

Day-of-the-Week Effects Among Mutual Funds

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We extend the evidence on day-of-the-week effects by examining the return patterns of ten open-end mutual fund asset classes to establish whether previously observed predictabilities in stock returns are reflected in mutual fund asset-class returns. This determination is consequential because institutional characteristics may permit the exploitation of this well-documented pattern by using mutual funds. We then propose two trading strategies to exploit salient empirical regularities and test these rules empirically. Empirical testing reveals that daily dynamic trading strategies exist that can reduce risk and increase returns resulting in improved Sharpe and Treynor measures. Furthermore, Treynor-Mazuy and Henriksson-Merton timing measures are positive.

Introduction

As discussed in the introductory article by Pettengill (2003), there is a large literature on the Monday effect. A day-of-the-week effect for a particular type of security exists if (1) the returns for that type of security are greater on some days of the week than others (a trading day effect), or (2) the returns on that security over a trading period are not proportional to the number of calendar days affected (a calendar day effect). Because returns for a given day are traditionally measured from the close of the previous trading day, Monday's returns would be computed from Friday's close to Monday's close, a period that includes three calendar days.

As discussed in the introductory article, most research shows that Monday returns are radically different from other days of the week and are often negative. Therefore, most of the research on the day-of-the-week effect has focused on the Monday effect, this issue's subject. Monday is only one day of the week, however,

and it is important to study the Monday effect in the context of possible differential returns for other days. This is one rationale for including data for days other than Monday in a Monday effect paper. This examination also provides one of this paper's contributions to the literature.

Even though the existence of a Monday effect is intellectually interesting, it has been regarded as something that could not be traded profitably. The average weekend decline of 0.089 percent found by Siegel (1998) would amount to only \$0.0445 for a \$50 stock which is less than the bid-ask spread that prevailed during the period studied. As discussed in the introductory article, many other references make this same point including French (1980), Kim (1988), Bessembinder and Hertz (1993), Ko and Lee (1993), and Chow, Hsiao, and Solt (1997).¹ Consequently, the only potential for profiting from the day-of-the-week effect through trading individual stocks would be through changing the timing of trades that are already planned, such as timing purchases for Mondays and sales for Fridays.

A potentially profitable strategy for exploiting a Monday effect exists if the investor uses mutual funds or variable annuities because, in most cases, investors can escape transaction costs such as bid-ask spreads and commissions. Often, investors can transfer between funds at no expense. This is true for most retirement plans, variable annuities, and mutual fund families, although some mutual fund families and variable annuities restrict the frequency of trades or impose fees. Compton and Kunkel (1999) illustrate that making trades within a tax-deferred, no transfer-cost retirement account can generate high risk-adjusted returns. Using the TIAA-CREF's accounts, they propose switching to CREF's stock account on Monday and then switching back to CREF's money market account on Friday, earning three days (Saturday, Sunday, and Monday) of returns over the weekend. They suggest that their trading strategy can be applied to other retirement accounts and to variable annuities, but they fail to test the strategy with other fund groups. Therefore, our second contribution to the literature is that we extend the work of Compton and Kunkel (1999) by providing such tests here.

Our results for mutual fund asset classes should also extend to other retirement accounts, which frequently permit transaction free exchanges between funds. The reason for this is that we examine asset class returns that are fabricated from actual mutual funds that are used as the investments in these types of accounts. These retirement accounts have the additional virtue of being tax deferred, and hence they do not generate the steady stream of highly taxed short-term capital gains that would be generated by a trading strategy applied to mutual funds in a taxable account. Using retirement accounts also avoids the heavy tax-accounting burden that would

¹Chow, Hsiao, and Solt (1997) do find some degree of exploitability by shorting SPDRS. The details of Chow, Hsiao, and Solt's approach, and the limitations of their study, are discussed in the survey article by Pettengill (2003).

accrue from the numerous transactions that would be required to exploit a day-of-the-week effect in individual stocks.

Extant research suggests that there are advantages to examining the returns from different types of stock funds because it is probable that various types of stocks have different patterns for a weekly effect. Sias and Starks (1995) find that the day-of-the-week anomaly is largest for institutional stocks, suggesting that the effect would be bigger for mutual funds than for portfolios of individual stocks. Thus, our third contribution to the literature is to examine various types of stock funds to ascertain the similarity of calendar effects for various asset classes.

At this point it is important to highlight that a day-of-the-week pattern in stock returns is not a necessity for a useful switching pattern to exist. Suppose that the average Monday return for stocks is the same as other weekdays. This would imply that stocks have one day's return over Friday's close to Monday's close while bond and money market funds might have three days of returns. (Table 2, panel A, documents that money-market returns on Mondays are approximately three times the magnitude of the return for other days of the week.) These three days of returns could easily exceed the stocks' returns, especially on a risk-adjusted basis.

There are also other investment vehicles beside stocks, notably bonds, which need to be studied. Most bond fund returns result from interest that is accrued evenly over every calendar day (which means that three days of interest return should be reflected in the closing prices on Mondays). Because the accrued interest is received on bond sales, anything less than three days of earnings over the weekend would be a very interesting effect. Therefore, we include the patterns of bond returns in this study.

Another reason to examine non-stock funds is that in order to understand the profitability of any trading system that is in stocks only part of the time, it is essential to look at the returns on the assets when they are not in stock funds. A trading system that is out of stocks at certain times has to be invested in something else, such as bonds or a money-market fund. Conceivably, a seasonal in these non-stock funds could neutralize any benefits from being out of stocks. For example, imagine that bond funds decreased in value more than stock funds do on Mondays—this would eliminate a profitable trading strategy.

Our study differs from most previous studies because the majority of those studies do not allow for any returns from investing in other assets when the investor is out of the stock market, although such returns are a real part of the total return of any portfolio. Additionally, most previous studies do not provide risk-adjusted returns. Therefore, our final contribution to the literature is that we consider the effects of both of these factors in this paper.

Data

We use the Morningstar Principia Pro database to identify all funds that were in continuous operation from January 2, 1990 through October 31, 2000.² We then sort those funds by the CDA investment objectives. Because open-end mutual funds are permitted to change the objective if shareholders approve the change, we consulted Morningstar and eliminated any funds that changed objectives during the period of study. The purpose of eliminating these funds was to ensure, as much as possible, the homogeneity of funds representing each investment objective class. This is important because we want to capture the uniqueness of the return properties of each asset class. Therefore, keeping the investment objectives classes pure will prevent any potential differences in the return patterns for different investment objectives from masking each other when combined.

Using Dial Data's daily net asset value (NAV) and distribution data for each of the selected funds, we computed daily total returns. To ensure the quality of the data we follow the screening procedure of Busse (1999).³ Our final sample consists of 2,739 daily returns for 542 open-end mutual funds in ten fund categories. The number of daily returns ranged from 523 for Monday to 563 for Tuesday (the slight differences are due to holidays). Table 1 lists the asset classes investigated and their descriptors.

Table 1—Asset Class Descriptors

The abbreviation used for each asset class is listed in column one, and the asset class that it represents is listed in column two. Column three provides the number of funds in our sample for each class during the period from January 2, 1990 through October 31, 2000

Descriptor	Asset Class	Number of Funds
AG	Aggressive Growth	21
GRO	Growth	175
GI	Growth and Income	92
EI	Equity Income	32
BAL	Balanced	29
MB	Municipal Bond	72
GLE	Global Equity	22
INT	Non-US Equity	35
MCAP	Mid Cap	21
SCAP	Small Cap	43

²Although we are interested in day-to-day effects, the disappearance (survivorship bias) of some funds should not be a major concern in this paper. One reason for this belief is that disappearing funds would likely be poor performing funds (e.g., have lower average returns for each day of the week) but would be expected to have the same daily return pattern.

³Missing NAVs and errors in distributions dates account for less than 1 percent of our sample. Distributions are recorded one or two days before or after the actual distribution date (ex-dividend date for the fund). Following Busse (1999), we use *Moody's Dividend Record: Annual Cumulative Issue* to verify and to correct the missing distributions dates and NAV for funds.

Computation of Returns

Continuously compounded daily returns are computed for each fund by taking the natural logarithm of the change in daily value for each of the 2,739 days in our sample, as shown in equation (1)

$$R_{i,t} = \ln \frac{\text{value}_{i,t}}{\text{value}_{i,t-1}} \quad (1)$$

where $R_{i,t}$ is the return on fund i during the period t , and $\text{value}_{i,t}$ is the value of an investment in fund i at time t .

After the returns for each fund within an investment objective classification were computed, an equally-weighted index return for each investment objective group was computed by summing the returns of the individual funds (i) within the investment objective classification (o), and computing their average daily return using equation (2).

$$R_{o,t} = \ln \frac{\sum_{i=1}^n R_{i,t}}{n} \quad (2)$$

$R_{o,t}$ is the average return on investment objective class (o) during the period t . This procedure resulted in developing ten sets of equally-weighted daily return indices.

Development of Trading Rules

In order to conduct empirical investigation, we divided our sample into two subsamples with an approximately equal number of observations. The first subsample contains 1,369 daily observations from January 2, 1990 through May 31, 1995, and the holdout sample contains 1,370 daily observations from June 1, 1995 through October 31, 2000. Our exploration uses the initial subsample to investigate return patterns and to develop trading rules, and tests those rules on the holdout sample.

Table 2 reports the descriptive statistics for our sample of mutual funds for the five-year period starting in 1990 and provides evidence of a Monday effect for many types of funds, but not for all.⁴ In particular, aggressive growth, municipal bond, global equity, non-US equity, mid-cap, and small-cap funds exhibit negative returns on Monday. Growth, growth and income, equity income, and balanced funds, however, do not. Inspection of the tables also shows that there are differences in the daily returns between non-Monday days of the week. These differences in returns appear large enough to be potentially exploitable.

⁴Similar analysis was conducted on the 1995-2000 period to investigate a Monday shift. Our analysis examined year-by-year results and aggregate results over the five-year period. We find no evidence of a Monday shift, and the results are qualitatively unchanged.

Table 2—Day-of-the-Week Descriptive Statistics

Column one lists the asset classes and columns two through seven present the days of the week (the number of observations (N) is in parenthesis). “Combined” represents the average of all days of the week. Panel A presents the average returns in basis points and absolute t-statistics (in parenthesis below average returns). The t-statistics are for the test of the null hypothesis that the average return for that day of the week is equal to average of all days of the week. Panel B presents the standard deviations of returns. The average returns and standard deviations of CREF’s Money Market (MM) fund for each day of the week are also presented in the last row of panel A and panel B. The sample period is from January 2, 1990 through May 31, 1995

Panel A: Mean Returns

Asset Classes	Combined (N = 1369)	Monday (N = 261)	Tuesday (N = 281)	Wednesday (N = 279)	Thursday (N = 276)	Friday (N = 272)
AG	1.643	-5.560 (1.215)	-0.643 (0.439)	11.380 (2.274)**	2.574 (0.203)	-0.025 (0.389)
GRO	1.046	2.947 (0.407)	-2.510 (0.846)	8.620 (2.073)**	-0.970 (0.516)	-2.830 (0.971)
GI	1.106	6.203 (1.259)	-1.400 (0.720)	5.492 (1.416)	-2.100 (0.938)	-2.440 (0.985)
EI	1.026	5.142 (1.266)	-0.469 (0.545)	4.985 (1.717)	-2.580 (1.404)	-1.780 (0.996)
BAL	0.891	4.157 (1.137)	-0.031 (0.376)	4.510 (1.670)*	-1.340 (0.917)	-2.750 (1.235)
MB	-0.153	-3.340 (2.544)**	-0.061 (0.084)	2.135 (2.180)**	0.994 (0.960)	-0.706 (0.209)
GLE	1.179	-5.650 (1.426)	2.132 (0.270)	3.902 (0.946)	4.273 (1.019)	0.813 (0.124)
INT	0.528	-7.560 (1.504)	4.336 (1.070)	-2.200 (0.775)	3.860 (0.897)	3.770 (0.872)
MCAP	1.487	-2.618 (0.706)	-0.927 (0.536)	11.21 (2.379)**	1.535 (0.011)	-2.100 (0.863)
SCAP	1.841	-5.840 (1.507)	-2.850 (1.050)	10.92 (2.340)**	4.724 (0.716)	1.822 (0.005)
CREF MM	1.984	4.147 (21.910)***	1.647 (4.071)***	1.385 (14.117)***	1.420 (13.731)***	1.443 (10.391)***

Note: ***, **, and * denote the level of significance at 1 percent, 5 percent and 10 percent respectively

Panel B: Standard Deviations of Returns

Asset Classes	Combined (N = 1369)	Monday (N = 261)	Tuesday (N = 281)	Wednesday (N = 279)	Thursday (N = 276)	Friday (N = 272)
AG	0.0081	0.0096	0.0087	0.0072	0.0076	0.0071
GRO	0.0068	0.0075	0.0070	0.0061	0.0065	0.0066
GI	0.0058	0.0065	0.0058	0.0052	0.0057	0.0059
EI	0.0045	0.0053	0.0046	0.0039	0.0043	0.0046
BAL	0.0043	0.0046	0.0041	0.0036	0.0040	0.0049
MB	0.0026	0.0020	0.0019	0.0018	0.0020	0.0044
GLE	0.0058	0.0077	0.0059	0.0048	0.0050	0.0049
INT	0.0066	0.0087	0.0060	0.0059	0.0062	0.0061
MCAP	0.0076	0.0094	0.0076	0.0068	0.0071	0.0069
SCAP	0.0070	0.0082	0.0075	0.0065	0.0067	0.0060
CREF MM	0.0002	0.0002	0.0001	0.0001	0.0001	0.0001

Based on the observed results, we propose two trading rules. The first trading rule is a simple trading rule that follows French (1980), Kim (1988), Chow, Hsiao, and Solt (1997), and Compton and Kunkel (1999) by assuming that investors shift their money into a money market fund on Friday to avoid the negative Monday return and then switch the money back into the risky mutual fund on Monday.

The second trading rule is more complex and uses all daily-return-pattern information. This complex trading rule assumes that investors would shift their investments out of risky mutual funds and into money market funds to avoid the day(s) of the week when average returns of the mutual fund class are historically negative. This rule allows investors to escape the average negative returns of the fund's investment objective and to enjoy the low, but less-risky, returns of money market funds. By way of example, investors in aggressive growth, municipal bond, or mid-cap funds would switch their investment into money market funds to avoid negative returns on Monday, Tuesday, and Friday because these categories of funds displayed negative returns on these three days of the week during the sample period. Therefore, these investors are only in risky investments on Wednesday and Thursday. Investors of growth, growth and income, equity income, or balanced funds will switch into money market funds on Tuesday, Thursday, and Friday. The strategies for other asset classes are similar. Table 3 presents our complex trading strategy.

Table 3—Complex Trading Strategy for Mutual Fund Asset Classes

This table presents our complex trading strategy. Column one lists the asset classes. Column two lists the days of the week when an investor will be in the asset class whereas column three lists the day(s) of the week when an investor will be in the money market fund

Asset Classes	Days In-the-Fund	Days Out-of-the-Fund
AG	Wed, Thu	Mon, Tue, Fri
GRO	Mon, Wed	Tue, Thu, Fri
GI	Mon, Wed	Tue, Thu, Fri
EI	Mon, Wed	Tue, Thu, Fri
BAL	Mon, Wed	Tue, Thu, Fri
MB	Wed, Thu	Mon, Tue, Fri
GLE	Tue, Wed, Thu, Fri	Mon
INT	Tue, Thu, Fri	Mon, Wed
MCAP	Wed, Thu	Mon, Tue, Fri
SCAP	Wed, Thu, Fri	Mon, Tue

Empirical testing will be conducted for both the simple and complex trading rules using data from the hold out sample period. Thus, this is a realistic test of what might have happened if someone had observed the pattern for one period (1990-1995) and then applied the strategy to the second period. Because the division of the data into two distinct periods was completed before the results were known, this procedure provides protection against data mining effects.

Our strategies use a money market fund as an alternative place to park investments instead of investing in funds. We use the money market fund as proxy

for the risk-free rate below because using a money market fund is a more realistic approach for examining an applied trading rule than the traditional T-bill return. Investors in a mutual fund, variable annuity, or retirement account usually can shift into a money market account with a phone call or an internet site visit. Shifting to T-bills requires selling the fund, obtaining cash (after the sale has settled), and then buying T-bills. This takes more than one day. Furthermore, if the funds are in a variable annuity or many types of retirement accounts, T-bills cannot be purchased at all. We follow Miller and Prather (2000) and use the money market fund of the TIAA-CREF retirement annuity as a proxy for the returns on a money market account.

Exploitability of Day-of-the-Week Patterns

We will begin by presenting the empirical results of the simple Monday-only trading strategy, and then we will explore the success of the more complex trading strategy that uses all day-of-the-week patterns.

Simple Day-of-the-Week Trading Rule

Table 4 presents the average arithmetic return (in basis points), standard deviation (risk), and Sharpe (1966) and Treynor (1965) ratios for a buy-and-hold strategy and the simple trading strategy for each of the ten asset classes. Again, this simple trading strategy assumes that investors shift their money into a money market fund on Friday to avoid the negative Monday return and then switch the money back into the risky mutual fund on Monday.

The Sharpe measure (S) and Treynor (T) measure are computed as:

$$S = \frac{R_p - R_f}{\sigma_p} \text{ and } T = \frac{R_p - R_f}{\beta_p}, \text{ respectively,}$$

where R_p is the portfolio return, R_f is the risk-free return, σ_p is the portfolio standard deviation, and β_p is the portfolio systematic risk.

The largest positive arithmetic return occurs when using the trading rule with the aggressive growth portfolio (5.7218 bp). The higher relative returns of the trading rule are not limited to the aggressive growth portfolio. The proposed trading rule's returns are higher than those of buy-and-hold strategies for each of the other investment objectives. This is an extremely important result because, as we discussed earlier, investors are out of the risky investment over the weekend and Monday. Therefore, due to the result that the returns of the trading rules are higher than the returns of buy-and-hold strategies, and risks should be lower, the trading rule may be beneficial to investors because it may permit garnering superior risk-adjusted returns.

Our suspicions regarding risk are confirmed. Although selling at Friday's close avoids the risk of adverse events over Saturday and Sunday, such as the break out of war or natural disasters, the fact is that the standard deviations over the three-day

period are only slightly greater (and sometimes less) than the other days of the week. This suggests that the relevant risks occur primarily when there is trading (risks related to trading time rather than calendar time). As also shown by Table 4, risks (standard deviations) are also reduced for the trading rules in each of the investment objectives studied. Again, this was no surprise because the proposed trading strategy involves being out of the market part of the time. This is also important because, as we saw above, the returns for the trading rules were higher than those of buy-and-hold strategies. Thus, the trading rule portfolios provide higher returns per unit of risk than the buy-and-hold portfolios.

In terms of modern portfolio theory, this suggests that investors could profit from such a strategy. A buy-and-hold portfolio can be constructed with a mix of a money market fund and a fund in any other asset class that would have the same risk as the trading strategy. The proposed trading strategy would have a higher return. Thus, it would dominate a buy-and-hold strategy. This would leave the investor in a better financial position (i.e., he reaches a combination of risk and return that is preferred).^{5,6}

⁵In practice, investors might limit their day-of-the week trading to tax-sheltered accounts because of the numerous trades required and the complexity such a strategy would create for tax reporting (not to mention the replacement of long-term gains by short-term gains). There are probably many individuals with substantial wealth in retirement funds that would find a day-of-the-week strategy useful.

⁶Day-of-the-week strategies, while benefiting the individual investor, might not be in the interest of other holders of the funds. The fund families would incur extra administrative costs from such frequent trading (as would a retirement plan or variable annuity within which such trades were being made). If only a few investors attempted frequent trading and the fund was experiencing net inflows, the only effect might be larger net inflows on some days than on others. If more than a few investors used strategies that involved frequent trading there would be days of net outflows for the fund. If large sums were traded by day-of-the-week rules, the funds would incur large expenses (spreads and commissions) in buying and selling securities in order to stay fully invested. At best a fund that realized that it received net buying on some days and net selling on others, might adopt a policy of timing its purchases for the days that it received funds and timing its sales for the days it lost funds. It might also maintain larger cash reserves so it would not have to buy and sell securities. It should be realized that frequent trading is not in the interests of funds and that fund instruments should be designed to restrict such trading. This can be done by placing limitations on the frequency of trading or by adding trading fees. Of course, any such restrictions should be disclosed before sale and investors should not be offered products with assurances of the easy trading only to have the fund later try to prevent or reduce trading. Given that profitable and utility-enhancing strategies appear to exist, funds should anticipate that eventually they will have to deal with frequent trading and should design their products accordingly. Prospectuses might provide for small fees per trade to cover the additional administrative costs of placing trades and either also place limits on the number or frequency of trades or impose fees that are a percentage of value for trades that are quickly reversed.

Table 4—Risk and Return of the Simple Trading Strategy

Column one is the asset class and columns two through four are the average arithmetic returns in basis points, standard deviations of returns, Sharpe, and Treynor measures during the June 1, 1995 through October 31, 2000 period. Each column is split into buy-and-hold and trading rule sub-columns to facilitate comparison of the trading rules with the buy-and-hold strategies

Asset Class	Return		Risk (Std. Dev)		Sharpe Ratio		Treynor Ratio	
	Buy-and-Hold	Trading Rule	Buy-and-Hold	Trading Rule	Buy-and-Hold	Trading Rule	Buy-and-Hold	Trading Rule
AG	3.0095	5.7218	0.0124	0.0108	0.0072	0.0333	0.0001	0.0004
GRO	2.9780	4.8255	0.0104	0.0092	0.0083	0.0296	0.0001	0.0004
GI	2.5597	3.0573	0.0090	0.0080	0.0050	0.0118	0.0001	0.0002
EI	1.5293	2.2571	0.0068	0.0060	-0.0086	0.0024	-0.0001	0.0000
BAL	0.8042	1.7000	0.0067	0.0059	-0.0195	-0.0070	-0.0002	0.0001
MB	-0.2110	1.1336	0.0018	0.0016	-0.1309	-0.0606	-0.0081	-0.0035
GLE	1.7306	3.0088	0.0073	0.0065	-0.0052	0.0138	-0.0001	0.0002
INT	1.1768	2.9473	0.0076	0.0066	-0.0123	0.0126	-0.0003	0.0004
MCAP	3.3022	5.7803	0.0119	0.0104	0.0099	0.0351	0.0001	0.0005
SCAP	2.7493	5.6564	0.0104	0.0091	0.0061	0.0388	0.0001	0.0005

Another approach to examining our results is to use timing models. Treynor and Mazuy (TM, 1966) pioneered performance attribution studies by illustrating that performance can be dichotomized into security selection and market timing components. If fund managers maintain constant risk, the characteristic line will be linear with the scatter inversely related to diversification. Alternately, market timing attempts cause curvature in the characteristic line, and the curvature and scatter will depend on the proportion of correct (and incorrect) guesses and the magnitude of the gambles. While alternative procedures to create separable selectivity and timing measures exist, none have achieved the widespread acceptance enjoyed by the Henriksson and Merton (HM, 1981) model. The Henriksson and Merton model is fundamentally different from the Treynor and Mazuy model because it only assumes that the macroforecaster can forecast whether stocks or bonds will perform better in the subsequent period. Because our strategy is a classic market-timing strategy, we compute the Treynor and Mazuy and Henriksson and Merton models using both the CRSP VW and S&P 500 indexes as market proxies.⁷ The equations for Treynor and Mazuy and Henriksson and Merton models are:

$$\text{TM: } R_p - R_f = \alpha + \beta(R_m - R_f) + \gamma(R_m - R_f)^2 + \varepsilon \quad (3)$$

$$\text{HM: } R_p - R_f = \alpha + \beta(R_m - R_f) + \gamma(R_m - R_f)D + \varepsilon \quad (4)$$

where $R_p - R_f$ is the portfolio excess return, $R_m - R_f$ is the market excess return, and α , β , and γ are the estimated coefficients for selectivity, systematic risk, and market timing respectively. The Treynor and Mazuy measure uses the second moment of excess market returns to capture curvature in the regression whereas the Henriksson

⁷We include only results for the CRSP VW index in this paper; however, results for the S&P 500 index are qualitatively similar.

and Merton measure uses a dummy variable (D) where D is 1 if the market return exceeds the risk free returns ($R_m > R_f$) or 0 otherwise.

Most literature suggests that mutual funds (or other managed portfolios) display perverse market timing ability when compared to an unmanaged index. Despite those indications of perverse timing, the perverse timing may not be the result of decisions made by active portfolio managers. Warther (1995) argues that some indications of perverse timing are the result of fund flows into mutual funds that are correlated with expectations of future market performance. If managers cannot rapidly invest these funds, the cash position of the fund will increase causing the beta to decrease. Therefore, while it would appear that the manager decreased the beta at the wrong time, the beta decrease was not due to a managerial decision but due to an externality. Further, Edelen (1999) finds that monthly cash flows are capable of explicating some negative timing ability.

Our results in Table 5 stand in stark contrast to usual timing results because seven of the ten asset classes exhibit statistically positive timing ability with the Treynor and Mazuy measure, and the Henriksson and Merton measure results in Table 6 are qualitatively similar. One plausible reason for the success of our trading strategy is that it is possible that daily returns can be successfully forecasted but

Table 5—Treynor-Mazuy Results for the Simple Trading Strategy

The results of the Treynor-Mazuy model for the simple trading rule are presented below for the period from June 1, 1995 through October 31, 2000. Columns two through five present the coefficients for the risk-adjusted returns in basis points (α), systematic risks (β), market timing (γ), and coefficient of determinations (R^2). The number of observations (N) is 1370 for each asset class. Absolute t-statistics are presented below the parameter estimate

Asset Classes	α	β	γ	R^2
AG	-4.7113 (2.4849)**	0.8230 (49.1654)***	3.4513 (5.6834)***	0.6395
GRO	-6.1335 (4.8058)***	0.7674 (68.1034)***	4.1737 (10.2105)***	0.7725
GI	-6.6116 (5.3563)***	0.6447 (59.1549)***	3.6154 (9.1450)***	0.7192
EI	-4.7988 (4.6091)***	0.4578 (49.8027)***	2.1957 (6.5844)***	0.6451
BAL	-5.4093 (4.9883)***	0.4399 (45.9487)***	2.3264 (6.6984)***	0.6072
MB	-1.2363 (2.6663)***	0.0285 (6.9718)***	0.0906 (0.6101)	0.0346
GLE	-1.9615 (1.3253)	0.3830 (29.3111)***	0.7143 (1.5068)	0.3895
INT	-0.0655 (0.0365)	0.2195 (13.8530)***	-0.2394 (0.4164)	0.1277
MCAP	-4.5554 (2.5809)***	0.8083 (51.8687)***	3.4347 (6.0758)***	0.6638
SCAP	-2.7062 (1.6018)	0.6703 (44.9381)***	2.3479 (4.3389)***	0.5978

Note: ***, **, and * denote the level of significance of 1 percent, 5 percent and 10 percent respectively

mutual fund portfolio managers may not be able to exploit the day-of-the-week patterns in security returns due to transaction costs. If individual investors can also forecast daily return patterns and are able to escape transaction costs by trading fund shares at no charge, those investors (1) may be able to shift funds between investment objective classes to avoid some negative returns and (2) may contribute to the documented perverse timing as discussed by Warther (1995) and Edelen (1999).

Table 6—Henriksson and Merton Results for the Simple Trading Strategy

The results of Henriksson-Merton model for the simple trading rule are presented below for the period from June 1, 1995 through October 31, 2000. Columns two through five present the coefficients for risk-adjusted returns in basis points (α), systematic risks (β), market timing (γ), and coefficient of determinations (R^2). The number of observations (N) is 1370 for each asset class. Absolute t-statistics are presented below the parameter estimates

Asset Classes	α	β	γ	R^2
AG	-4.0452 (1.5819)	0.7653 27.2249***	0.0873 (1.8231)*	0.6319
GRO	-7.6407 (4.3638)***	0.6691 (34.7652)***	0.1658 (5.0575)***	0.7596
GI	-8.4783 (5.0415)***	0.5526 (29.8946)***	0.1582 (5.0256)***	0.7074
EI	-5.9283 (4.2204)***	0.4019 (26.0318)***	0.0960 (3.6499)***	0.6374
BAL	-6.0444 (4.1244)***	0.3877 (24.0637)***	0.0871 (3.1735)***	0.5972
MB	-1.2111 (1.9567)*	0.0271 (3.9861)***	0.0021 (0.1804)	0.0343
GLE	0.9219 (0.4666)	0.4049 (18.6444)***	-0.0535 (1.4450)	0.3894
INT	3.4106 (1.4260)	0.2669 (10.1526)***	-0.0978 (2.1839)**	0.1306
MCAP	-4.1683 (1.7488)*	0.7475 (28.5279)***	0.0941 (2.1075)**	0.6558
SCAP	-1.1139 (0.4907)	0.6451 (25.8516)***	0.0297 (0.6990)	0.5924

Note: ***, **, and * denote the level of significance of 1 percent, 5 percent and 10 percent respectively

Complex Trading Rule

Tables 7 through 9 for the complex trading strategies replicate those of the simple trading strategies presented in Tables 4 through 6. Again, the complex trading rules assume that investors would shift their investments out of risky mutual funds and into money market funds to avoid the day(s) of the week when average returns of the mutual fund class are historically negative. Table 7 reveals that the largest positive arithmetic return is for using the trading rule with the small-cap portfolio (7.0515 bp). The complex trading rule's returns are also higher than those of a buy-and-hold strategy for aggressive growth, municipal bond, global equity, non-US equity, and mid-cap funds. Risks (standard deviations) are also reduced for the

trading rule in each asset class studied. The trading rule portfolios frequently provide higher returns per unit of risk than buy-and-hold portfolios. This is true for all but growth, growth and income, equity income, and balanced funds.

Table 7—Risk and Return for the Complex Trading Strategy

Column one lists the asset class and columns two through four are the average arithmetic returns in basis points, standard deviations of returns, Sharpe, and Treynor measures from the June 1, 1995 through October 31, 2000 period. Each column is split into buy-and-hold and trading rule sub columns to facilitate comparison of the trading rules with the buy-and-hold strategies

Asset Class	Return		Risk (Std. Dev)		Sharpe Ratio		Treynor Ratio	
	Buy-and-Hold	Trading Rule	Buy-and-Hold	Trading Rule	Buy-and-Hold	Trading Rule	Buy-and-Hold	Trading Rule
AG	3.0095	4.0144	0.0124	0.0075	0.0072	0.0255	0.0001	0.0005
GRO	2.9780	0.8391	0.0104	0.0062	0.0083	-0.0204	0.0001	-0.0004
GI	2.5597	1.9313	0.0090	0.0054	0.0050	-0.0034	0.0001	-0.0001
EI	1.5293	1.4694	0.0068	0.0041	-0.0086	-0.0157	-0.0001	-0.0003
BAL	0.8042	0.5909	0.0067	0.0041	-0.0195	-0.0369	-0.0002	-0.0009
MB	-0.2110	1.4847	0.0018	0.0010	-0.1309	-0.0610	-0.0081	-0.0054
GLE	1.7306	3.0088	0.0073	0.0065	-0.0052	0.0138	-0.0001	0.0002
INT	1.1768	2.8494	0.0076	0.0056	-0.0123	0.0132	-0.0003	0.0004
MCAP	3.3022	4.7837	0.0119	0.0069	0.0099	0.0387	0.0001	0.0008
SCAP	2.7493	7.0515	0.0104	0.0078	0.0061	0.0637	0.0001	0.0010

Comparing the risks and returns of the complex trading rules in Table 7 to those of the simple trading rules in Table 4 reveals that the simple trading rules produce higher returns in seven of the ten asset classes. This is strong evidence that the Monday effect is stronger, and therefore more exploitable, than the other, possibly more transitory, days of the week. The risks of the simple strategies are higher than those of the complex strategies for nine of the ten asset classes. Despite having higher risks, the Sharpe measures suggest that the reward-to-variability ratios are better for the simple trading rules in six of ten asset classes while the Treynor measures are correspondingly better in five of ten asset classes.⁸

Our results for the Treynor and Mazuy measures in Table 8 for the complex trading rules show that three asset classes exhibit statistically positive timing ability. Additionally, the results for the Henriksson and Merton measures in Table 9 are similar to those of the Treynor and Mazuy measures. While fewer asset classes produce statistically significant positive timing, results are qualitatively similar.

Comparing the market timing tests (Treynor-Mazuy) of the complex trading rules in Table 8 to those of the simple trading rules in Table 5 reveals that the simple strategy produces more statistically positive timing coefficients. Similar results are also found using the Henriksson-Merton tests in Table 6 and Table 9. Therefore, it appears that using additional information about day-of-the-week patterns has little

⁸Both simple and complex trading rules are the same for global equity (GLE) funds. Therefore, both trading rules produce similar results for GLE.

Table 8—Treyner-Mazuy Results for the Complex Trading Strategy

The results of Treynor-Mazuy model for the complex trading rules are presented below for the period from June 1, 1995 through October 31, 2000. Columns two through five present the coefficients for risk-adjusted returns in basis points (α), systematic risks (β), market timing (γ), and coefficient of determinations (R^2). The number of observations (N) is 1370 for each asset class. Absolute t-statistics are presented below the parameter estimates

Asset Classes	α	β	γ	R^2
AG	-1.7573 (0.9470)	0.3709 (22.6359)***	1.4749 (2.4816)**	0.2734
GRO	1.3757 (0.9405)	0.3154 (24.4181)***	-3.806 (8.1228)***	0.3553
GI	1.9553 (1.516)	0.2561 (22.5000)***	-3.0781 (7.4532)***	0.3185
EI	0.8610 (0.8423)	0.1837 (20.3536)***	-2.1833 (6.6685)***	0.2760
BAL	-0.3523 (0.3325)	0.1680 (17.9610)***	-1.8158 (5.3503)***	0.2247
MB	-0.9311 (3.1166)***	0.0126 (4.7865)***	0.2055 (2.1474)**	0.0178
GLE	-1.9615 (1.3253)	0.3830 (29.3111)***	0.7143 (1.5068)	0.3895
INT	0.0135 (0.0089)	0.1797 (13.3458)***	-0.2078 (0.4254)	0.1197
MCAP	-1.1119 (0.6574)	0.3553 (23.7921)***	1.6567 (3.0581)***	0.2933
SCAP	2.7538 (1.6107)*	0.4750 (31.4693)***	-0.3074 (0.5615)	0.4291

Note: ***, **, and * denote the level of significance of 1 percent, 5 percent and 10 percent respectively

positive impact on trading rule results. Furthermore, it appears that a simple trading strategy that incorporates a Monday seasonal dominates a buy-and-hold strategy.

Conclusion

Extant literature documents day-of-the-week effects in security returns but provides no operational strategy to capitalize on those return patterns apart from altering the timing of intended trades. One justification for the reluctance to pursue dynamic trading strategies with individual securities is that transaction costs such as bid-ask spreads and commissions exceed salient return predictabilities. Transaction costs may be escaped by trading mutual funds (and variable annuities). In addition, daily patterns of mutual funds return classes have escaped empirical scrutiny.

Using 2,739 daily return observations from 542 mutual funds in ten unique investment objectives, we analyze the pattern of daily returns and potential exploitability of those return patterns. Our investigation splits the sample and uses the initial subsample to investigate return patterns and to develop trading rules and then tests those rules on the holdout sample.

Results intimate that straightforward trading rules exist that can both enhance returns and moderate risk. This leads to the capability to engender enhanced risk-

adjusted returns when compared with a buy-and-hold strategy. Both Sharpe and Treynor measures reveal that the dynamic trading strategies produce superior risk-adjusted returns compared to a buy-and-hold strategy for the same asset class. Moreover, Treynor-Mazuy and Henriksson-Merton market timing models suggest that dynamic trading rules based on historical return patterns yield positive timing measures for some strategies. In summary, dynamic trading strategies can enhance the risk-return tradeoff. Furthermore, in most cases, simply trading to exploit the long-documented Monday effect is the most effective solution. This profitability exists despite the widely-reported shift in Monday returns for large-firm securities.

Table 9—Henriksson and Merton Results for the Complex Trading Strategy

The results of Henriksson-Merton model for the complex trading rules are presented below for the period from June 1, 1995 through October 31, 2000. Columns two through five present the coefficients for risk-adjusted returns in basis points (α), systematic risks (β), market timing (γ), and coefficient of determinations (R^2). The number of observations (N) is 1370 for each asset class. Absolute t-statistics are presented below the parameter estimate

Asset Classes	α	β	γ	R^2
AG	1.0420 (0.4198)	0.3772 (13.8240)***	-0.0282 (0.6068)	0.2704
GRO	4.0934 (2.0666)**	0.4215 (19.3589)***	-0.1862 (5.0199)***	0.3364
GI	3.1527 (1.8052)*	0.3297 (17.1734)***	-0.1245 (3.8079)***	0.2982
EI	1.5168 (1.0982)	0.2335 (15.3777)***	-0.0833 (3.2202)***	0.2581
BAL	0.4743 (0.3329)	0.2129 (13.5934)***	-0.0766 (2.8708)***	0.2132
MB	-1.3024 (3.2661)***	0.0041 (0.9417)	0.0159 (2.1298)**	0.0177
GLE	0.9219 (0.4666)	0.4049 (18.6444)***	-0.0535 (1.4450)	0.3894
INT	2.6392 (1.2981)	0.2160 (9.6664)***	-0.0745 (1.9621)**	0.1220
MCAP	0.7587 (0.3349)	0.3467 (13.9231)***	0.0015 (0.0354)	0.2884
SCAP	5.5922 (2.4537)**	0.5159 (20.5911)***	-0.0833 (1.9511)**	0.4305

Note: ***, **, and * denote the level of significance of 1 percent, 5 percent and 10 percent respectively

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