis are displayed in Table 3. The median from the time-series minima for our 78 mutual funds is 0.21, while the median from the time-series maxima is 0.92. This indicates that the estimated market exposures vary considerably over time for these funds. These findings suggest further that many funds tend to hold cash, probably for liquidity reasons as suggested by Edelen (1999). Also, many funds do not fully hedge their market exposure when they expect stock markets to have negative returns. The findings on this difference between the minimum and maximum exposure motivate the use of our dynamic approach to mutual fund performance evaluation.[15]

Equation (10) contains a random exposure shock, $\eta_{i,t}$, to allow for market exposure changes unrelated to the other components of the model. These random changes represent uncertainty in the market exposure that does not influence the conditional expected return. For example, this term includes exposure shocks due to management change. For several funds our estimation results indicate that the term $\eta_{i,t}$ is unimportant. This can be seen in Table 3, where the lower 10th percentile of $\widehat{\sigma}_\eta$ is 0.01. For the median fund $\widehat{\sigma}_\eta = 0.12$, which suggests that random market exposure changes can be sizeable, corresponding to a 95%-confidence interval of 0.48. These random changes in beta also influence the total vari-

[15] Recently, Spiegel, Mamaysky & Zhang (2003) also use a dynamic state-space model in order to select mutual fund managers.

Figure 6: Relative importance of components in the mutual fund return decomposition. The return is split up in 7 parts $R^e_{i,t} = \alpha_i + \rho_i \left(\beta_{i,t-1} - \overline{\beta}_i\right) R^e_{m,t} + \overline{\beta}_i R^e_{m,t} + \tau_i \left(R^e_{m,t} - \widehat{R}^e_{m,t}\right) R^e_{m,t} + \delta_i' X_{t-1} R^e_{m,t} + \eta_{i,t} R^e_{m,t} + \varepsilon_{i,t}$, which are displayed in the figure in the same order from the bottom to the top of the figure. The relative importance is calculated by $share_{i,t} = \frac{|c_{i,t}|}{\sum_{i=1}^{7} |c_{i,t}|}$, where $c_{i,t}$ is the cross-sectional average of component i at time t.



ance of the conditional expected return. Conditional on the market return, the variance is increased by $\sigma^2_\eta \left(R^e_{m,t}\right)^2$. This gives an impression of the variability of the unexplained fund returns that can be attributed to random variation in the market exposure.

The residual variance of the fund return is $\sigma^2_\eta \left(R^e_{m,t}\right)^2 + \sigma^2_\varepsilon$. For the median fund, the second term is estimated to be $\widehat{\sigma}_\varepsilon = 0.92$ percent per month. In contrast to equity mutual funds, for which most of the return variation can be explained by standard factor models, these fund returns behave differently. Apparently, most funds are not fully diversified, and potential investors should be aware of this when deciding about adding an asset allocation fund to their portfolio. A graphical representation that indicates the importance of these residuals can be found in Figure 6, in which the time-series properties of the sample of funds are analyzed in more detail. To construct this figure, each of the 7 components of $R^e_{i,t}$

from equation (9) are equally weighted over the 78 funds in our sample. Thus, we obtain cross-sectional averages of the components on the right-hand side of

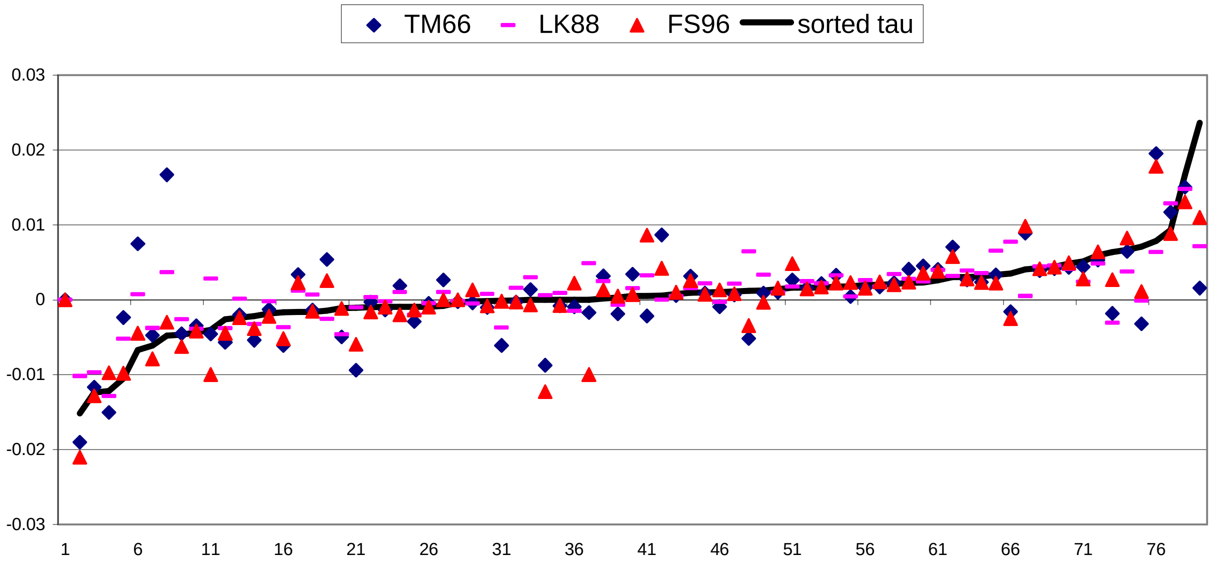
$$R^e_{i,t} = \alpha_i + \overline{\beta}_i R^e_{m,t} + \rho_i \left(\beta_{i,t-1} - \overline{\beta}_i\right) R^e_{m,t} + \delta_i' X_{t-1} R^e_{m,t} + \tau_i \left(R^e_{m,t} - \widehat{R}^e_{m,t}\right) R^e_{m,t} + \eta_{i,t} R^e_{m,t} + \varepsilon_{i,t} \tag{11}$$

for each point of our sample. This cross-sectional average can be interpreted as a fund-of-fund with equals weights in each of the individual asset allocation funds. If we denote these cross-sectional averages by $\overline{c}_{j,t}$, it is possible to calculate the average contribution of each of the components over time as

$$share_{j,t} = \frac{|\overline{c}_{j,t}|}{\sum_{i=1}^{7} |\overline{c}_{j,t}|}.$$

The annually smoothed shares $share_{i,t}$ are plotted in Figure 6. As can be seen, the most important part can be explained by the long-term beta exposure. Both selectivity and timing do not appear to be important. Note that the error terms ε and η are correlated over firms, as they can make a substantial contribution to fund returns. From 1992–2002, the contribution of ε decreased substantially. This indicates that idiosyncrasies in fund returns can be diversified better towards the end of the sample. At the same time, the influence of η is stronger at the end (and beginning) of the sample period. This allows for the possibility that there is a common component in the unexplained changes in the manager's market exposure changes against which an investor cannot diversify away by investing in many funds. We also observe an increased importance of the macro economic factors in the first half of the 1990s. This suggests that mutual fund managers were reacting similarly on on macro economic information during this 5-year period.

Figure 7: **Estimated market timing skills across different models.** For each of the 78 asset allocation funds in our sample, we estimate the model with time-variation in market exposures using our model and three well-known performance evaluation models; Lockwood and Kadiyala (1988, LK88), Ferson and Schadt (1996, FS96) and Treynor and Mazuy (1966, TM66). We rank the funds on the basis of the timing estimate from our model, and display the timing estimates that result from the other models. The closer the symbols to the black line, the closer the timing estimate from that model corresponds to the timing measure from our model.



4.4 Relation with other models

For the return decomposition above, we used the dynamic model as described in equations (9)–(10). As noted earlier, under certain parameter restrictions these models reduce to well-known performance evaluation models. In this subsection, we analyze the differences in estimated manager skills by using our extended model and the restricted models from the existing literature.

In order to investigate this, we have graphically displayed the coefficients from our model in ascending order. This is represented by the black line in Figure 7. The corresponding estimates from the stochastic timing model Lockwood & Kadiyala (1988) are displayed in rectangles, the conditional timing model Ferson & Schadt (1996) in triangles, and the traditional timing model Treynor & Mazuy (1966) in diamonds. As could be expected, the existing performance analyses are in many cases not much different from our model, since our model is a generalization and might reduce to the existing models depending on the mutual fund performance data. However, in notable cases the timing coefficients differ substantially, which can be seen by the dispersion of the dots at a certain point at the x-axis. Several funds that show excellent positive timing coefficients by the Treynor & Mazuy (1966) analysis, end up in the left part of the graph, suggesting weak timing skills when a more general model is analyzed. The reverse is also true, some funds with high timing skill according to our model, seem to have no timing according to the simple model. Moreover, some of the most negative timing funds by the Ferson & Schadt (1996) or positive timing funds from the Lockwood & Kadiyala (1988) model are in the middle of the graph, indicating no timing ability within our model. Misspecification of the performance evaluation model in such cases could lead to erroneous inference, and hence giving the wrong investment advice for potential investors in asset allocation mutual funds. The selectivity estimates seem more robust against the timing specification of the model, as can be seen from Figure 8. Although a couple of differences are substantial the models here show much more resemblance.

5 Turnover, expenses, and performance

The fund managers of our sample of asset allocation funds can be expected to actively change the market exposure of their fund. However, it is unclear whether funds with high or low turnover are successful market timers.[16] A related question is whether funds with higher

[16] In addition, it is unclear on which horizon these funds time. We assume a monthly timing horizon, but in Goetzmann, Ingersoll & Ivkovic (2000) it is shown that daily timing ability may be hard to detect using monthly data.

Figure 8: **Estimated alphas across different models.** For each of the 78 asset allocation funds in our sample, we estimate the model with time-variation in market exposures using our model and three well-known performance evaluation models; Lockwood and Kadiyala (1988, LK88), Ferson and Schadt (1996, FS96) and Treynor and Mazuy (1966, TM66). We rank the funds on the basis of the alpha estimate from our model, and display the alpha estimates that result from the other models. The closer the symbols to the black line, the closer the selecivity estimate from that model corresponds to the selectivity measure from our model.

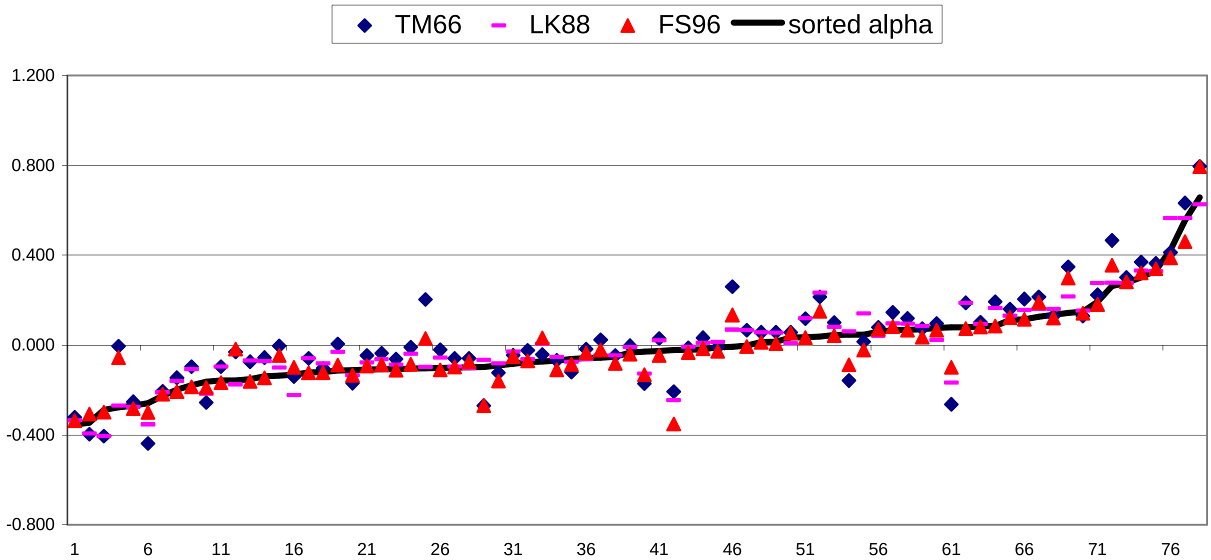


Table 4: **Relation between turnover, expenses, and management skill.** In the column with rank the bucket number is displayed, with each bucket consisting of 10 mutual funds, except bucket 4 and 5, which consist of only 9. In the subsequent columns the average raw returns (period 1995-2002), standard deviation, expense ratio, turnover rate, and the sum of selectivity (alpha) and timing returns (in percentages per year, calculated over entire sample period). In Panel A the funds are ranked on average turnover rate, and in Panel B on average expense ratio.

Panel A: Mutual funds ranked on average turnover rate.

	average return	expense ratio	turnover rate	alpha + timing	σ_η	σ_ε
sort 1	0.77	1.25	247.40	0.72	0.20	1.33
sort 2	0.85	1.28	130.29	0.53	0.17	1.38
sort 3	0.75	1.14	101.06	-0.69	0.12	1.02
sort 4	0.79	0.93	77.89	-0.41	0.15	1.27
sort 5	0.79	1.42	60.86	-0.45	0.12	1.58
sort 6	0.83	1.30	46.94	-0.15	0.13	1.34
sort 7	0.95	1.20	36.31	0.21	0.18	0.93
sort 8	0.93	0.85	19.14	0.35	0.09	1.12

Panel B: Mutual funds ranked on average expense ratio.

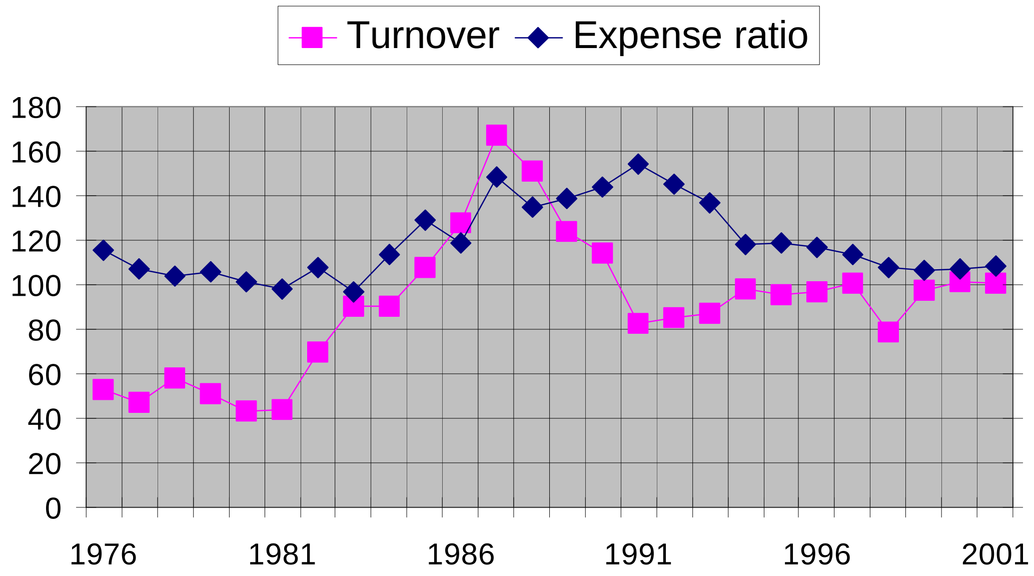
	average return	expense ratio	turnover rate	alpha + timing	σ_η	σ_ε
sort 1	0.88	2.05	99.14	1.04	0.25	1.81
sort 2	0.93	1.55	78.48	-0.02	0.22	2.03
sort 3	0.74	1.30	138.04	-0.57	0.19	1.15
sort 4	0.81	1.23	78.35	-0.31	0.11	0.94
sort 5	0.85	1.07	97.39	-0.21	0.17	0.91
sort 6	0.84	0.96	89.97	-0.32	0.05	0.77
sort 7	0.69	0.83	101.41	-0.15	0.12	1.44
sort 8	0.91	0.37	40.81	0.67	0.06	0.83

expense ratios are expected to perform better. We analyze the relation between the selectivity and expert timing performance of the funds and their average turnover and expense ratio. How the average turnover and expense ratios evolve over time can be seen from Figure 9. As can be seen, turnover and expense ratios are somewhat higher in the middle of the sample period. Wermers (2000) also finds that funds have increased their turnover over time, but that expense ratios are fairly stable.

We rank the mutual funds by their average turnover (see Table 1 for the individual turnover and expense ratios), and divide them in eight groups. Each group consists of 10 mutual funds, except the middle two have nine. The averages of these groups can be found in Table 4, Panel A. The average turnover of the top and bottom groups is 19 and 247 percent. The average security in the group of funds with low turnover stays in the portfolio about 5 years, while the average for the high turnover funds is 5 months. The average turnover for the whole sample is 95, indicating that each asset is traded about once per year. The relation between the turnover rates and expense ratios across groups is not immediately clear, but for the funds with lowest turnover, expense ratios are also lowest. This might be due to the lower transactions costs these funds are incurring by their infrequent trading behavior. The selectivity and expert timing returns of low and high turnover funds are higher than the average, 35 bp for the lowest turnover funds and 72 bp for the highest turnover funds. Wermers (2000), using a holdings-based decomposition, also finds that high turnover funds have higher average returns than low-turnover funds. He finds that funds with average turnover have the lowest selectivity as measured by the Carhart (1997) four-factor alpha. In contrast, Elton, Gruber, Das & Hlavka (1993) find that Jensen's alphas with respect to a three-factor model (market, small-cap, and bonds) are lower for funds with higher turnover or higher expense ratios.

We also rank the funds based on their expense ratio. Again, lowest expense ratios are associated with low turnover rates, but for the other groups the relation is less clear-cut. We see for this ranking, displayed in Panel B of Table 4, that management skill is highest for the group with highest average expenses. The second best performing group contains the funds with lowest expense ratio. Hence, as in the case with ranking on turnover, the average fund underperform the funds with more extreme expense ratios. In a Bayesian framework, Busse & Irvine (2002) model investor's prior beliefs about management skills to be centered around

Figure 9: **Cross-sectional average of fund expense ratio and expense ratio, 1976-2001.** The scale on left y-axis is for the turnover rate (in percentages per year) and the right y-axis is the expense ratio (in percentage per year).



the negative of the expense ratio. Our results indicate that manager skills are positively related to expense ratios and hence provide evidence against investor's prior beliefs in the model of Busse & Irvine.

6 Conclusions

We investigate the investment performance of asset allocation mutual funds. In order to achieve this goal, we decompose the conditional expected return of the funds in five parts. Two of these, selectivity and expert timing, are related to management skill, and the other three capture time-variation in the market exposure. The model we use to estimate these components reduces to the well-known performance evaluation models of Lockwood & Kadiyala (1988) and Ferson & Schadt (1996) under certain restrictions. For several funds in our empirical investigation these existing models are restrictive. In some cases conclusions about the importance of selectivity and timing change once these restrictions are relaxed.

We determine the relative importance of these components by investigating a representative sample of 78 mutual funds with an asset allocation objective. Our results indicate that these funds vary their market exposure substantially over time. However, the cross-sectional expected return difference due to time-variation are small. The returns to market timing are absent on average, although some fund managers have significant timing ability. The negative correlation between selectivity and timing that is reported in this line of literature is also present in our results. This may be explained by option-like strategies that these fund managers employ. A portfolio with fund managers that perform well on selectivity and timing is therefore hard to construct by investors. Further, we find that there appears to be a common component in idiosyncratic fund returns, implying that these are also hard to diversify away for an investor.

We also investigate the relationship between turnover and expense ratios with the performance of these funds. We confirm the holdings-based results from Wermers (2000) that high and low turnover funds seem to have better manager skill. In addition, we also find that highest and lowest average expense ratios are indicative of better management skill.

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