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Cross-autocorrelations among asset classes

Evidence from the mutual fund industry

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Abstract

Purpose – The purpose of this paper is to examine asset class cross-autocorrelations at the macro-level by exploring the return associations among mutual fund asset classes. The low transactions costs of trading mutual funds make this extension important since informed traders can potentially use mutual funds to exploit asset class return cross-autocorrelations that were not exploitable with individual securities.

Design/methodology/approach – The Granger causality tests and correlation results are employed to ascertain whether significant relationships exist among asset classes. Using a time series of 2,739 daily returns for 641 mutual funds comprising 20 asset classes, trading strategies are developed using the initial sample and evaluated out-of-sample on a risk-adjusted basis.

Findings – Both the cross-autocorrelations and Granger causality tests suggest that most of the domestic equity asset class returns can predict future global and international equity returns. Further, the trading-rule portfolios provide a greater return per unit of risk (Sharpe and Treynor ratios) thus dominating all buy-and-hold portfolios. Risk-adjusted excess returns (Jensen's α) of the trading rules are positive and statistically significant at the 1 per cent level. The results of trading strategies also reveal that there are no statistically significant return differences between load and no-load funds.

Research limitations/implications – Redemption fees seem to be standard practice now, except for money market funds and funds specially designed for market timers. Thus, the trading strategy returns of this paper overestimate actual returns. However, investors may still find the proposed trading strategies beneficial because redemptions fees can be avoided if investors get the opportunities to trade in mutual fund supermarkets. The trading strategies may have implications for other international markets where the sizes and styles of the mutual funds' assets are increasing enormously with a few trading restrictions.

Originality/value – A noteworthy and original contribution of this study is the two-day Granger causality test. This paper documents that the duration of mutual funds' return predictability extends beyond a one-day horizon. The duration of daily mutual fund return predictability is believed to be unexplored and should be of considerable relevance to practitioners and regulators.

Keywords Unit trusts, Assets, Rate of return, Cause and effect analysis

Paper type Research paper

1. Introduction

Evidence indicates that stocks display a palpable quantity of short-term predictability. Hamao *et al.* (1990) detail spillover effects between USA and international markets whereas Lo and MacKinlay (1999) find positive correlation between large and small stock indices. While transactions costs prohibit investors from exploiting the predictability using individual securities, Miller and Prather (2000) find exploitability

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among TIAA/CREF annuities. Chalmers *et al.* (2001), Goetzmann *et al.* (2001), Boudoukh *et al.* (2002), Greene and Hodges (2002) and Zitzewitz (2003) also find exploitable predictabilities for US-based international mutual funds.

We focus on macro-level returns and suggest that one type of mutual fund can be used to predict other type(s) of funds. We investigate the macro-issue of whether predictable elements exist in mutual fund asset class returns for three reasons. First, Connor and Korajczyk (1991) point out that comparing indexes of asset class returns results in a lower residual variance in the regression and more precise estimates of the parameters. Second, if mutual funds exhibit similar macro-return predictability, informed investors can possibly exploit this return pattern at the micro-level since costs of trading a mutual fund are much lower than the costs of trading a portfolio of securities. Finally, if mutual fund returns contain a predictable component, the actions of informed traders to exploit these predictabilities could have considerable implications for portfolio managers and mutual fund companies.

To analyze asset class patterns, we construct 20 equally weighted asset class indices for 2,739 trading days. We employ Granger causality and correlation results to ascertain whether significant relationships exist among asset classes. Using the observed relationships, we examine the way informed traders might formulate dynamic trading strategies. An original contribution of our study is the two-day Granger causality test. We document that the duration of mutual funds' return predictability extends beyond a one-day horizon. To our knowledge, the duration of daily mutual fund return predictability is unexplored and should be of considerable relevance to practitioners and regulators. Another contribution of our paper is that we use a unique dataset that includes both dividend and capital gains distributions which provides more accurate empirical results.

The organization of this paper is as follows. Section 2 presents the limits of market efficiency. Section 3 presents data and methodology. Section 4 presents empirical results on return predictability, and evaluates trading strategies. Section 5 concludes the paper.

2. The limits of market efficiency

The contention that knowledgeable traders may eliminate price predictability through their trading has an obvious weak point. The round-trip transactions costs (commissions and the spread paid to the market maker) of buying a stock to exploit a minor degree of predictability can exceed the profits; thus, a small amount of predictability may persist.

The magnitude of spreads is constrained since they must provide an ample profit to cover loses to traders with superior information. The classic information trader is someone who possesses information not known to the market maker. When he sells to the market maker, the market maker anticipates making his usual small spread. However, when the market maker tries to sell the stock, he finds that the price has dropped and he takes a loss. These losses may be rare, but they are also likely to be large; therefore, many small profits earning only the spread will be needed to offset them. The theory of market making holds that the more informed traders there are, the greater the market maker's losses to the informed traders will be, and the larger the spread must be to persuade the market makers to continue to make a market.

This is where the theory of market making conflicts with the theory that informed traders would eliminate minor predictabilities in stock prices. *Ceteris paribus*, informed traders would eliminate the predictabilities; however, as the number of informed traders increases, the market makers have to increase their spreads to avoid losing money to the informed traders. These increased spreads restrict the informed traders' ability to profit from predictable price fluctuations. This situation will occur whenever the predictable element is due to predictable fluctuations in demand for a security, or type of security. If a few professional traders become aware of the predictable element, their trading would cause the market makers to lose money. Before long, the market makers would increase spreads, limiting the extent to which informed traders could profit from predictabilities.

2.1 Aggregation and identification of predictabilities

While individual securities show a low predictability, when these securities are combined into portfolios the predictability may be higher or different in nature (Lo and MacKinlay, 1999). Studying mutual funds is one way to quickly study portfolios since each fund represents a portfolio. Of course, the funds can be combined into groups of similar funds, providing an even higher degree of diversification. This aggregation of funds may be important since Najand and Prather (1999) find heterogeneous risk within mutual fund asset classes.

There is a large literature on the predictability of mutual fund returns. Bauman and Miller (1994), Brown and Goetzmann (1995), Elton *et al.* (1996), Grinblatt and Titman (1992), Gruber (1996) and Malkiel (1995) conclude that there is very little predictability over a period of years. However, Carhart (1997) and Hendricks *et al.* (1993) find evidence that returns over the next year have a low level of predictability. In contrast to the multi-year perspective of earlier research, we concentrate on the predictability of daily returns at the macro-level.

An investor attempting to exploit stock market return regularities by buying and selling a large portfolio would find that the transactions costs left him with negative returns. However, at the micro-level, mutual funds can be traded with negligible costs[1]. Within a fund family, transfers can often be made free of charge. Even between fund families, trades can often be made at zero or low cost. Usually one can sell shares in a mutual fund back to the fund for net asset value (NAV) and the proceeds can be reinvested in a new no-load fund at no expense[2].

Predictabilities in returns that have been reduced by the action of informed stock traders to the point where they can no longer be exploited at a profit may still be consistent with exploitable predictabilities in mutual fund returns. Miller and Prather (2000) and Miller *et al.* (2003) argue that mutual funds lack the same self-correcting forces that individual stock trades possess.

One source of predictability may arise from the customs in the mutual fund business. Investors buy and sell mutual funds based on the last available prices (which may frequently be stale) at the time of the US markets' closing. As a result, one would expect international stock funds to lag US prices by one trading day, which would enable an investor to predict their returns from the returns of US stock funds. This is done by trading international funds when US markets close, but at prices that existed when the Asian or European markets closed. Some international funds reserve the right to use "fair prices" which are to be based on all available information. However, during the period of this study such adjustments appear to be made only on the occasions where it is clear that using the closing prices in the home market would be unfair.

3. Empirical examination

3.1 Data

We select a sample of open-end mutual funds and sort them by their investment objectives. Morningstar was consulted and any funds that changed objectives, converted from a closed-end fund, or converted from a limited partnership during the period of study were eliminated. This is important since the objective is to capture the uniqueness of the return properties of each asset class. To mitigate small sample bias problem we include both load and no-load funds in our sample.

Open-end funds issue new shares and redeem existing shares at prices based on NAVs computed after the market close (usually 4:00 p.m. NY time) each trading day. Daily NAV and distribution data for each fund during the period 2 January 1990 through 31 October 2000 was obtained from Dial data. To ensure the quality of the data, we follow the screening procedure of Busse (1999)[3]. The final sample consists of 2,739 daily returns for 641 mutual funds in 20 investment objective categories. Table I presents the assets classes utilized and their descriptors.

3.2 Methodology

Continuously compounded daily returns for each of the sample funds for the 2,739 days are computed as $R_{i,t} = \ln(\text{Value}_{i,t}/\text{Value}_{i,t-1})$, where $R_{i,t}$ is the return on fund i during the period t, $\text{value}_{i,t-1}$ is the NAV of an investment in fund i at time $t-1$ and $\text{value}_{i,t}$ is the value of an investment in fund i at time t.

Using computed returns, an equally weighted daily index for each investment objective group is constructed by summing the returns of the individual funds, (i), within the investment objective classification, (o), and computing their average as $R_{0,t} = \sum_{i=1}^{n} R_{i,t}/n$, where $R_{\mathrm{o},t}$ is the average return on investment objective class (o) during the period t. This results in 20 equally weighted daily return indices.

Following Richardson and Peterson (1999), we utilize Granger causality to ascertain lead and lag relationships in returns between various asset class indices. Our tests for

Descriptor	Asset class
AG	Aggressive growth
GRO	Growth
GI	Growth and income
EI	Equity income
BAL	Balanced
BIO	Health and bio-technology
REAL	Real estate
FIN	Financial
TECH	Technology and telecommunications
UTIL	Utilities
ENR	Energy and natural resource
MET	Precious metals
LBD	General bond – long term
SBD	General bond – short- and intermediate-term
MB	Municipal bond
GLB	Global income
GLE	Global equity
INT	Non-US equity
MCAP	Mid-cap
SCAP	Small cap

Notes: Abbreviations for each of the asset class are provided in column 1 and the asset classes that they represent are provided in column 2

Table I.
Asset class descriptors

return predictability use Equations (1) and (2):

$$R_{i,t} = \alpha + \sum_{k=1}^{n} \beta_{i,k} R_{i,t-k} + \sum_{k=1}^{n} \beta_{j,k} R_{j,t-k} + \varepsilon_t, \tag{1}$$

$$R_{j,t} = \delta + \sum_{k=1}^{n} \gamma_{i,k} R_{i,t-k} + \sum_{k=1}^{n} \gamma_{j,k} R_{j,t-k} + \nu_t, \tag{2}$$

where n is the number of lags estimated; $R_{i,t}$ is the return series for asset class i; $R_{j,t}$ is the return series for asset class j; α and δ are the estimated intercepts; $\beta_{i,k}$ and $\gamma_{i,k}$ are the coefficients for asset class i's return series lagged $t-k$ periods; $\beta_{j,k}$ and $\gamma_{j,k}$ are the coefficients for asset class j's return series lagged $t-k$ periods; and ε_t and υ_t are the normally distributed error terms.

4. Empirical results

To conduct empirical investigation, we divide our sample into two subsamples with an approximately equal number of observations. This permits testing cross-autocorrelation and developing trading rules with one subsample and then testing the dominance of those rules over a buy-and-hold strategy using the holdout sample. The first subsample contains 1,369 daily observations from 2 January 1990 through 31 May 1995 and the holdout sample contains 1,370 daily observations from 1 June 1995 through 31 October 2000.

4.1 Contemporaneous correlations

Table II provides an instantaneous correlation matrix for the asset classes in the sample. This table is of interest since it shows that it is possible to achieve diversification by combining different asset classes and suggests that because many instantaneous correlations are low, it may be possible for dynamic trading strategies to exist if lead–lag relationships exist among asset classes. The relatively low correlation between non-US equity (international) funds and other categories of funds suggest that international funds can be used to reduce risk when combined with domestic US funds. The observed correlations are also low between bond and global income funds and other classes of funds. The highest correlation (0.955) is between growth funds (GRO) and growth and income funds (GI) and the lowest positive correlation is between non-US equity funds (INT) and short- and intermediate-term general bond funds (0.005).

4.2 Tests of Granger causality and possible exploitation

Table III presents the F-statistic (and p-value) for testing the null hypothesis that one asset class Granger causes another. Of 380 possible test pairs, 180 test pairs yielded significant lead–lag relationships at the 5 per cent level. Finding 180 significant causalities at the 5 per cent level is far above the two or three that would be expected from chance. An investor attempting to maximize the probability of receiving a positive return in the next period would move funds based on the strength of the statistical relationship. Therefore, the highest F-statistic was used as the starting point. Once that first asset move has been made, the procedure was repeated to find the asset class that the current asset class returns could predict best. The procedure is repeated indefinitely.

F-statistics suggest that the strongest six relationships are for domestic equity asset class returns (EI, GRO, GI, BAL, FIN and MCAP) predicting future global equity (GLE) returns. Furthermore, the strongest of these six relationships is that the return on equity income funds (EI) predicts global equity funds (F-statistic 226.3). This will be

	AG	GRO	GI	EI	BAL	BIO	REAL	FIN	TECH	UTIL
AG	1.000	0.913	0.817	0.706	0.781	0.839	0.603	0.744	0.885	0.430
GRO	0.913	1.000	0.955	0.886	0.904	0.823	0.608	0.835	0.866	0.511
GI	0.817	0.955	1.000	0.954	0.932	0.746	0.595	0.835	0.765	0.548
EI	0.706	0.886	0.954	1.000	0.908	0.654	0.595	0.827	0.672	0.566
BAL	0.781	0.904	0.932	0.908	1.000	0.717	0.599	0.799	0.738	0.556
BIO	0.839	0.823	0.746	0.654	0.717	1.000	0.487	0.638	0.736	0.373
REAL	0.603	0.608	0.595	0.595	0.599	0.487	1.000	0.621	0.511	0.433
FIN	0.744	0.835	0.835	0.827	0.799	0.638	0.621	1.000	0.688	0.468
TECH	0.885	0.866	0.765	0.672	0.738	0.736	0.511	0.688	1.000	0.413
UTIL	0.430	0.511	0.548	0.566	0.556	0.373	0.433	0.468	0.413	1.000
ENR	0.571	0.599	0.615	0.598	0.573	0.463	0.402	0.494	0.506	0.358
MET	−0.015	−0.070	−0.097	−0.108	−0.112	−0.048	−0.025	−0.119	−0.043	−0.110
LBD	0.031	0.075	0.137	0.114	0.132	0.039	0.066	0.082	0.026	0.090
SBD	0.033	0.042	0.046	0.056	0.074	0.032	0.067	0.055	0.034	0.063
MB	0.141	0.210	0.248	0.299	0.308	0.129	0.285	0.266	0.115	0.246
GLB	0.118	0.186	0.224	0.276	0.291	0.138	0.383	0.201	0.087	0.223
GLE	0.736	0.661	0.601	0.529	0.589	0.595	0.717	0.586	0.620	0.356
INT	0.403	0.359	0.331	0.319	0.334	0.327	0.641	0.351	0.305	0.226
MCAP	0.914	0.937	0.869	0.790	0.827	0.801	0.598	0.813	0.865	0.449
SCAP	0.945	0.899	0.806	0.723	0.768	0.805	0.645	0.771	0.854	0.416

	ENR	MET	LBD	SBD	MB	GLB	GLE	INT	MCAP	SCAP
AG	0.571	−0.015	0.031	0.033	0.141	0.118	0.736	0.403	0.914	0.945
GRO	0.599	−0.070	0.075	0.042	0.210	0.186	0.661	0.359	0.937	0.899
GI	0.615	−0.097	0.137	0.046	0.248	0.224	0.601	0.331	0.869	0.806
EI	0.598	−0.108	0.114	0.056	0.299	0.276	0.529	0.319	0.790	0.723
BAL	0.573	−0.112	0.132	0.074	0.308	0.291	0.589	0.334	0.827	0.768
BIO	0.463	−0.048	0.039	0.032	0.129	0.138	0.595	0.327	0.801	0.805
REAL	0.402	−0.025	0.066	0.067	0.285	0.383	0.717	0.641	0.598	0.645
FIN	0.494	−0.119	0.082	0.055	0.266	0.201	0.586	0.351	0.813	0.771
TECH	0.506	−0.043	0.026	0.034	0.115	0.087	0.620	0.305	0.865	0.854
UTIL	0.358	−0.110	0.090	0.063	0.246	0.223	0.356	0.226	0.449	0.416
ENR	1.000	0.130	0.028	0.013	0.113	0.148	0.504	0.314	0.568	0.570
MET	0.130	1.000	−0.026	−0.024	−0.064	0.060	0.080	0.106	−0.046	−0.005
LBD	0.028	−0.026	1.000	0.037	0.126	0.119	0.028	0.024	0.060	0.042
SBD	0.013	−0.024	0.037	1.000	0.737	0.072	0.020	0.005	0.037	0.042
MB	0.113	−0.064	0.126	0.737	1.000	0.294	0.142	0.111	0.192	0.182
GLB	0.148	0.060	0.119	0.072	0.294	1.000	0.396	0.518	0.153	0.134
GLE	0.504	0.080	0.028	0.020	0.142	0.396	1.000	0.802	0.662	0.727
INT	0.314	0.106	0.024	0.005	0.111	0.518	0.802	1.000	0.347	0.422
MCAP	0.568	−0.046	0.060	0.037	0.192	0.153	0.662	0.347	1.000	0.911
SCAP	0.570	−0.005	0.042	0.042	0.182	0.134	0.727	0.422	0.911	1.000

Notes: Instantaneous correlations of all sample pair combinations are provided. Columns 1 and 2 provide the asset class descriptors. The sample is from 2 January 1990 to 31 May 1995

Table II. Instantaneous correlations among asset classes

the basis for our first trading rule (Rule 1). The next strongest set of relationships is for domestic equity returns (GI, EI, BAL, GRO, MCAP and FIN) predicting future non-US (INT) returns. Furthermore, the strongest of these six relationships is that the returns on growth and income funds (GI) predict non-US (INT) fund returns (F-statistics 153.3). This will be the basis for our second trading rule (Rule 2)[4].

Table III.
Pair-wise Granger causality tests for one lag

	AG	GRO	GI	EI	BAL	BIO	REAL	FIN	TECH	UTIL
AG		0.024	5.975	17.316	4.484	7.025	29.887	0.401	0.026	0.020
		(0.878)	(0.015)	(0.000)	(0.034)	(0.008)	(0.000)	(0.527)	(0.871)	(0.888)
GRO	34.310		6.635	11.366	4.013	1.372	56.351	0.002	8.120	0.758
	(0.000)		(0.010)	(0.001)	(0.045)	(0.242)	(0.000)	(0.966)	(0.004)	(0.384)
GI	17.648	0.464		8.047	0.847	1.823	58.985	0.293	7.197	1.444
	(0.000)	(0.496)		(0.005)	(0.358)	(0.177)	(0.000)	(0.588)	(0.007)	(0.230)
EI	22.231	0.088	0.057		0.208	0.336	67.870	0.859	7.679	2.566
	(0.000)	(0.767)	(0.812)		(0.648)	(0.562)	(0.000)	(0.354)	(0.006)	(0.109)
BAL	16.727	0.238	1.408	10.039		1.069	69.312	4.886	5.408	2.446
	(0.000)	(0.626)	(0.236)	(0.002)		(0.301)	(0.000)	(0.027)	(0.020)	(0.118)
BIO	14.346	0.160	0.492	1.784	1.180		22.688	0.005	2.767	0.022
	(0.000)	(0.690)	(0.483)	(0.182)	(0.278)		(0.000)	(0.945)	(0.096)	(0.883)
REAL	0.621	1.910	0.165	2.645	0.056	3.218		4.741	2.977	0.671
	(0.431)	(0.167)	(0.684)	(0.104)	(0.813)	(0.073)		(0.030)	(0.085)	(0.413)
FIN	27.514	5.191	11.164	20.785	8.779	0.222	68.365		9.845	2.919
	(0.000)	(0.023)	(0.001)	(0.000)	(0.003)	(0.638)	(0.000)		(0.002)	(0.088)
TECH	16.405	2.304	7.734	9.717	5.603	0.271	24.235	0.016		0.049
	(0.000)	(0.129)	(0.005)	(0.002)	(0.018)	(0.603)	(0.000)	(0.900)		(0.824)
UTIL	0.567	0.210	0.027	0.710	0.073	0.228	10.724	0.633	0.696	
	(0.452)	(0.647)	(0.869)	(0.400)	(0.786)	(0.633)	(0.001)	(0.426)	(0.404)	
ENR	2.441	4.169	0.391	0.072	0.000	4.718	6.630	3.415	5.228	0.138
	(0.118)	(0.041)	(0532)	(0.789)	(0.990)	(0.030)	(0.010)	(0.065)	(0.022)	(0.710)
MET	1.903	0.068	0.056	0.300	0.090	0.153	7.685	0.000	2.206	0.516
	(0.168)	(0.795)	(0.813)	(0.584)	(0.765)	(0.696)	(0.006)	(0.988)	(0.138)	(0.473)
LBD	0.899	0.210	1.650	0.035	0.039	0.173	1.045	0.353	0.599	0.245
	(0.343)	(0.647)	(0.199)	(0.851)	(0.843)	(0.678)	(0.307)	(0.553)	(0.439)	(0.621)
SBD	1.389	1.013	0.903	1.082	1.514	0.108	5.723	1.483	1.793	1.382
	(0.239)	(0.314)	(0.342)	(0.298)	(0.219)	(0.742)	(0.017)	(0.223)	(0.181)	(0.240)
MB	1.692	0.058	0.277	0.235	0.026	0.001	5.033	0.008	0.441	1.444
	(0.194)	(0.810)	(0.599)	(0.628)	(0.872)	(0.976)	(0.025)	(0.930)	(0.507)	(0.230)

(continued)

	AG	GRO	GI	EI	BAL	BIO	REAL	FIN	TECH	UTIL
GLB	0.679	0.258	1.026	0.929	0.735	2.359	0.005	0.062	0.010	0.661
	(0.410)	(0.611)	(0.311)	(0.335)	(0.391)	(0.125)	(0.946)	(0.804)	(0.919)	(0.416)
GLE	28.237	6.207	0.039	6.766	0.037	17.602	0.162	3.172	17.036	0.254
	(0.000)	(0.013)	(0.843)	(0.009)	(0.848)	(0.000)	(0.687)	(0.075)	(0.000)	(0.614)
INT	13.973	7.116	0.669	0.004	1.531	10.051	5.319	14.084	15.398	0.737
	(0.000)	(0.008)	(0.413)	(0.947)	(0.216)	(0.002)	(0.021)	(0.000)	(0.000)	(0.391)
MCAP	43.432	4.095	8.367	12.269	5.788	0.042	45.629	0.301	10.248	0.538
	(0.000)	(0.043)	(0.004)	(0.000)	(0.016)	(0.837)	(0.000)	(0.583)	(0.001)	(0.463)
SCAP	0.038	4.261	0.586	5.056	0.393	10.411	18.569	2.331	0.751	0.449
	(0.845)	(0.039)	(0.444)	(0.025)	(0.531)	(0.001)	(0.000)	(0.127)	(0.386)	(0.503)
	ENR	MET	LBD	SBD	MB	GLB	GLE	INT	MCAP	SCAP
AG	6.077	2.419	5.092	0.073	13.220	8.234	98.959	77.274	0.215	10.748
	(0.014)	(0.120)	(0.024)	(0.788)	(0.000)	(0.004)	(0.000)	(0.000)	(0.643)	(0.001)
GRO	16.003	7.286	8.645	0.158	12.254	10.958	221.179	137.497	1.271	48.380
	(0.000)	(0.007)	(0.003)	(0.691)	(0.000)	(0.001)	(0.000)	(0.000)	(0.260)	(0.000)
GI	18.232	10.095	17.235	0.457	13.374	8.752	219.325	153.341	0.118	21.205
	(0.000)	(0.002)	(0.000)	(0.499)	(0.000)	(0.003)	(0.000)	(0.000)	(0.731)	(0.000)
EI	18.174	13.135	9.960	0.565	13.382	7.357	226.290	151.655	0.499	18.943
	(0.000)	(0.000)	(0.002)	(0.452)	(0.000)	(0.007)	(0.000)	(0.000)	(0.480)	(0.000)
BAL	13.277	8.029	20.619	0.526	22.038	19.447	212.539	151.559	25.606	19.490
	(0.000)	(0.005)	(0.000)	(0.468)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BIO	0.909	2.953	2.935	0.014	5.815	3.682	101.313	75.464	1.259	16.937
	(0.341)	(0.086)	(0.087)	(0.906)	(0.016)	(0.055)	(0.000)	(0.000)	(0.262)	(0.000)
REAL	1.360	12.607	6.397	0.249	12.605	0.217	37.843	37.085	3.890	1.678
	(0.244)	(0.000)	(0.012)	(0.618)	(0.000)	(0.641)	(0.000)	(0.000)	(0.049)	(0.195)
FIN	24.085	7.071	7.507	0.884	15.257	6.304	185.012	104.506	3.422	33.536
	(0.000)	(0.008)	(0.006)	(0.347)	(0.000)	(0.012)	(0.000)	(0.000)	(0.065)	(0.000)
TECH	6.921	2.437	4.231	0.075	7.978	8.043	95.404	71.433	2.927	24.817
	(0.009)	(0.119)	(0.040)	(0.785)	(0.005)	(0.005)	(0.000)	(0.000)	(0.087)	(0.000)

(continued)

Table III.

Table III.

	AG	GRO	GI	EI	BAL	BIO	REAL	FIN	TECH	UTIL
UTIL	1.587	3.455	6.155	1.075	15.541	9.491	35.934	45.585	0.078	0.413
	(0.208)	(0.063)	(0.013)	(0.300)	(0.000)	(0.002)	(0.000)	(0.000)	(0.781)	(0.521)
ENR		5.598	0.814	0.023	6.688	5.325	33.851	56.040	6.343	0.565
		(0.018)	(0.367)	(0.880)	(0.010)	(0.021)	(0.000)	(0.000)	(0.012)	(0.452)
MET	1.977		2.772	1.515	0.695	0.651	7.001	13.332	0.181	0.833
	(0.160)		(0.096)	(0.219)	(0.405)	(0.420)	(0.008)	(0.000)	(0.671)	(0.361)
LBD	0.177	0.000		0.023	0.342	0.733	6.269	4.579	0.262	0.368
	(0.674)	(0.983)		(0.879)	(0.559)	(0.392)	(0.012)	(0.033)	(0.609)	(0.544)
SBD	1.964	0.659	0.972		10.284	1.958	2.977	3.340	3.104	0.933
	(0.161)	(0.417)	(0.324)		(0.001)	(0.162)	(0.085)	(0.068)	(0.078)	(0.334)
MB	5.812	7.301	12.723	0.042		1.323	21.373	18.779	0.788	0.167
	(0.016)	(0.007)	(0.000)	(0.838)		(0.250)	(0.000)	(0.000)	(0.375)	(0.683)
GLB	0.625	2.477	14.011	0.629	4.966		10.545	6.787	0.001	0.004
	(0.429)	(0.116)	(0.000)	(0.428)	(0.026)		(0.001)	(0.009)	(0.981)	(0.951)
GLE	0.275	3.083	3.625	0.152	11.832	5.428		36.395	17.335	19.152
	(0.600)	(0.079)	(0.057)	(0.697)	(0.001)	(0.020)		(0.000)	(0.000)	(0.000)
INT	1.204	7.515	0.584	0.619	0.570	1.228	3.212		14.266	19.701
	(0.273)	(0.006)	(0.445)	(0.432)	(0.450)	(0.268)	(0.073)		(0.000)	(0.000)
MCAP	18.087	5.827	6.200	0.046	10.319	5.285	177.022	108.000		60.697
	(0.000)	(0.016)	(0.013)	(0.830)	(0.001)	(0.022)	(0.000)	(0.000)		(0.000)
SCAP	4.413	6.104	3.647	0.007	9.339	2.853	94.862	64.553	6.643	
	(0.036)	(0.014)	(0.056)	(0.933)	(0.002)	(0.091)	(0.000)	(0.000)	(0.010)	

Notes: Results of Granger causality tests for a one-day lag period are presented for each possible test pair combination. A matrix of the F-statistics (p-value in parenthesis) for the Granger causality test of lead and lag relationships is presented for the initial sample of 1,369 trading days between 2 January 1990 and 31 May 1995. The test statistics are for testing the null hypothesis that the asset class returns in the row do not Granger the asset class returns in the column for one-day lag (i.e. asset classes in rows are predictor variables and asset classes in columns are predicted variables)

Exploitation of the strength and direction of Granger relationships requires the implementation of a trading rule. Rule 1 suggests moving assets out of EI and into GLE following good (positive) EI returns. Once the investor has his assets in GLE, he will seek the asset class that GLE leads most strongly. On a positive return for GLE, he will move his assets into non-US equity funds (INT). Following a positive return in INT, assets would shift into small cap funds (SCAP). Finally, following a positive return in SCAP funds, the above procedure would then require shifting the assets from SCAP to GLE. In summary, by using the most positive statistical relationship as the base and moving from one asset class to the next based on the significance of the Granger relationship, the results suggest that the first trading rule would use EI to predict GLE, GLE to predict INT, INT to predict SCAP and SCAP to predict GLE. Once the investor has revisited an asset class previously visited (global equity), the cycle could repeat itself. Similarly, our second trading rule would use GI to predict INT, INT to predict SCAP, SCAP to predict GLE and GLE to predict INT.

4.3 Practical limitations

A limitation of trading on a one-day lag is that it presupposes that an investor could determine returns on the asset class during any given day, sell the fund at the close of business on that day and immediately reposition the assets. However, since this study is using open-end mutual funds as the securities underlying the asset class, instantaneous trading is not possible. The approach selected to deal with this complication was to examine the two-day lag structure to determine if the delay in transactions causes the predictability to disappear. If the two-day lag remains significant, exploitation of information embedded in asset class returns may be feasible.

4.4 Granger tests of two-day lag

Granger causality results for a two-day lag are reported in Table IV. The procedure used is identical to that used for the results in Table III. The important finding is that the pattern of asset predictabilities is not altered (Rules 1 and 2 continue to exist). These results are identical to those reported in Table III except that the statistical relationship is slightly weaker[5].

4.5 Empirical results of informed trading strategies

We begin by using two-day lagged returns and moving funds using trading Rule 1 (i.e. EI to predict GLE, GLE to predict INT, INT to predict SCAP and SCAP to predict GLE) and Rule 2 (i.e. GI to predict INT, INT to predict SCAP, SCAP to predict GLE and GLE to predict INT) to determine if the strategies would improve the risk–return relationship.

The returns, risks and Sharpe (1966) measures for both buy-and-hold strategies and the proposed trading strategies are presented in Table V. Notably, (i) the two highest arithmetic returns are for the trading strategies tested and (ii) the proposed trading strategies exhibit less volatility compared with other fund portfolios. However EI, BAL, REAL, UTIL, LBD, SBD, MB, GLB, GLE and INT funds exhibited lower standard deviations compared to both trading rules 1 and 2. Importantly, the Sharpe measures of the Rule 1 portfolio (0.0799) and Rule 2 portfolio (0.0658) are higher than any buy-and-hold strategy. Thus, the trading-rule portfolios provide a greater return per unit of risk thus dominating all buy-and-hold portfolios.

The Jensen (1968) measure is computed to determine whether the positive risk-adjusted returns are statistically significant. The Jensen measure is computed as $R_p - R_f = \alpha + \beta(R_m - R_f) + \varepsilon$, where R_p is portfolio return, R_f is risk-free return, R_m is market return, α is the risk-adjusted return, β is the systematic risk and ε is the error

Table IV.
Pair-wise Granger causality tests for two lags

	AG	GRO	GI	EI	BAL	BIO	REAL	FIN	TECH	UTIL
AG		0.974	4.072	8.881	3.177	3.278	18.258	2.944	0.722	1.517
		(0.378)	(0.017)	(0.000)	(0.042)	(0.038)	(0.000)	(0.053)	(0.486)	(0.220)
GRO	17.582		3.885	5.630	2.662	1.267	30.846	0.897	5.624	1.138
	(0.000)		(0.021)	(0.004)	(0.070)	(0.282)	(0.000)	(0.408)	(0.004)	(0.321)
GI	9.155	0.349		4.792	0.719	1.721	30.082	0.278	4.401	1.075
	(0.000)	(0.705)		(0.008)	(0.487)	(0.179)	(0.000)	(0.758)	(0.012)	(0.342)
EI	11.394	0.642	0.508		0.818	0.226	34.311	0.714	5.332	1.662
	(0.000)	(0.526)	(0.602)		(0.442)	(0.798)	(0.000)	(0.490)	(0.005)	(0.190)
BAL	9.052	0.594	1.002	6.201		1.334	34.859	2.335	3.486	1.248
	(0.000)	(0.552)	(0.367)	(0.002)		(0.264)	(0.000)	(0.097)	(0.031)	(0.288)
BIO	7.657	0.501	1.076	1.025	1.422		15.536	1.270	2.271	0.615
	(0.000)	(0.606)	(0.341)	(0.359)	(0.242)		(0.000)	(0.281)	(0.104)	(0.541)
REAL	0.169	0.788	0.246	1.298	0.204	1.300		2.184	0.825	0.439
	(0.845)	(0.455)	(0.782)	(0.273)	(0.816)	(0.273)		(0.113)	(0.438)	(0.645)
FIN	15.064	3.136	6.152	10.660	5.094	0.349	35.301		7.705	3.217
	(0.000)	(0.044)	(0.002)	(0.000)	(0.006)	(0.706)	(0.000)		(0.000)	(0.040)
TECH	8.048	1.235	4.032	4.813	3.086	0.188	13.021	1.285		0.414
	(0.000)	(0.291)	(0.018)	(0.008)	(0.046)	(0.829)	(0.000)	(0.277)		(0.661)
UTIL	0.274	0.303	0.193	0.381	0.175	0.206	5.762	0.572	1.130	
	(0.760)	(0.739)	(0.824)	(0.684)	(0.839)	(0.814)	(0.003)	(0.564)	(0.323)	
ENR	2.837	4.292	2.688	0.628	2.214	2.713	6.798	3.703	4.130	1.445
	(0.059)	(0.014)	(0.068)	(0.534)	(0.110)	(0.067)	(0.001)	(0.025)	(0.016)	(0.236)
MET	0.985	0.311	0.380	0.260	0.932	0.892	3.852	0.624	1.120	0.435
	(0.374)	(0.733)	(0.684)	(0.771)	(0.394)	(0.410)	(0.021)	(0.536)	(0.327)	(0.648)
LBD	0.519	0.118	1.503	0.044	0.585	0.105	0.632	0.182	0.369	0.135
	(0.596)	(0.888)	(0.223)	(0.957)	(0.557)	(0.901)	(0.531)	(0.833)	(0.692)	(0.874)
SBD	0.730	0.517	0.539	0.547	1.036	0.059	2.924	0.808	0.880	1.368
	(0.482)	(0.596)	(0.584)	(0.579)	(0.355)	(0.943)	(0.054)	(0.446)	(0.415)	(0.255)
MB	1.015	0.228	0.528	1.169	0.403	0.006	2.560	1.558	0.429	0.751
	(0.363)	(0.796)	(0.590)	(0.311)	(0.669)	(0.994)	(0.078)	(0.211)	(0.651)	(0.472)
GLB	0.444	0.644	1.158	1.568	1.333	1.893	0.109	0.468	0.007	0.942
	(0.642)	(0.525)	(0.315)	(0.209)	(0.264)	(0.151)	(0.897)	(0.627)	(0.993)	(0.390)

(continued)

	AG	GRO	GI	EI	BAL	BIO	REAL	FIN	TECH	UTIL
GLE	13.490	3.166	0.486	3.694	0.767	8.188	0.987	2.338	6.706	1.037
	(0.000)	(0.042)	(0.615)	(0.025)	(0.465)	(0.000)	(0.373)	(0.097)	(0.001)	(0.355)
INT	6.671	4.118	1.509	0.512	1.915	4.261	4.803	7.448	6.744	0.979
	(0.001)	(0.016)	(0.221)	(0.599)	(0.148)	(0.014)	(0.008)	(0.001)	(0.001)	(0.376)
MCAP	23.641	2.857	5.209	6.239	3.366	0.026	27.071	2.352	8.487	1.593
	(0.000)	(0.058)	(0.006)	(0.002)	(0.035)	(0.974)	(0.000)	(0.096)	(0.000)	(0.204)
SCAP	2.033	3.726	1.847	2.819	1.451	4.460	13.320	2.694	2.548	2.129
	(0.131)	(0.024)	(0.158)	(0.060)	(0.235)	(0.012)	(0.000)	(0.068)	(0.079)	(0.119)
	ENR	MET	LBD	SBD	MB	GLB	GLE	INT	MCAP	SCAP
AG	3.603	4.060	4.089	0.365	6.162	4.473	50.777	38.900	0.175	5.006
	(0.028)	(0.017)	(0.017)	(0.694)	(0.002)	(0.012)	(0.000)	(0.000)	(0.840)	(0.007)
GRO	8.236	4.978	7.089	0.662	5.969	5.777	110.882	69.634	0.489	23.604
	(0.000)	(0.007)	(0.001)	(0.516)	(0.003)	(0.003)	(0.000)	(0.000)	(0.613)	(0.000)
GI	9.078	6.231	12.414	0.645	6.524	4.614	110.427	76.836	0.110	10.130
	(0.000)	(0.002)	(0.000)	(0.525)	(0.002)	(0.010)	(0.000)	(0.000)	(0.896)	(0.000)
EI	9.118	7.424	8.826	0.468	6.761	3.974	113.557	76.092	0.400	8.818
	(0.000)	(0.001)	(0.000)	(0.627)	(0.001)	(0.019)	(0.000)	(0.000)	(0.670)	(0.000)
BAL	6.888	5.490	16.746	0.393	11.064	10.188	106.919	75.688	12.162	9.648
	(0.001)	(0.004)	(0.000)	(0.675)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BIO	0.616	3.469	2.416	0.336	2.837	1.931	54.374	39.157	0.658	7.608
	(0.540)	(0.031)	(0.090)	(0.715)	(0.059)	(0.145)	(0.000)	(0.000)	(0.518)	(0.001)
REAL	0.725	6.913	6.277	0.125	5.258	0.773	19.354	18.578	1.331	0.806
	(0.485)	(0.001)	(0.002)	(0.883)	(0.005)	(0.462)	(0.000)	(0.000)	(0.264)	(0.447)
FIN	13.789	3.673	7.090	0.417	7.261	4.158	94.354	55.243	2.060	16.645
	(0.000)	(0.026)	(0.001)	(0.659)	(0.001)	(0.016)	(0.000)	(0.000)	(0.128)	(0.000)
TECH	3.868	2.447	3.229	0.800	3.869	4.006	49.222	35.408	0.995	11.032
	(0.021)	(0.087)	(0.040)	(0.449)	(0.021)	(0.018)	(0.000)	(0.000)	(0.370)	(0.000)
UTIL	0.913	2.354	5.691	0.599	7.741	4.746	18.116	22.555	0.089	0.158
	(0.401)	(0.095)	(0.003)	(0.550)	(0.000)	(0.009)	(0.000)	(0.000)	(0.915)	(0.853)

(continued)

Table IV.

Table IV.

	AG	GRO	GI	EI	BAL	BIO	REAL	FIN	TECH	UTIL
ENR		4.136 (0.016)	0.811 (0.445)	0.104 (0.901)	2.832 (0.059)	2.761 (0.064)	20.108 (0.000)	28.982 (0.000)	4.028 (0.018)	1.775 (0.170)
MET	1.112 (0.329)		1.953 (0.142)	0.983 (0.374)	0.556 (0.573)	0.449 (0.638)	3.539 (0.029)	6.686 (0.001)	0.498 (0.608)	0.399 (0.671)
LBD	0.089 (0.915)	0.082 (0.921)		0.011 (0.989)	0.177 (0.838)	0.935 (0.393)	3.270 (0.038)	2.306 (0.100)	0.168 (0.846)	0.211 (0.810)
SBD	1.475 (0.229)	0.560 (0.571)	0.968 (0.380)		6.023 (0.002)	0.999 (0.369)	1.484 (0.227)	1.643 (0.194)	1.713 (0.181)	0.624 (0.536)
MB	3.703 (0.025)	3.597 (0.028)	11.898 (0.000)	0.122 (0.885)		0.708 (0.493)	10.894 (0.000)	9.886 (0.000)	0.514 (0.598)	0.426 (0.653)
GLB	0.827 (0.438)	1.374 (0.253)	15.339 (0.000)	0.305 (0.737)	2.615 (0.074)		5.328 (0.005)	3.756 (0.024)	0.312 (0.732)	0.252 (0.777)
GLE	0.478 (0.620)	6.252 (0.002)	4.479 (0.012)	0.175 (0.840)	4.654 (0.010)	2.841 (0.059)		18.123 (0.000)	7.198 (0.001)	8.980 (0.000)
INT	0.774 (0.462)	5.759 (0.003)	1.500 (0.224)	0.333 (0.717)	0.137 (0.872)	0.660 (0.517)	1.814 (0.163)		6.392 (0.002)	8.863 (0.000)
MCAP	9.673 (0.000)	4.646 (0.010)	5.250 (0.005)	0.638 (0.528)	4.844 (0.008)	2.675 (0.069)	89.436 (0.000)	55.416 (0.000)		29.521 (0.000)
SCAP	3.119 (0.045)	4.714 (0.009)	3.186 (0.042)	0.191 (0.826)	4.322 (0.013)	1.481 (0.228)	51.450 (0.000)	33.947 (0.000)	3.743 (0.024)	

Notes: Results of Granger causality tests for a two-day lag period are presented for each possible test pair combination. A matrix of the *F*-statistics (*p*-value in parenthesis) for the Granger causality test of lead and lag relationship is presented for the initial sample of 1,369 trading days between 2 January 1990 and 31 May 1995. The test statistics are for testing the null hypothesis that the asset class returns in the row do not Granger the asset class returns in the column for two-day lag (i.e. asset classes in rows are predictor variables and asset classes in columns are predicted variables)

Asset Class	Return	Standard deviation	Return/risk	Sharpe ratio
AG	0.000301	0.012430	0.024211	0.007198
GRO	0.000298	0.010395	0.028649	0.008305
GI	0.000256	0.008971	0.028533	0.004964
EI	0.000153	0.006824	0.022409	−0.008579
BAL	0.000080	0.006739	0.011932	−0.019450
BIO	0.000543	0.011954	0.045421	0.027712
REAL	0.000060	0.005135	0.011647	−0.029491
FIN	0.000520	0.012474	0.041679	0.024723
TECH	0.000634	0.017421	0.036376	0.024232
UTIL	0.000310	0.007630	0.040609	0.012894
ENR	0.000191	0.009967	0.019194	−0.002020
MET	−0.000778	0.015280	−0.050940	−0.064740
LBD	−0.000049	0.002798	−0.017348	−0.092487
SBD	−0.000021	0.001638	−0.012834	−0.140485
MB	−0.000021	0.001769	−0.011924	−0.130873
GLB	−0.000148	0.002392	−0.061692	−0.149380
GLE	0.000173	0.007346	0.023559	−0.005226
INT	0.000118	0.007595	0.015495	−0.012345
MCAP	0.000330	0.011946	0.027642	0.009939
SCAP	0.000275	0.010443	0.026326	0.006074
Rule 1	0.000893	0.008571	0.104144	0.079908
Rule 2	0.000761	0.008175	0.093109	0.065786

Notes: Risk and return of asset classes are provided for holdout sample (from 1 June 1995 through 31 October 2000). Column 1 is the asset class; columns 2 and 3 are the average arithmetic returns and standard deviation of returns. Column 4 provides the risk–return relationship by displaying the average arithmetic return divided by the standard deviation. Column 5 provides the Sharpe measure

Table V. Risk and return of sample portfolios

term. We use the Center for Research in Security Prices (CRSP) value-weighted index as the market proxy and money market fund as a proxy for the risk-free rate.

Table VI reveals that the risk-adjusted excess returns of the trading rules are positive and statistically significant at the 1 per cent level. The alpha for trading rule 1 (0.006775) per day is approximately 16.94 per cent per year, while the alpha for trading rule 2 (0.0005113) per day is approximately 12.78 per cent per year. Additionally, systematic risks of the trading rules ($\beta = 0.591$ for trading Rule 1 and $\beta = 0.549$ for trading Rule 2) are much less than that of the market index. We find similar results using the CRSP equally weighted index and S&P 500 index. The superior Jensen

	A	*T*	*p*-value	*B*	R^2	*N*
Rule 1	0.0006775 (0.000153)	4.4096	0.0000	0.591 (0.0147)	0.572	1370
Rule 2	0.0005113 (0.000146)	3.4868	0.0000	0.549 (0.0145)	0.569	1370

Notes: Results of market model regressions are presented below for trading rules 1 and 2. Column 2 through 4 present the daily risk-adjusted return (α), the *t*-statistic and *p*-value for the two-tailed hypothesis test that risk-adjusted return equals zero. Columns 5 through 7 present the systematic risk (β), co-efficient of determination (R^2) and the number of observations (*N*). Standard errors are in parenthesis below the coefficient estimates

Table VI. Risk-adjusted return of trading rules measures provide confirmatory evidence that informed investors are able to exploit asset class return predictabilities in open-end mutual funds. To achieve this result, 424 and 416 trades were made for Rules 1 and 2, respectively. The average trading frequency is approximately 6.5 trades per month.

We also investigated whether our trading strategies work better with no-load funds than load funds. There are 311 no-load and 330 load (285 with front-load and 45 with back-load) funds in our sample. Results of Granger causality tests, autocorrelations and cross-autocorrelations for both load and no-load funds are qualitatively similar to the combined sample. Results of trading strategies also reveal that there are no statistically significant return differences between load and no-load funds. Overall, our findings suggest that both load and no-load funds are subject to similar kind of predictability and exploitation. These findings are consistent with Goetzmann *et al.* (2001).

Admittedly, load fees may eliminate some of the profitable opportunities of our trading strategies for load funds. In most families suitable funds can be found that can be transferred among without paying loads (once the initial load has been paid). It is also important to realize that the load fees are usually low or zero for investors who invest a large amount of money in fund complexes. Investors also enjoy unrestricted and transaction-free exchange privileges between load and no-load funds within the same fund family. Mutual funds also offer breakpoint discounts that allow investors to purchase load funds with discounts. Besides, investors can return to the same family of funds within 30 to 90 days without paying load fees. Prudent investors may take advantages of all these small effects and avoid fees when trading load funds[6].

5. Conclusion

We examine whether mutual fund asset classes exhibit predictable return patterns. Empirical results suggest that significant cross-autocorrelations exist among asset classes at the macro-level. This finding is important to investors and portfolio managers since this cross-autocorrelation may be exploitable at the micro-level. Using the observed relationships, we explored how informed traders may use this information to exploit the relationships. Results suggest that a dynamic trading strategy provides a higher return per unit of risk than any of the asset class portfolios. Additionally, the trading rule has superior Sharpe and Jensen performance measures compared with a buy-and-hold strategy. Therefore, tactical asset allocation using past asset class returns of open-end mutual funds may be a viable tactic on average.

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