FINANCIAL SERVICES REVIEW

Financial Services Review 13 (2004) 285–302

Asset allocation decisions of mutual fund investors

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Abstract

I extend the Warther (1995) evidence to show that stock market returns are related to contemporaneous flows into mutual funds that invest in risky stocks and bonds, but are unrelated to flows into funds that invest in safer stocks and bonds. I examine whether common sources of predictability in returns and flows can explain this contemporaneous relation. I find that variables with predictive ability for stock returns, such as the lagged one-month T-bill rate and the lagged term premium, also predict flows into the risky categories of mutual funds.

Keywords: Mutual funds; Asset allocation; Personal investing; Predictability in stock and bond returns

1. Introduction

Mutual funds have increased in popularity over the last 20 years. According to the Investment Company Institute (ICI), assets under management have grown from $50 billion in the early 1970s to $6.4 trillion by the end of 2002.[1] The increase in popularity of mutual funds has led to speculation in the popular press that stock market returns respond to price pressure created by fund flows.[2] Academic literature has thus far shown only weak support for this price pressure hypothesis (Warther, 1995; Adler and Yi, 1998; Edelen and Warner, 2001; Goetzmann and Massa, 1999).

In the first part of this paper, I re-examine the flow-return relation to determine whether a different classification of mutual funds than the one adopted by Warther (1995) provides stronger support for the price pressure hypothesis. I find that flows into high-risk categories,

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whether stock funds or bond funds, are significantly related to contemporaneously measured stock and bond returns. However, flows into low-risk stock and bond funds are unrelated to stock market returns. The introduction of risk into the flow-return relation as a factor suggests that price pressure can only be a partial explanation for the relation between flows and market returns.

I examine an alternate hypothesis that aggregate flows and market returns respond to common sources of predictability. Single (Merton, 1980; Friend and Blume, 1975) and multiperiod models (Ait-Sahalia and Brandt, 2001) of the optimal investment and consumption policies of a risk averse investor demonstrate that investors' allocation of their wealth to a risky asset depends on the expected return to the risky asset, on the expected volatility of returns and on the coefficient of relative risk aversion. These models imply that variables that can predict future expected returns and future volatility should also predict flows into risky categories of mutual funds.

I identify a set of instrumental variables to proxy for time-variation in the distribution of stock and bond returns,[3] and test whether these instrumental variables can predict aggregate flows into the various categories of mutual funds. The tests show that the one-month T-bill rate and the term premium, variables that have been shown to predict future market returns, also predict flows into the four fund categories. Variables with predictive power for future volatility can predict flows into low-risk stock and low-risk bond funds. Finally, Ilmanen's (1995) proxy for time-varying risk aversion has weak predictive power for flows into high-risk stock and bond funds. Overall, the various instrumental variables have the highest explanatory power for flows into low-risk bond funds (R^2 = 22.03%) and the lowest explanatory power for flows into high-risk bond funds (R^2 = 6.88%).

It is well known that mutual fund investors chase past performance (Chevalier and Ellison, 1997; Sirri and Tufano, 1998) in selecting individual mutual funds. Other studies examine how fund loads, expenses and other fund-specific variables affect inflows into individual mutual funds (Cook and Hebner, 1992/1993). These papers focus on the selection of individual mutual funds. Yet it is well known that the portfolio allocation decision is an even more critical determinant of portfolio performance than the selection of individual funds. This paper fills the gap by showing that investors profit from timing their portfolio allocations with changes in the macroeconomy. Our paper is also unique in that we simultaneously study how aggregate flows are affected by three different sources of variation in the distribution of future stock returns. Ait-Sahalia and Brandt (2001) examine how asset allocations respond to joint variation in market premium and volatility. Other studies of asset allocations have focused only on time varying equity premium (Campbell and Viceira, 1999; Kandel and Stambaugh, 1996), or on time-varying volatility (Fleming, Kirby, and Ostdiek, 2000).

In Section 2, I document the relation between flows and returns to various asset categories. In Section 3, I develop an analytical model of the optimal portfolio policy of a utility maximizing agent. In Section 4, I describe the empirical methodology. Test results are discussed in Section 5. In Section 6, I examine the economic value of timing flows. In Section 7, I present conclusions.

Table 1
Panel A: The average number of funds in each ICI category from 1976/1 through 1995/11

Basic fund category	Average number of funds	Standard deviation	Number of funds at the beginning	Number of funds at the end
Aggressive	211.00	67.78	92.00	347.00
Balanced	70.60	52.50	22.00	205.00
Corporate-bond	268.40	529.76	28.00	1431.50
Flexible	42.40	27.35	4.00	95.00
GNMA	56.50	25.28	7.00	89.00
Government-bond	185.30	99.22	22.00	337.00
Growth-income	262.74	112.43	98.00	479.00
Growth	360.60	133.56	154.00	96.00
High yield bond	78.89	24.77	32.00	99.00
Income-bond	127.30	74.91	39.00	315.00
Income-equity	63.10	32.15	17.00	112.00
Income-mixed	89.50	30.57	38.00	164.00
International-equity	105.60	92.87	9.00	364.00
Long term-muni	179.30	70.88	60.00	308.00
National-taxable Money Market	123.40	25.44	70.00	157.00
Precious-metal	27.10	9.42	6.00	34.00
State-muni bond	293.50	204.76	22.00	712.00
State-tax exempt money market	81.50	55.39	6.00	168.00
Tax exempt money market	476.20	117.41	305.00	664.00
Global-equity	60.70	43.35	12.00	170.00
Global-bond	47.05	46.44	1.00	143.00

Panel B: Allocation of the 17 original fund categories to the four risk-based categories

Risk category	Original fund categories	Market beta (t statistic)
Equity high-risk	Aggressive Growth, Growth	1.70 (3.28)
Equity low-risk	Income-equity, Growth-Income Balanced, Flexible Income-mixed.	1.29 (2.83)
Bond high-risk	Corporate Bond, GNMA High Yield Bond	0.52 (5.08)
Bond low-risk	Government bonds, Income-bond Long term Muni, National taxable Money Market, State Muni-bond, State Tax Exempt Money Market, Taxable Money Market.	−0.42 (−0.84)

The market beta was obtained by regressing the monthly percentage change in total asset value of each risk category on market returns in a market model regression. t statistics are in parentheses. The time period for the regression is 1976/2 through 1995/11.

2. The relation between aggregate flows and asset returns

2.1. Data

Monthly aggregate fund flow data were obtained from various sources for the period from January 1976 through November 1995.[4] The ICI, our primary data source, classifies funds into 21 categories on the basis of the securities underlying the funds. The classification into these 21 categories remained constant over the interval under study in this paper, but changed after 1995. Hence, we confine our analysis to the period ending in 1995. In Table 1 we report the number of funds included in each category by ICI. The table shows that the average number of funds is the highest in the tax-exempt money market category (476.2). The third and fourth columns of Table 1 show that there was a significant increase in the number of funds in most fund categories from the beginning to the end of the sample period. In particular, the table shows a large increase in the number of funds in the corporate bond and state-municipal bond categories.

Warther (1995) classifies the categories in Table 1 into four groups based on asset class and finds that flows into stock funds are positively correlated with contemporaneous stock returns, but are unrelated to bond returns. I re-examine the Warther (1995) evidence by classifying funds not only on asset class, but also on the risk characteristics of the securities held by the funds. Such a two-way classification yields the following categories: high-risk stock funds, low-risk stock funds, high-risk bond funds, and low-risk bond funds. International funds are eliminated from the study to keep the study's focus on domestic securities. Precious metal funds are also eliminated because of ambiguity in the risk classification of this asset class. Finally, I exclude option-income funds because of insufficient data. Panel A of Table 1 describes how the remaining ICI fund categories were combined into the four risk-based groups.

I estimate the market beta for each fund category to determine whether the classifications are consistent with conventional measures of risk. I approximate returns to each risk group as the monthly change in the value of total assets of that group, and regress these returns on the market return. I report the beta coefficients in Panel B of Table 1. The coefficients are consistent with the risk classification; high-risk stock funds have the highest beta coefficient (1.70), followed by low risk stock funds (1.29), high-risk bond funds (0.52), and low-risk bond funds (−0.42), respectively.

For each ICI fund category, I calculate net sales as the sum of new additions, exchanges-in less the sum of exchanges-out and redemptions. Reinvested dividends are excluded from the calculation of net sales. The aggregated net sales across all ICI fund categories comprising a risk group are the net sales for that group.

I plot the time series graphs of net sales in Fig. 1. The gray shaded areas in Fig. 1 are the periods of recession as dated by the National Bureau of Economic Research. Business cycle variations in net sales are evident in Fig. 1. Panel A shows that net sales into the equity high-risk category decline at the start of a recession, and increase towards the end of the recession. This pattern in net sales is particularly evident during the recession from July 1990 to March 1991. Panel B shows that net sales into the equity low risk category also decline at the start of the recession, but to a lesser extent than sales into the equity high risk category. Panel C shows that net sales into the bond high-risk category decline at the start of a recession, but increase gradually as the economy emerges out of recession. Finally, Panel D shows that net sales into the low risk bond category actually increase at the start of a recession and remain positive throughout the recessionary period. Thus, Fig. 1 shows that flows shift out of high-risk categories and into the low-risk bond category during recessions.

Fig. 1 shows that net sales into all four categories display non-stationarity, short-run auto-correlation and a structural shift. Non-stationarity is indicated by an upward trend in net sales. Lower volatility in net sales before 1984 indicates a structural shift. I eliminate the trend and auto-correlated component in net sales. Detrending is achieved by dividing net

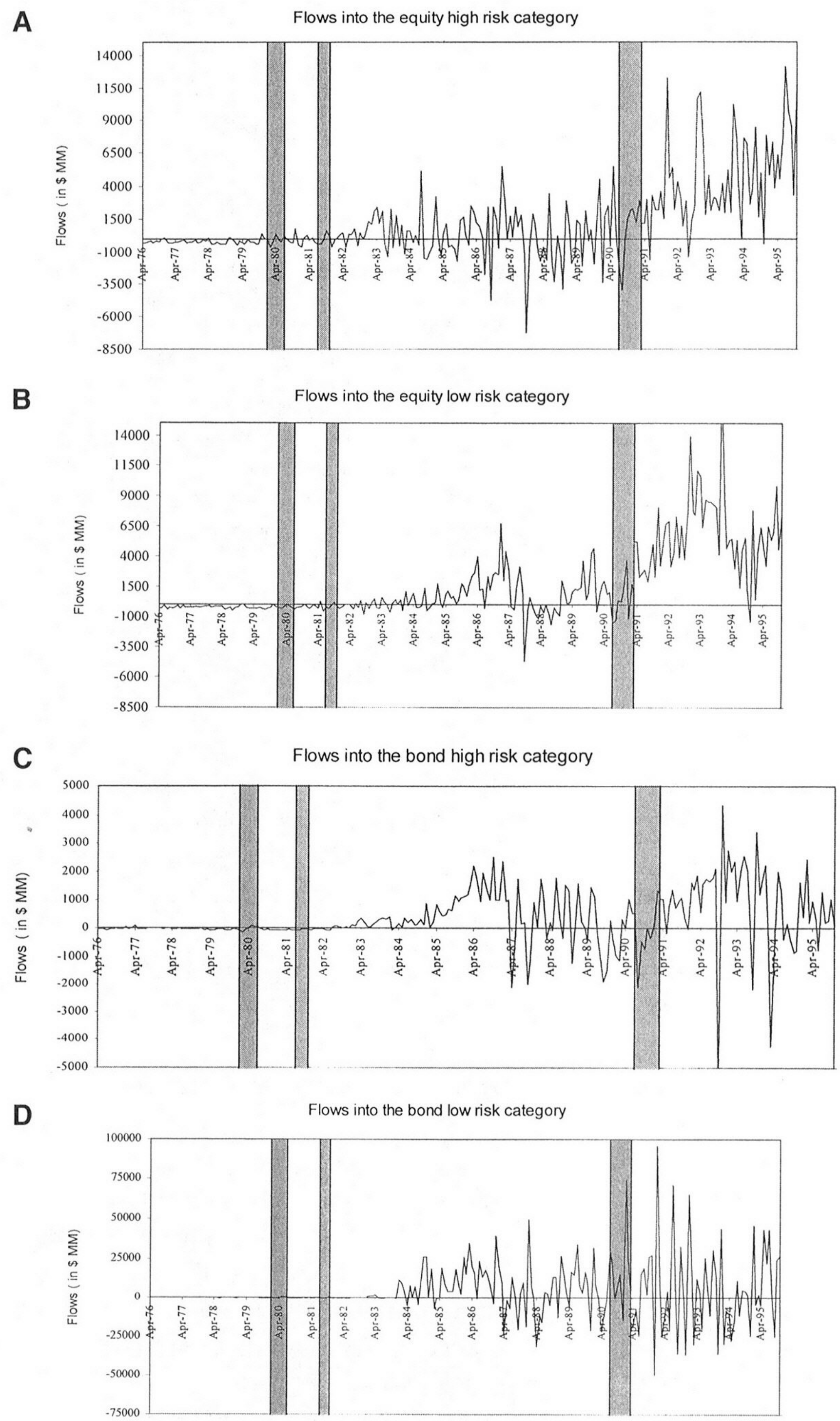

Fig. 1. Net sales into the four risk categories. Monthly net sales (flows) in each of the four categories are calculated as the sum of new additions, exchanges-in less the sum of exchanges-out, and redemptions. Net sales are plotted in the figure for the period from April 1976 to November 1995. The gray shaded areas represent recessions as dated by the National Bureau of Economic Research (NBER). (A) Net sales into the equity high-risk category; (B) Net sales into the equity low-risk category; (C) Net sales into the bond high-risk category; (D) Net sales into the bond low-risk category.

Table 2
Univariate statistics of normalized sales and AR(3) estimates

Category	Mean	AR(3) estimates					
		Intercept	Lag1	Lag2	Lag3	Adj-R^2 (%)	c^2 test for no first-order autocorrelation in residuals
Equity-high risk	2.49	0.53 (2.86)	0.29 (3.68)	0.30 (4.2)	0.26 (3.70)	48.46	0.13 (0.72)
Equity-low risk	−1.53	0.26 (2.04)	0.43 (6.68)	0.16 (2.49)	0.37 (6.15)	85.23	0.04 (0.84)
Bond-high risk	0.28	0.26 (2.53)	0.42 (3.51)	0.15 (1.20)	0.22 (2.94)	45.9	0.15 (0.72)
Bond-low risk	12.46	5.88 (3.19)	0.02 (0.25)	0.06 (10.95)	0.46 (5.34)	21.38	0.002 (0.97)

Sales are normalized by the level of the S&P 500 index in the previous month. An AR(3) regression is estimated for normalized sales into each of the four risk based categories. (Normalized sales)$_{it}$ = a + b_1 (Normalized sales)$_{it-1}$ + b_2 (Normalized sales)$_{it-2}$ + b_3 (Normalized sales)$_{it-3}$ + e_t.

The estimation period is from 1976/4 through 1995/11. The table presents the mean of the normalized flows and the AR estimates. Numbers in parentheses are t statistics of the coefficients from the AR(3) regression.

sales by the level of the S&P 500 index in the previous month. The auto-correlated component is eliminated by estimating an AR(3) model and obtaining the residuals:

$$NS_{it} = \alpha + \beta_{i1}NS_{it-1} + \beta_{i2}NS_{it-2} + \beta_{i3}NS_{it-3} + \varepsilon_{it} \quad (1)$$

where NS_{it} is the normalized net sales into the i^{th} risk based category.

In Table 2, I present the average net sales into each group and the regression estimates from Eq. (1). For each risk group, the coefficients on all the lags are positive and statistically significant even up to the third lag. I use the LM test proposed by Godfrey (1978) and Breusch (1979) to test for auto-correlation in the residuals. The χ^2 statistics and the corresponding p-values indicate that the residuals are not auto-correlated for any of the four risk categories.

2.2. *Regressions of stock and bond returns on unanticipated sales*

I begin the empirical tests by examining the relation between contemporaneously measured unanticipated sales into each of the four risk based groups and the returns to stocks and bonds. Unanticipated sales are the residuals from Eq. (1). Stock returns are proxied by returns to the S&P 500 index and by returns to the CRSP small capitalization index. Bond returns are proxied by the returns to the CRSP U.S. Treasury Bonds index, the returns to the Salomon Brother's Long Term High-Grade corporate bonds index and the returns to U.S. T-bills. The monthly returns data on the stock and bond indexes are obtained from the CRSP indices file. I estimate regressions of the return to each stock and bond index on unanticipated sales into each of the four risk based groups, and on a January and December dummy. The monthly dummies are included in the regressions to control for any seasonality in flows induced by seasonality in stock returns (Keim, 1989).

Regression results are presented in Table 3 (Panels A–D). In Panel A, returns to the stock and bond indexes are regressed on unanticipated sales into the equity high-risk group. The

Table 3
Regressions of returns on various assets on unanticipated sales into each of the risk based categories

Panel A: The flow variable is unanticipated sales into the equity high risk category

Dependent variable return on:	Intercept	Unanticipated sales into equity high-risk category	Jan.	Dec.	R^2 (%)
S&P 500	0.0019 (0.50)	0.0036 (4.8)	0.004 (0.39)	0.0055 (0.71)	18.15
CRSP small cap	0.0028 (0.52)	0.0037 (4.07)	0.030 (2.65)	0.0045 (0.47)	14.21
Corporate bonds	0.0069 (2.81)	0.001 (2.68)	−0.006 (−0.89)	−0.001 (−0.16)	1.26
U.S. T-bonds	0.0065 (2.53)	0.0011 (2.77)	−0.008 (−1.04)	0.0001 (0.03)	1.94
T-bills	0.0064 (19.26)	−0.0002 (−4.69)	−0.0001 (−0.34)	0.0004 (0.84)	14.17

Panel B: The flow variable is unanticipated sales into the equity low risk category

Dependent variable return on:	Intercept	Unanticipated sales into equity low-risk category	Jan.	Dec.	R^2 (%)
S&P 500	0.007 (1.85)	0.0008 (1.82)	0.008 (0.71)	0.009 (1.04)	0.9
CRSP small cap	0.0096 (1.69)	0.0005 (0.91)	0.034 (2.75)	0.009 (0.91)	2.2
Corporate bonds	0.008 (3.02)	0.0002 (0.67)	−0.005 (−0.71)	−0.0001 (−0.007)	−0.9
U.S. T-bonds	0.008 (2.85)	0.00032 (0.99)	−0.007 (−0.86)	0.0011 (0.16)	−0.6
T-bills	0.007 (19.51)	−0.0002 (−7.54)	−0.0002 (−0.63)	0.0005 (1.28)	32.5

Panel C: The flow variable is unanticipated sales into the bond high-risk category

Dependent variable return on:	Intercept	Unanticipated sales into bond high-risk category	Jan.	Dec.	R^2 (%)
S&P 500	0.0048 (1.3)	0.005 (3.25)	0.005 (0.50)	0.011 (1.20)	5.1
CRSP small cap	0.0068 (1.24)	0.0047 (2.11)	0.032 (2.60)	0.01 (1.02)	4.4
Corporate bonds	0.005 (1.94)	0.004 (4.21)	−0.007 (−1.17)	0.0007 (0.12)	4.9
U.S. T-bonds	0.0048 (1.74)	0.0042 (3.89)	−0.0092 (−1.26)	0.002 (0.31)	4.7
T-bills	0.0063 (17.2)	−0.0004 (−3.6)	−0.0001 (−0.31)	0.0001 (0.21)	−0.13

Panel D: The flow variable is unanticipated sales into the bond low risk category

Dependent variable return on:	Intercept	Unanticipated sales into bond low risk category	Jan.	Dec.	R^2 (%)
S&P 500	0.009 (2.91)	0.00011 (1.04)	0.004 (0.33)	0.013 (1.49)	−0.13
CRSP small cap	0.011 (2.58)	0.0001 (0.11)	0.034 (2.5)	0.0098 (0.97)	1.85
Corporate bonds	0.006 (2.61)	0.0002 (3.04)	−0.01 (−2.08)	0.005 (0.83)	2.7
U.S. T-bonds	0.006 (2.35)	0.00025 (2.69)	−0.017 (−2.08)	0.007 (0.97)	2.8
T-bills	0.006 (16.5)	−0.00001 (−0.78)	−0.0002 (−0.34)	0.00001 (0.05)	−0.75

Monthly returns to five asset groups are regressed on unanticipated sales into one of the four risk based categories, and on January and December dummies. The returns to the five asset groups are the returns to the S&P 500 index, the returns to the CRSP small capitalization index, the returns on the Salomon Brother's Long Term High-Grade corporate bonds index, the returns to the CRSP U. S. Treasury Bonds index, and the returns to U.S. T-bills. Estimation period: 1976/4 through 1995/11. Numbers in parentheses are t statistics.

results show that returns to the stock indexes and to the bond indexes, are significantly positively related to unanticipated flows into the equity high-risk group. Unanticipated flows into this category are negatively related only to the T-bill return. Overall, flows into the equity high-risk category have the highest explanatory power for returns to the S&P 500 index ($R^2 = 18.15\%$).

Similar results are obtained in Panel C of Table 3 with unanticipated sales into the bond high-risk group as the independent variable. Panels B and D of Table 3 show that returns to the stock indexes are uncorrelated with unanticipated sales into the safer categories of mutual funds. Panel B shows that unanticipated sales into the equity low-risk category is correlated negatively with the return to the U.S. T-bill and Panel D shows that unanticipated sales into the bond low-risk category are correlated only with the returns to the bond indexes.

The January seasonal is positive and statistically significant for the returns to the CRSP small cap index (Panels A–C) and is negative and statistically significant for the returns to corporate bonds and U.S. T-bonds (Panel D). The December seasonal is never significant in any regression.

I examine the robustness of the results in Table 3 with a multivariate regression of returns to the stock and bond indexes on unanticipated sales into all four fund categories. It is possible that the cross-asset relation between flows and returns in Panels A and C of Table 3 is spuriously induced by cross-correlation between flows into the four groups. Results from this robustness check are qualitatively similar to those in Panels A–D of Table 3.[5]

It is clear from the results in Table 3 that the cross-asset flow-return relations cannot be explained by price pressure induced by buying demand. A more likely explanation is that flows respond to the same information that affects returns to both stock and bond funds. In the next section we conduct a formal analysis of the investor's problem to determine the factors that affect flows.

3. The investor's problem

Flows into asset k, in any time period t, are given by:

$$\text{flow}_{\text{kt}} = \alpha_{kt} W_t - (1 + g_{kt})(\alpha_{kt-1} W_{t-1}) \quad (2)$$

where g_{kt} is the capital gain on asset k, W_t is total wealth, α_{kt} is the proportion of wealth invested in asset k and flow_{kt} is the net inflow into security k. Substituting for W_t in Eq. (2) as the product of W_{t-1} and the return R_{pt} on the total portfolio between t-1 and t, yields:

$$\text{flow}_{\text{kt}} = (\alpha_{kt} - \alpha_{kt-1}) W_{t-1} + (R_{pt} - g_{kt}) \alpha_{kt-1} W_{t-1} \quad (3)$$

Eq. (3) demonstrates that fund flows occur either in response to a change in the optimal portfolio weight invested in asset k, or because of rebalancing following a run-up or a decline in asset k's return relative to the portfolio return. α_{kt}, the weight in the risky asset, is determined each period as the solution to the investor's problem.

I use a continuous time approach, rather than the standard mean-variance analysis to solve for α_{kt}, the optimal weight in the risky asset. There is controversy about the form of the utility function that is required by the mean variance paradigm.[6] The continuous time approach avoids the difficulty of selecting the most appropriate utility function.

I assume that there are two risky assets and a risk-free asset. The continuous-time specification of the budget constraint for the kth investor over an infinitesimal planning period, dt is:

$$W_{k,t+dt} = W_{kt}\{1 + [\alpha_{\kappa,1}E(r_1 - r_f)dt + \alpha_{\kappa,1}\sigma_1 y(t)\sqrt{dt} + \alpha_{\kappa,2}E(r_2 - r_f)dt + \alpha_{\kappa,2}\sigma_2 z(t)\sqrt{dt} + r_f\,dt]\} \quad (4)$$

where W_{kt} denotes the kth investor's wealth at time t, $\alpha_{\kappa,1}$ is the proportion of the kth investor's wealth invested in the first risky asset, σ_1, σ_2, r_1, and r_2 are the standard deviations and returns to risky asset 1 and 2, respectively. y(t) and z(t) are standardized normal random variates. The investor's objective is to maximize her expected utility of wealth, $E(U(W_{k,t+dt}))$. By expanding $U(W_{k,t+dt})$ about $W_{k,t}$ using Ito's lemma, and taking expectations, the objective function becomes:

$$Max\ \ U(W_{kt}) + U'(W_{kt})W_{kt}[r_f + \alpha_{k,1}E(r_1 - r_f) + \alpha_{k,2}E(r_2 - r_f)]dt + \frac{1}{2}U'(W_{kt})W_{kt}^2[\alpha_1^2\sigma_1^2 + \alpha_2^2\sigma_2^2 + \alpha_1\alpha_2\sigma_1\sigma_2\rho]dt \quad (5)$$

The optimal allocations, $\alpha_{k,1}$ and $\alpha_{k,2}$ are obtained by setting the derivatives with respect to $\alpha_{k,1}$, and $\alpha_{k,2}$ equal to zero:

$$\alpha_{k,1} = \left[\frac{E(r_1 - r_f)}{\sigma_1^2} - \frac{1}{2}\frac{E(r_2 - r_f)\rho}{\sigma_2\sigma_1}\right]\frac{1}{C_{kt}}\cdot\frac{1}{)1 - 1/4\rho^2)}$$

and

$$\alpha_{k,2} = \left[\frac{E)r_2 - r_f)}{\sigma_2^2} - \frac{1}{2}\frac{E(r_1 - r_f)\rho}{\sigma_2\sigma_1}\right]\cdot\frac{1}{C_{kt}}\cdot\frac{1}{(1 - 1/4\rho^2)} \quad (6)$$

where C_{kt} is the Pratt (1964) measure of relative risk aversion defined as:

$$C_{kt} = W_{kt}[-U''(W_{kt})/U'(W_{kt})] \quad (7)$$

Eq. (6) shows that the optimal weights are complex functions of the expected risk premium, of the covariance matrix, and of risk aversion. *Ceteris Paribus*, the weight in a risky asset increases with the expected risk premium on the asset, decreases with expected volatility and decreases with Pratt's measure of risk aversion.

4. Empirical methodology

I use an instrumental variables approach to empirically test whether fund flows respond to the three factors identified by Eq. (6). The variables used to model time-varying expected returns to stocks and bonds are: (1) the dividend yield on a market index (DIV), (2) the one-month T-bill rate (TB), (3) Term spread (TERM), (4) Default spread (DEF), (5) January dummy (JAN), and (6) December dummy (DEC). TERM is the difference in the yield of the 10-year T-bond and the one-month T-bill rate. DEF is the difference in yield on a 10-year corporate bond index and the yield on a 10-year T-bond. Several studies have shown that these variables can predict future returns to stocks and bonds.[7]

I use an ARIMA model (French, Schwert, and Stambaugh, 1987; Schwert, 1989) to predict expected volatility of monthly stock returns. The reader is referred to Schwert (1989) for details on the estimation methodology.

The proxy for time-varying risk-aversion, INVW, is based on Ilmanen (1995). INVW is calculated as the ratio of the exponentially weighted average of the past 36 months of real wealth levels to the current level of real wealth.[8] The current level of real wealth is proxied by the inflation-adjusted level of the S&P 500. A higher INVW implies a higher level of risk aversion. A second proxy for time-varying risk aversion is motivated by Campbell and Cochrane (1999), and Brandt and Wang (2001), and utilizes data on real consumption that is obtained from CITIBASE.

The empirical tests are based on a system of equation approach rather than on OLS regressions. An OLS approach fails in this application because it does not incorporate the interdependence among fund flows. The interdependence arises when flows into a fund category occur not in direct response to a change in an economic variable, but through a rebalancing among fund categories necessitated by the budget constraint.

The system of equations incorporate the interdependence among fund flows and are written as:

$$
\begin{aligned}
F_{1,t} &= \alpha_1 + \beta_{11}F_{2,t} + \;---\; + \beta_{j1}F_{j,t} + \gamma_1\mathbf{Z}_{t-1} + \delta_1 TAV_{1,t-1} + \varepsilon_{1,t} \\
F_{2t} &= \alpha_2 + \beta_{12}F_{1,t} + \;---\; + \beta_{j2}F_{j,t} + \gamma_2\mathbf{Z}_{t-1} + \delta_2 TAV_{2,t-1} + \varepsilon_{2,t} \qquad (8) \\
F_{jt} &= \alpha_j + \beta_{1j}F_{1,t} + \;---\; + \beta_{j-1,j}F_{j-1,t} + \gamma_j\mathbf{Z}_{t-1} + \delta_j TAV_{j,t-1} + \varepsilon_{j,t}
\end{aligned}
$$

The endogenous variables, F_{jt} are the unanticipated flows into the j^{th} fund category. The exogenous variables are the information variables represented by the vector **Z** and the lagged total asset values, $TAV_{j,t-1}$, of the j^{th} fund category. The inclusion of lagged total asset values makes Eq. (8) a just-identified system. Lagged total asset values are also included to control for lagged wealth invested in a fund category, and to control for arbitrary changes in the classification of a mutual fund.

5. Results

5.1. Flows, time-varying market premium, and time-varying risk aversion

I estimate the first set of structural equations with instrumental variables for time-varying risk aversion and time-varying stock and bond return premia. The estimation is based on a two-stage least squares method. In the first stage, the reduced form of the structural equation is estimated using OLS. In the second stage, the estimated values from the first stage are substituted for the endogenous variables on the RHS of Eq. (8) and the resulting equation is estimated using OLS. The marginal impact of an independent variable is measured by 'impact multipliers,' which are the coefficients obtained from an estimation of the reduced form. These coefficients are presented in Table 4.

Table 4
Reduced form parameters

The table has the reduced form parameters from an estimation of the simultaneous equations:

$F_{1,t} = a_1 + b_1 F_{2,t} + c_1 F_{3,t} + d_1 F_{4,t} + e_1 JAN_{t-1} + f_1 DEC_{t-1} + g_1 TB_{t-1} + h_1 TERM_{t-1} + i_1 DEF_{t-1} + j_1 DIV_{t-1} + k_1 INVW_{t-1} + l_1 NVEQHI_{1,t-1}$

$F_{2,t} = a_2 + b_2 F_{1,t} + c_1 F_{3,t} + d_1 F_{4,t} + e_1 JAN_{t-1} + f_1 DEC_{t-1} + g_1 TB_{t-1} + h_1 TERM_{t-1} + i_1 DEF_{t-1} + j_1 DIV_{t-1} + k_1 INVW_{t-1} + l_1 NVEQLO_{1,t-1}$

$F_{3,t} = a_3 + b_3 F_{1,t} + c_1 F_{2,t} + d_1 F_{4,t} + e_1 JAN_{t-1} + f_1 DEC_{t-1} + g_1 TB_{t-1} + h_1 TERM_{t-1} + i_1 DEF_{t-1} + j_1 DIV_{t-1} + k_1 INVW_{t-1} + l_1 NVBDHI_{1,t-1}$

$F_{4,t} = a_4 + b_4 F_{1,t} + c_4 F_{2,t} + d_4 F_{3,t} + e_4 JAN_{t-1} + f_4 DEC_{t-1} + g_4 TB_{t-1} + h_4 TERM_{t-1} + i_4 DEF_{t-1} + j_4 DIV_{t-1} + k_4 INVW_{t-1} + l_4 NVBDLO_{4,t-1}$

F_1 through F_4 are the unanticipated sales into the four risk categories. The exogenous variables are January (JAN) and December (DEC) dummies, the one month T-bill rate (TB), the term spread between 10 year government bonds and the 3 month T-bill (TERM), the yield spread between corporate bonds rated BBB and lower and 10 year government bonds (DEF), the dividend yield on the S&P 500 index (DIV), a proxy for relative risk aversion (INVW) and lagged total asset values of the equity high risk (NVEQHI), equity low risk (NVEQLO), bond high risk (NVBDHI) and bond low risk (NVBDLO) categories. Numbers in parentheses are the t-statistics and the numbers in curly brackets indicate the change in the endogenous variable measured in standard deviations from the mean, that can be attributed to a 1% increase in an exogenous variable over its mean. Estimation period: 1976/4-1995/4.

	Unanticipated sales into			
Exogenous variables	Equity high risk category	Equity low risk category	Bond high risk category	Bond low risk category
Intercept	-6.67 (-1.69)	1.95 (0.73)	0.11 (0.07)	21.62 (0.84)
JAN	1.57 (1.92), {0.43}	0.48 (0.88), {0.2}	0.79 (2.47), {0.57}	33.74 (6.31}, {1.35}
DEC	2.34 (2.85), {0.65}	2.40 (4.33), {1.01}	0.01 (0.04), {0.007}	-20.17 (-3.75), {-0.80}
TB	-0.56 (-2.13), {-1.14}	-0.40 (-2.24), {-1.25}	-0.28 (-2.75), {-1.52}	-4.25 (-2.47), {-1.25}
TERM	-0.78 (-1.98), {-0.38}	-0.59 (-2.25), {-0.44}	- 0.34 (-2.21), {-0.44}	-5.70 (-2.23), {-0.40)
DEF	0.66 (0.70), {0.22}	-0.29 (-0.46), {-0.15}	-0.19 (-0.51), {-0.17}	-2.45 (-0.40), {-0.12}
DIV	0.39 (0.42), {0.44}	0.11 (0.17), {0.19}	-0.06 (-0.17), {-0.18}	1.07 (0.18), {0.17}
INVW	8.98 (1.61), {2.35}	1.82 (0.49), {0.71}	3.45 (1.58), {2.35}	15.29 (0.42), {0.57}
NVEQHI	-0.002 (-0.26), {-0.16}	0.00004 (0.007), {0.005}	0.006 (1.91), {1.29}	0.14 (2.52), {1.64}
NVEQLO	0.0009 (0.2), {0.10}	-0.003 (-0.75), {-0.53}	0.005 (-2.59), {-1.54}	-0.11 (-3.22), {-1.84}
NVBDHI	-0.002 (-1.53), {0.48}	-0.017 (-1.69), {0.62}	0.018 (-3.14), {-1.14}	-0.13 (-1.4), {-0.45}
NVBDLO	0.002 (2.48), {0.81}	0.0017 (2.74), {1.05}	0.0011 (3.04), {1.18}	0.011 (1.92), {0.64}
Adj. R^2 (%)	11.62	8.81	6.88	22.03

Table 4 also presents the impulse response functions. The impulse response function measures the change in the value of an endogenous variable because of a 1% increase in the magnitude of the exogenous variable over its mean. The unit of measurement for the change is the number of standard deviations from the mean. Table 4 shows that the T-bill rate and the term premium have significant predictive power for flows into each of the four categories. Flows decrease with an increase in either the T-bill rate, or with an increase in the term premium. The T-bill rate has the biggest impact on unanticipated flows into the bond high-risk category, which decline by 1.25 standard deviations when the rate on the T-bill increases by 1%. Investors appear to reduce their investments in risky assets in response to a slowdown in future economic activity (Fama, 1990) signaled by the increase in the T-bill rate and term premium.

INVW, the proxy for time varying relative risk aversion is positively related to unanticipated flows into equity high risk funds; a 1% increase in INVW leads to a 2.3 standard deviation increase in flows. An explanation for the positive coefficient is that INVW proxies for the wealth effect rather than for risk aversion. Ilmanen (1995) argues that a higher magnitude of lagged wealth (the numerator of INVW) relative to current wealth (the denominator) implies a higher level of risk aversion. The positive coefficient in Table 4 instead suggests that higher lagged wealth leads to an increase, rather than a decrease, in investor risk tolerance. Qualitatively similar results are obtained when I use the ratio of lagged consumption to current consumption as an alternative proxy for risk aversion.

The coefficients on lagged total assets in Table 4 indicate evidence of both rebalancing and momentum trading.[9] The coefficient on lagged total asset value of the bond low risk category is positive for flows into the two equity categories and for flows into the bond high-risk category. The positive coefficient indicates that investors rebalance their portfolios by increasing their weight on risky assets after an increase in cash-or cash equivalent assets. There is also evidence that investors rebalance by shifting out of high-risk bond funds following significant wealth accumulation in that category. Evidence of momentum investing comes from the low risk fund categories. Table 4 shows that unanticipated flows into the equity low risk and bond low risk categories are positively related to lagged total assets invested in each of these two categories, respectively.

The explanatory power of the model for flows into the four categories is not large. The highest R^2 is obtained for flows into the low risk bond category (adjusted R^2 of 22.03%), and the lowest R^2 is obtained for flows into the high risk bond category (adjusted R^2 of 6.88%).

Perhaps the model has low explanatory power for fund flows because it allows for time variation in the market premium only. Fama and French (1988) show that in addition to the market factor, size, and value factors also have explanatory power for returns. Therefore, flows may respond to time variation in the size and value premia, as well.[10] Based on a study by Lettau and Ludvigson (2001), I add the log consumption-wealth ratio, denoted by *cay*, as an additional instrumental variable in Eq. (8). Unfortunately, I find that the explanatory power of the model decreases across all four risk categories when *cay* is added to the regressions. Hence, these results are omitted from the tables.

5.2. Predictability because of time varying market volatility and risk aversion

I include instrumental variables for time-varying stock volatility and time-varying risk aversion in the second set of structural equations. According to Eq. (6), fund flows should decline if investors expect future returns to be more volatile. I estimate volatility using the Schwert (1989) methodology and substitute the estimated volatility, $|\hat{\varepsilon}_t|$, as the **Z** variable in Eq. (8). I also include INVW, the time varying risk aversion proxy as an exogenous variable on the RHS of the four equations. The parameters from an estimation of the reduced form of Eq. (8) are in Table 5.

The results show that mutual fund investors respond to an increase in expected variance of stock returns by reducing their investment in the equity low-risk category of funds, and by increasing their allocation to the bond low risk category of funds. A 1% increase in the future variance of stock returns leads to a 0.57 standard deviation decline in unanticipated flows into the equity low risk category and a 1.04 standard deviation increase in flows into the bond low-risk category.

Unanticipated flows into the equity high risk and bond high-risk categories are also negatively related to the expected variance of stock returns, but the coefficients are not statistically significant. Perhaps, investors take into account a higher market premium predicted by the higher variance in deciding their optimal allocation into this category.

The coefficient on INVW is positive and is statistically significant only for flows into the equity high-risk category. As discussed in the previous section, we conjecture that INVW proxies for lagged wealth, rather than for time varying risk aversion. Other coefficients, namely those associated with lagged total asset values, have the same signs as the corresponding coefficients in the previous table.

The R^2 in Table 5 are all uniformly lower than in Table 4. The highest R^2 is obtained for flows into the bond low-risk category (8.97%), and the lowest R^2 (1.24%) is obtained for flows into the bond high-risk category.

6. Economic significance of predictability in flows

The results in Tables 4 and 5 demonstrate that mutual fund investors dynamically rebalance their portfolios in response to a change in the future distribution of stock and bond returns and to a change in their wealth level. In this section, I ascertain whether such portfolio rebalancing is profitable on average. I estimate an OLS regression with full period unanticipated flows into each category as the dependent variable. The independent variables are the instrumental variables with the highest explanatory power for unanticipated flows, which from Tables 4 and 5 are lagged wealth, and instrumental variables for time-varying stock and bond premia.

The coefficients obtained from the OLS regression are combined with the actual values of the instrumental variables each month to obtain a one-month ahead forecast of unanticipated flows into the four fund categories. Each fund category is sorted into three groups on the basis of these forecasted flows. Average and median returns are calculated for each of these three groups and are presented in Table 6.

Table 5
Reduced form estimates

The table has the reduced form parameters from an estimation of the simultaneous equations:

$$F_{1,t} = a_1 + b_1 F_{2,t} + c_1 F_{3,t} + d_1 F_{4,t} + e_1 \text{ ARMA}_{t-1} + f_1 \text{ INVW}_{t-1} + g_1 \text{ NVEQHI}_{1,t-1} + \varepsilon_{1t}$$
$$F_{2,t} = a_2 + b_2 F_{1,t} + c_2 F_{3,t} + d_1 F_{4,t} + e_1 \text{ ARMA}_{t-1} + f_1 \text{ INVW}_{t-1} + g_1 \text{ NVEQLO}_{1,t-1} + \varepsilon_{1t}$$
$$F_{3,t} = a_3 + b_3 F_{1,t} + c_3 F_{2,t} + d_1 F_{4,t} + e_1 \text{ ARMA}_{t-1} + f_1 \text{ INVW}_{t-1} + g_1 \text{ NVBDHI}_{1,t-1} + \varepsilon_{1t}$$
$$F_{4,t} = a_4 + b_4 F_{1,t} + c_4 F_{2,t} + d_4 F_{3,t} + e_4 \text{ ARMA}_{t-1} + f_4 \text{ INVW}_{t-1} + g_4 \text{ NVBDLO}_{4,t-1} + \varepsilon_{4t}$$

where the endogenous variables, F_1 through F_4 are unanticipated sales into the four risk categories. The exogenous variables are the predicted volatility of market returns (ARMA), the proxy for relative risk aversion (INVW) and the lagged total asset values of the equity high risk category (NVEQHI), equity low risk category (NVEQLO), bond high risk category (NVBDHI) and the bond low risk category (NVBDLO).

The numbers in parentheses are the T-statistics and the numbers in curly brackets indicate the change in the endogenous variable measured in standard deviations from the mean, that can be attributed to a 1% increase in an exogenous variable over its mean. Estimation period: 1976/4-1995/4.

	Unanticipated sales into			
Exogenous variable	Equity high risk category	Equity low risk category	Bond high risk category	Bond low risk category
Intercept	-7.99 (-2.2)	0.018 (0.008)	-1.97 (-1.38)	-28.34 (-1.14)
ARMA	-31.10 (-1.16), {-0.27}	-43.05 (-2.35), {-0.57}	-1.11 (-0.11), {-0.02}	836.17 (4.5), {1.04}
INVW	8.98 (2.48), {2.3}	1.39 (0.56), {0.54}	1.94 (1.35), {1.32}	-6.87 (-0.3), {-0.25}
NVEQHI	-0.012 (-1.56), {-0.97}	-0.008 (-1.43), {-0.99}	0.003 (0.81), {0.65}	0.11 (2.05), {1.29}
NVEQLO	0.007 (1.6), {0.81}	0.003 (0.93), {0.53}	-0.001 (-0.91), {-0.31}	-0.059 (-2.07), {-0.99}
NVBDH1	-0.0096 (-0.9), {-0.23}	0.0002 (0.02), {0.007}	-0.00 (-1.35), {-0.38}	0.038 (0.53), {0.13}
NVBDLO	0.0016 (2.54), {0.65}	0.0008 (1.89), {0.5}	0.0004 (1.64), {0.43}	-0.002 (-0.49), {-0.12}
Adj. R^2 (in %)	7.12	2.08	1.24	8.97

Table 6
Profitability of the dynamic rebalancing strategy

Fund category	Returns to the three groups sorted on the basis of predicted flows (in %)			F-tests (H_0: Median returns to the three groups, within each fund category, are equal)
	Lowest	Medium	Highest	
Equity high risk	−0.083 (0.53)	0.385 (0.52)	2.93** (2.65)**	6.59 {0.00}
Equity low risk	−0.366 (−0.007)	0.900** (0.900)**	2.399** (1.970)**	5.74 {0.00}
Bond high risk	−0.170 (−0.064)	−0.570 (0.340)	0.092 (0.230)	0.35 {0.70}
Bond low risk	0.009 (0.034)	0.230 (0.150)	0.250 (0.230)	3.37 {0.04}

A full period regression is estimated with unanticipated flows into the four fund categories as the dependent variable and instrumental variables for time-varying stock and bond return premia as independent variables. The coefficients from the regression are used to obtain one-month ahead forecasts of unanticipated flows. Each fund category is sorted into three groups on the basis of the magnitude of forecasted flows. The returns to each fund category in the forecast month is calculated as the percentage change in total asset value. The table presents the mean and median return to each fund category in the three groups. Numbers in parentheses are median returns. Numbers in curly brackets are the p-values of the F test. Data period: 1976/5 through 1995/5. ** indicates statistical significance at the 5% confidence level.

The table shows that the abnormal return earned by an investor in the equity high-risk category when flows are predicted to be the highest, is positive and statistically significant, at the mean and at the median. In fact, a strategy of increasing flows in the months when flows are predicted to be higher, and decreasing flows in months when they are predicted to be lower, earns a return of 3.01% [2.93% − (−0.083)].

There is similar evidence in favor of timing flows into the equity low-risk category. The timing strategy generates a return of 2.77% [2.399 − (−0.366)] per month for this category, which is statistically significant. Timing turns out to be profitable even in the bond low-risk category. The average monthly return is 0.25% in months when flows are predicted to be the highest and is 0.009% in months when flows are predicted to be at their lowest.

Timing is unprofitable only for the bond high risk category. A strategy of increasing flows in the months when predicted flows are higher earns a return of only 0.09%, which is not significantly different from the return of −0.17% earned in the months with the lowest predicted flows.

7. Conclusions

The paper sets out to investigate the linkage between contemporaneous stock returns and unanticipated flows into equity funds. The first set of results demonstrate that flows into equity funds are also contemporaneously related to corporate and government bond returns. It is similarly shown that the impact of bond fund flows is not confined to bond returns, but also extends to stock market returns. I investigate whether these linkages can be explained by common sources of information that affect both flows and returns. I find a strong relation between flows and instrumental variables that can predict the future distribution of stock and bond returns. The relation between flows and these instrumental variables is both economically and statistically significant, particularly for the equity fund categories. These results are collectively interpreted as being supportive of the common information hypothesis.

This paper demonstrates a strategy for asset allocation across mutual fund investments. Individual investors have to choose the allocation of funds in their retirement plans, such as the 401(k) and 403(b) plans. I show in this paper that investors can profit by timing their asset allocations into the risky and safe sectors to respond to unanticipated shifts in the economy.

Throughout this paper I have ignored the impact of investor sentiment on flows into risky funds. Goetzmann, Massa, and Rouwenhorst (2001) find that an optimistic sentiment predicts higher flows into equity funds and lower flows into bond funds. This area is left for future research.

Notes

1. Mutual Fund Factbook, 2003, published by the ICI.
2. *Your Money, Markets and Fear of Cash Flow's role*, Los Angeles Times, August 11, 1996.
3. Fama and French (1989), Breen, Glosten, and Jagannathan (1989), Keim and Stambaugh (1986) find business cycle variations in the expected market risk premium. Time varying volatility in market returns has been documented by Christie (1982), Bollerslev, Engle, and Woolridge (1985). Ilmanen (1995) documents the significance of time varying risk aversion for bond returns.
4. We are grateful to ICI for providing us with data from 1984/1 through 1996/12 and to Vince Warther for providing us with data from 1976/1 through 1984/1.
5. The results in Table 3 are robust to an estimation over a shorter interval from 84:1 to 95:11 and to the elimination of the October 1987 observation from flows and returns.
6. See Campbell and Cochrane (1999), Sundaresan (1989), Constantinides (1990), and Mehra and Prescott (1985).
7. Fama and French (1988; 1989), Campbell and Shiller (1989), Fama and Schwert (1977), Ferson (1989), Fama (1990), Campbell (1987), and Keim and Stambaugh (1986).
8. Specifically, INVW is calculated as:

$$INVW_t = \frac{(W_{t-1} + 0.9*W_{t-2} + 0.9^2*W_{t-3} + \ldots)*0.1}{W_t}$$

   where W_t is the real level of the S&P 500 index.
9. Momentum trading involves buying winners and selling losers. Jegadeesh and Titman (1993) show that the momentum strategy earns positive abnormal returns.
10. I thank an anonymous referee for this suggestion.

Acknowledgment

I thank Rudi Schadt, Ned Elton, participants at the 1997 Texas Finance Symposium, and an anonymous referee for helpful comments. I thank the Investment Company Institute for providing the aggregate flow data. This is a revised version of a paper previously titled 'Predictability in Aggregate Flows into Mutual Funds.'

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