FINANCIAL
SERVICES
REVIEW

Financial Services Review 18 (2009) 355–380

Can individual investors duplicate professional momentum investing?

Glenn N. Pettengill[a,*], Susan M. Edwards[a], Frank T. Griggs[a]

[a]*Grand Valley State University, Grand Rapids, MI 49504, USA*

Abstract

Pettengill, Edwards and Schmitt (2006) compare the selections made by the professionals and the readers in *The Wall Street Journal* Dartboard Contest. They find that the selections of the professionals are significantly more profitable than the selections of the readers and argue that momentum investing is not a viable choice for individual investors. In this study, we investigate whether individual investors can benefit by mimicking investment choices of professionals as displayed in this contest. In order for individual investors to benefit from this information there must be discernable differences in the selections made by the readers and the pros. We examine a number of characteristics that have been shown to cause return differentials between securities, in general, and in momentum securities, in particular. If the selections of the pros and the readers differ with respect to these characteristics and these differences can explain the observed return differentials in the contest, then individual investors might be able to mimic the momentum investing of the pros. Because we find these characteristics do not explain the return differentials between the pros and the readers, we reject the proposition that individual investors can benefit by mimicking the momentum investing behaviors of the pros.

JEL classification: D82; G12; G14

Keywords: Momentum investing; Individual investors

1. Introduction

Since the seminal work of Jegadeesh and Titman (1993), a voluminous literature has demonstrated the existence of positive momentum across a wide variety of equity markets.

* Corresponding author. Tel.: +1-616-331-7430; fax: +1-616-331-7445.
E-mail address: pettengg@gvsu.edu (G.N. Pettengill).

Recent winners, as measured by returns in an intermediate pre-selection period, remain winners in a post-selection period. Winners repeat! Despite the size of this literature, the cause of momentum in security returns is uncertain;[1] however, the prevalence of evidence in favor of the existence of return momentum has led to suggestions that investment strategies could be undertaken to profit from this phenomenon. For instance, Griffin, Ji and Martin (2005) state that implementation of a momentum strategy is worth the serious consideration of portfolio managers. Likewise, Chan, Jegadeesh and Lakonishok (1996) argue that momentum investing constitutes a distinct style of portfolio management.

Based on academic findings, successful momentum investment would seem a fairly easy task even for relatively uninformed individual investors. All an investor would need to do is to amass a fair size portfolio of momentum securities, as identified by recent winners, and sit back and reap the profits as the winners repeat. Realistically, however, the disconnect between historical empirical results and implementation of investment strategies is often large.

In a recent study, Pettengill, Edwards and Schmitt (2006) (hereafter PES) examine the performance of two groups of participants in the dartboard contest conducted by *The Wall Street Journal*. PES compare the selections of readers (as a proxy for individual investors) and professional analysts (pros) selected by the *Journal* to participate in the contest. Consistent with the short-term nature of the contest, both the readers and the pros exhibit a strong tendency to select momentum securities (as measured by returns over the previous six-month period). They also find that the momentum choices made by the pros significantly outperform momentum selections made by the readers. PES find no significant difference in the performance of readers and pros when neutral or contrarian securities are selected. The authors do not directly address the cause of the tendency for pros to be better momentum investors than readers. In this paper, we test explanations for the pros' superior performance. If we can identify the characteristics that cause the return difference between the pros and the readers, we may provide individual investors with strategies to mimic and improve profitability from momentum investing.

The rest of the paper is organized as follows. Section 2 describes our sample and confirms and extends PES findings that the pros make superior selections of momentum securities. Section 3 discusses possible explanations for the pros' superior performance. Section 4 reports empirical tests. These tests fail to identify characteristics that differ in the momentum securities selected by the pros relative to the selections of the readers. Thus, individual investors cannot benefit from mimicking the momentum investing behavior of professional analysts based on the characteristics of the securities the pros choose. Section 5 concludes our paper by emphasizing that our empirical findings discourage an attempt by individual investors to mimic the momentum behavior of professional analysts. However, the success of momentum investing by professional analysts, in this narrow framework, allows the possibility that individual investors may benefit from the recommendations made by professional analysts concerning momentum securities.

2. Sample and return differentials

2.1. Sample description

This paper compares the performance of securities selected by professional and individual investors for *The Wall Street Journal* Dartboard contest. This contest began October 1988 and the final contest selections were made March 2002.[2] Throughout this period, the performance of securities selected by four professional investment analysts was compared to the market and to the performance of securities selected by the throw of darts by journal staffers. Beginning in May 1999, the *Journal* also invited readers to participate by sending stock selections to the contest via e-mail. Each month, the selections of four readers were randomly drawn to participate in the contest. Thus, the total potential sample includes 140 securities selected by the pros and 140 securities selected by the readers in 35 contests over the time period May 1999 through March 2002. The sample was reduced to 131 securities selected by the pros and 125 securities selected by the readers because of two requirements: (1) we require that the stock was not recommended for a short sell;[3] and (2) we require that the security have a minimum of seven months of return data both before and after the stock pick. Among these securities, our main focus of analysis is the 100 securities that we classify below as momentum securities.

In addition, the securities selected by throw of the darts, in each monthly contest, provide an excellent control group. Therefore, following Dickens and Shelor (2003), we use these selections as a test for robustness. Applying the same sample requirements as above, we form a sample of 137 securities from the 140 selections made by the throw of the darts during our sample period. Where appropriate, we calculate returns and make comparisons to our findings from the selections made by the pros and the readers.

2.2. Measuring pre-selection momentum

Following standard methodology of the momentum literature, we define momentum securities as those securities that have outperformed the market in the previous six-month period. Thus, in the six-month period prior[4] to each monthly contest, which we refer to as the classification period, we determine cumulative six-month returns for the selected securities. We place each of these securities into portfolio deciles based on cumulative returns for all securities included in the NYSE-AMEX-Nasdaq CRSP database. Decile 0 contains those securities that had the lowest cumulative returns in the six months before the contest. Decile 9 contains the securities that had the highest cumulative returns in the six-month period before the contest.

In his review of the momentum literature, Swinkels (2004) reports that studies variously defined momentum securities as those within the top decile, the top two deciles or the top three deciles of security performance over the sample's pre-selection period. We adopt the broadest classification criteria cited by Swinkels and also make comparisons within categories of this broad definition. Thus, securities with returns in deciles 7 through 9 are designated as momentum securities. Following PES, we identify two classifications in addition to momentum securities. We identify contrarian securities as selections having

Table 1 Percentage of selections within specified deciles

	Momentum (Deciles 7–9)	Neutral (Deciles 3–6)	Contrarian (Deciles 0–2)	Total
Pros	40.5%†	31.3%‡	28.2%	
	$n = 53$	$n = 41$	$n = 37$	$n = 131$
Readers	37.6%*	29.6%§	32.8%	
	$n = 47$	$n = 37$	$n = 41$	$n = 125$
Total	39.1%	30.5%	30.5%	
	$n = 100$	$n = 78$	$n = 78$	$n = 256$

In the six-month period before each monthly contest, which we refer to as the classification period, we determine cumulative six-month returns for the selected securities. We utilize these cumulative returns to place each of these sample securities into deciles based on cumulative returns for all securities included in the NYSE-AMEX-Nasdaq CRSP database. Momentum securities are defined as those selections within the top three deciles of security performance over the sample's classification period. We identify contrarian securities as selections that come from the bottom three deciles of all securities in the NYSE-AMEX-Nasdaq database. Selections in the middle four deciles are referred to as neutral securities. The values listed determine the percentage of total picks by the specified investor group that fall within the given decile classification. *Significantly over-represented at 0.05 level; †significantly overrepresented at 0.01 level; ‡significantly under-represented at 0.05 level; §significantly underrepresented at 0.01 level, based upon standard binomial tests.

returns that come from the bottom three deciles (deciles 0 through 2) of all securities' returns in the NYSE-AMEX-Nasdaq database. Securities having returns in the middle four deciles (deciles 3 through 6) are referred to as neutral selections.

Table 1 reports the percentage of the securities selected by the pros and the readers that are classified as momentum, neutral, and contrarian securities over the entire sample period. Our results indicate that both the pros and the readers concentrate their selections in momentum securities. For the pros, 40.5% of the selections are made from momentum securities. This percentage selection is significantly higher than the 30% that would be expected by chance at the 0.01 level according to a standard binomial test. For the readers, 37.6% of the selections are made from momentum securities. This percentage selection is significantly higher than the expected 30% at the 0.05 level according to a standard binomial test. Neutral selections are significantly under-represented from the expected 40% by both groups. The pros slightly under-represent contrarian securities and the readers slightly over-represent contrarian securities; the deviations are statistically insignificant in both cases. As a robustness check, we classify the selections made by the darts during this same contest period into momentum, neutral, and contrarian selections. We find no significant deviation from randomness in these classifications for the dartboard selections.

2.3. Measuring security performance

We compare market-adjusted returns of the selections of the readers and the pros for a six-month period, roughly corresponding to the length of the contest (months 0 through +5, where month 0 is the month in which the contest picks are announced), which we refer to as the contest period. We determine market-adjusted returns as the difference between the monthly return for the security and the monthly return for the NYSE-AMEX-Nasdaq valued-weighted index as reported in the CRSP database. Following PES and the general procedure in the momentum literature, we make comparisons without attempting to risk adjust the returns. The issue of risk-adjustment has been addressed in both the momentum literature and the dartboard literature as summarized below.

Momentum securities, by definition, experience return patterns not reflective of general market movement. Risk, for a momentum security, is simply that momentum will cease and possibly reverse. This risk may be associated with large market shifts, but this risk certainly does not associate with an estimate of market risk such as measured by beta. If momentum securities experience high returns in both up and down markets,[5] beta estimation in the pre-selection period would tend to suggest low values for market risk[6] and large alpha values. Similar difficulties would exist for adjusting for risk using the Fama-French three-factor model. Indeed, Fama and French (1996) find that their three-factor model does not compensate for momentum influences. On this basis one might argue for use of the Carhart (1997) four-factor model to risk adjust. However, such a practice would nullify our research agenda as we are trying to discover whether momentum securities "beat the market." Hence, we concur with Hong and Stein (1999), who argue that traditional asset-pricing models do not explain the behavior of momentum securities. In addition, we follow the general practice in the momentum literature, which tests for the success of a momentum strategy by adjusting security returns only for the general market movement.

Certainly some momentum papers risk-adjust returns. Cooper, Gutierrez and Hameed (2004) compare returns to a momentum strategy in up and down market states using three return measures: Raw returns, risk-adjusted returns using CAPM alone, and risk-adjusted returns using the Fama-French three-factor model. Their findings, for short-term returns, show no material difference between raw returns and risk-adjusted returns using either of the risk adjusting procedures. These results argue for the efficiency of comparability of market-adjusted returns against the need to risk-adjust momentum returns. Further, Cooper, Gutierrez, and Hameed indicate that the behaviorists' explanations of momentum (that their findings support) argue against the use of the Fama-French three-factor model, because the value premium would be seen as the result of mispricing rather than risk.

There has been similar controversy in the dartboard contest literature relative to risk-adjusting returns. *The Wall Street Journal* has argued that the pros beat the market on the basis that the pros earn a higher average six-month return than earned by the market. Academicians have argued that these comparisons do not properly adjust for risk (Wright, 1994). Liang (1999) finds, that in using the market model, the selections of the pros generate abnormal announcement day returns but negative risk-adjusted returns over a six-month period following the announcement.[7] Pettengill and Clark (2001), however, show that these results are because of the use of an alpha variable that is inflated by securities experiencing momentum before the sample selection. If abnormal returns are measured by substituting the risk-free return for alpha, selections of the dartboard securities experience, consistent with the *Journal*'s pronouncement, significantly positive abnormal returns. Results from the dartboard literature further support the use of market-adjusted returns to compare the performance of the selections of the readers and the pros.

2.4. Comparing return differentials

Based on the above conclusions, we compare market-adjusted returns for the pros and the readers from the top three momentum deciles. Panel A of Table 2 compares the average contest period cumulative market-adjusted returns of all momentum selections of the readers and the pros. Consistent with the findings of PES, the average six-month market-adjusted return of the pros is 19.98% higher than that of the readers for momentum selections. On an annualized basis, this finding represents a hefty difference of 43.95%. Although the pros do much better than the readers, we note that, consistent with PES, the readers' momentum picks also produce positive market-adjusted returns. However, this average market-adjusted return of 12.42% is not significantly greater than zero. We extend PES's findings by examining returns in a second six-month period (post-contest period) following the contest. The selections made by the pros continue to produce positive market-adjusted returns in the post-contest period, although the average market-adjusted returns are not significantly different from zero. The returns for the selections of the pros in the post-contest period are significantly higher than the returns for the selections of the readers at the 0.01 level. Indeed, the average six-month market-adjusted return of −16.94% for the readers' selections is significantly less than zero. These comparisons strengthen the case that pros are better momentum investors than the readers. The superior performance of the pros in the post-contest period, as discussed below, may result from the readers possibly selecting momentum securities after a substantial part of a momentum period has ended. Whatever the cause, the length of the success, following the selection of the picks, appears much longer for the pros.

We check for robustness on the performance results reported in Table 2 with the sample of the darts' selections. For each of the momentum securities selected by the throw of the dart, we calculate the six-month, market-adjusted, contest period returns. Based on the findings of the momentum literature, one would expect these securities to have positive market-adjusted returns. Further, if the pros are achieving greater returns than the readers other than by mere chance, we should find the returns to the darts' selections closer to the returns for the readers' selections than for the selections of the pros. Our expectations are met on both accounts.

The average market-adjusted return for the six-month contest period for the selections made by the darts is 10.22%. Although positive, this average market-adjusted return is less than one-third of the 32.40% average market-adjusted return of the selections made by the pros. This average market-adjusted return for the darts is, however, very similar to the 12.42% average market-adjusted return for the readers' selections. As with the market-adjusted returns of the readers, we cannot reject the hypothesis that the positive returns of the momentum dart selections occur by chance. Thus, the results from the selections made by the darts bolster the conclusion that the pros are "beating the market" and making superior selections relative to the selections of the readers.

The difference in the market-adjusted performance of the pros and the readers becomes more defined when we split the momentum sample into two groups. Panel B of Table 2 reports the performance of securities that were selected from Decile 9, those securities among the 10% with the highest returns. Panel C reports the performance of securities that were selected from Deciles 7 and 8, those securities with returns from the 70th through the 89th

Table 2 Comparison of contest and post-contest performance: Market adjusted six-month cumulated returns for the pros and the readers

Panel A: Top three deciles

	Contest period	Post-contest period
Pros	32.40%	5.80%
	(3.80)	(0.79)
	[0.0004]	[0.4336]
	n = 53	n = 53
Readers	12.42%	−16.94%
	(1.21)	(-3.04)
	[0.2343]	[0.0038]
	n = 47	n = 47
Pros-Readers	19.98%	22.74%
	(1.49)	(2.42)
	[0.0693]	[0.0087]
	n = 53, 47	n = 53, 47

Panel B: Top decile

	Contest period	Post-contest period
Pros	25.93%	−21.60%
	(1.64)	(-2.50)
	[0.1188]	[0.0225]
	n = 19	n = 19
Readers	24.59%	−27.06%
	(1.53)	(-4.28)
	[0.1393]	[0.0002]
	n = 27	n = 27
Pros-Readers	1.34%	5.46%
	(0.06)	(0.51)
	[0.4764]	[0.3067]
	n = 19, 27	n = 19, 27

Panel C: Deciles 7 and 8

	Contest Period	Post-contest period
Pros	36.01%	21.11%
	(3.58)	(2.23)
	[0.0011]	[0.0329]
	n = 34	n = 34
Readers	−4.01%	−3.28%
	(-0.40)	(−0.36)
	[0.6918]	[0.7256]
	n = 20	n = 20
Pros-Readers	40.02%	24.39%
	(2.83)	(1.84)
	[0.0034]	[0.0355]
	n = 34, 20	n = 34, 20

Market-adjusted returns (security return minus the CRSP value-weighted index return) are determined on a monthly basis for each security and then cumulated over the two six-month periods following the selection. The t value ( ) in the first two rows results from a standard paired t test comparing security and market returns. The p-value [ ] associates with a two-tail test, because there is no *a priori* judgment concerning the individual success of momentum investing for either group relative to the market. The t statistic ( ) in the third row results from a standard two-population test. The p-value [ ] results from a one-tail test, because it is assumed that Pros will be better at momentum investing than Readers.

percentiles. As reported in Panel B, among those securities with the highest momentum, the pros and the readers had almost identical market-adjusted returns. In both cases, although the average returns were around 25%, the variability in return was large and the average return was not significantly different from zero. In addition, in both cases the returns in the post-contest period were negative, similar in value, and significantly less than zero. Again, this finding raises the possibility that timing considerations contribute to the return differences between the readers and the pros.

In contrast to the similar performance of the two groups when the very hottest stock selections are compared, security selections with weaker momentum (Deciles 7 and 8) made by the pros have significantly higher market-adjusted returns than the selections made by the readers, as reported in Panel C of Table 2. In addition, the selections made by the pros in this group are greater than the returns of their selections from the top decile and continue to show significantly positive market-adjusted returns in the post-contest period. In contrast, the selections made by the readers are negative and substantially less than the returns of their selections from the hottest stocks. In addition, these returns continue to be negative and substantially less than the returns of the pros' selections in the post-contest period. Thus, it appears that the pros are especially proficient at selecting securities in an early momentum phase, as measured by market-adjusted returns.

3. Possible explanations for superior performance of the pros

3.1. Introduction

If the return differential between the readers and the pros can be explained by the characteristics of the stocks selected, individual investors may improve their momentum investing by selecting securities with characteristics that mimic the characteristics of the securities selected by the pros. In this section, we seek to identify security characteristics that might explain the return differential found between the momentum selections of the readers and the pros, with the ultimate goal of finding recommendations to improve momentum investing on the part of individual investors.

3.2. Timing of market conditions

Table 2 compares the performance of selections made by pros and readers over the entire sample period, May 1999 through March 2002. This sample period encompasses sharply different market regimes. The five contests, from May 1999 through September 1999, begin and end in the later stages of the dot-com bubble where one might expect momentum investing to be extremely profitable. We refer to this market regime as the momentum period. We identify a second market regime as the correction period. This market regime includes the performance of securities selected in contests beginning October 1999 through March 2000. These selections were made before the burst of the momentum bubble, but include the impact of that month in their contest period returns. The final grouping refers to the market regime existing for contests beginning April 2000 through March 2002. These contests occur during the prolonged bear market that began after the tech bubble burst in March 2000. We refer to this market regime as the bear market period.

Cooper, Gutierrez and Hameed (2004) show that naïve momentum strategies exhibit much greater success in up market states than in down market states. Thus, we would expect the profitability of momentum investing to vary across market regimes.

We hypothesize that the pros' superior performance, as reported in Table 2, simply results from greater adaptability to market conditions. If this premise were the case, we would expect to see the pros concentrate their momentum picks during the momentum period before the bursting of the dot-com bubble. In contrast, according to this hypothesis, the readers fail to adapt to changing market regimes and continue to conduct momentum investing in the bear market period. If this hypothesis is supported, we might find that the pros and readers are equally adept at momentum investing at any particular time period, but that the pros outperform the readers in terms of the entire sample because the pros are more selective about when they conduct momentum investing. Under this hypothesis, individual investors may benefit by modifying the timing of their momentum investing.

3.3. McKay's hypothesis

We investigate a second timing issue that is related to the selection of individual securities. Writing in *The Wall Street Journal*, McKay (2005) suggests that momentum investing is best left to professional analysts. He argues that individual investors who select momentum securities do so late in a security's momentum cycle and find that the winners they select turn to losers. This argument is consistent with the over-reaction literature that shows winners in a three- or five-year period, become losers in a subsequent period (see De Bondt and Thaler (1985, 1987). If McKay's hypothesis is correct, we should be able to show that the dartboard contest selections made by readers involve securities that have experienced momentum for a longer time period than the selections made by the professional analysts. In this case, we would expect the returns for the selections made by the professionals to be greater than the returns for the selections made by the readers across market regimes.

PES cite McKay's hypothesis as a possible explanation for the success of the pros relative to the readers. Our results reported in Table 2, showing significant differences in post-contest periods and showing differences in relative performance among momentum classes, is consistent with this hypothesis. PES do not, however, directly test for the validity of this hypothesis. In this paper, we provide a direct test of McKay's hypothesis. If this hypothesis is supported, individual investors may improve their momentum investing behavior by shunning momentum securities which have experienced momentum over a substantial time period.

3.4. Relative volume

The age of the investment cycle may be related to relative volume. Consistent with the behavioral explanations of stock price momentum (e.g., Daniel, Hirshleifer, and Subrahmanyam, 1998), volume in momentum securities may build as the momentum cycle ages. Thus, high volume momentum securities may be more likely to experience reversals.

Consistent with this argument, Lee and Swaminathan (2000) find that securities with high trading volume under-perform momentum securities with low trading volume. These findings lead to another hypothesis: Individual investors herd and buy high-volume momentum securities, and, professional investors find momentum securities before individual investors and purchase low-volume momentum securities. Thus, at least part of the difference in return performance of the professional and individual investors could be explained by a difference in relative volume of the selected securities. If this hypothesis is supported, individual investors may improve their momentum investing by measuring relative volume of momentum securities.

3.5. Other security characteristics

A substantial literature provides empirical evidence of the correlation between various security characteristics and security returns. Fama and French (1992, 1996) single out firm size and the book-to-market ratio as two characteristics with significant ability to differentiate cross-sectional security returns. Small firm securities have significantly higher returns than large firm securities. Securities with high book-to-market ratios (value securities) have significantly higher returns than securities with low book-to-market ratios (growth securities). We investigate the possibility that the professional analysts make selections that benefit from both the value and size premiums, and, that the individual investors select larger size, growth securities. If either or both of these suppositions prove accurate, we may provide an explanation for the superior performance of the pros from characteristics that the Fama-French three-factor model ascribes to risk. Thus, we investigate the security characteristics of the selections made by the pros and readers to search for a significant difference in size and book-to-market values that may explain return differentials. Modifying momentum investing, based on size and value characteristics, would be an easy step for individual investors if it is shown that these characteristics affect the readers' performance relative to the pros.

4. Explaining return differentials

4.1. An overview of testing procedures

In this section, we compare the selections of the readers and the pros to determine if these selections vary according to the criteria identified in Section 3. We conduct this analysis in two steps. First, we develop a comprehensive model including all of these variables and determine, if collectively, these variables can explain the superior performance of the pros. In the second step, because some factors may offset the influence of other factors in a comprehensive test, we test each factor individually to see if any of the factors identified in the previous section account for any part of the difference in return performance of the two groups. If, collectively or individually, these criteria explain the return differential between the readers and the pros, individual investors should be able to improve their momentum investing profitability by mimicking the selection criteria used by professional investment analysts.

4.2. A comprehensive model to explain return differentials

To determine if return differentials can be eliminated by timing and security considerations, we regress contest period returns of each momentum security selected for the contest against a dummy variable, representing selections made by the readers, and additional variables, measuring the considerations discussed above. Our model is represented by Eq. (1):

$$R_i = \alpha + \beta_1 * D_i + \beta_2 * R_{1i} + \beta_3 * R_{2i} + \beta_4 * DD_i + \beta_5 * RV_i + \beta_6 * S_i + \beta_7 * BtM_i + \varepsilon_I \quad (1)$$

where R_i measures the market-adjusted contest period return to selected momentum security i; D_i is a dummy variable that takes on a value 1 if the security was selected by a reader and is 0 otherwise; R_{1i} is a dummy variable that takes on a value of 1 if the security was selected during the momentum market regime and is zero otherwise; R_{2i} is a dummy variable that takes on a value of 1 if the security was selected during the correction market regime and is zero otherwise; DD_i measures the influence of McKay's hypothesis by finding the difference between momentum decile ranking in the classification period and the pre-classification period (as defined below); RV_i represents the average monthly decile rankings for relative volume for the security during the classification period; S_i tests for the influence of the size premium and represents the natural log of size for each selected security; BtM_i measures the impact of the value premium with the book to market ratio for each security; α and β_1 through β_7 represent OLS regression coefficients and ε_i represents the error term.

We elaborate on this model to indicate our goal and expectations. By regressing returns on these variables, we intend to capture the influence of each of the variables described above.[8] Critically, we examine whether these variables can explain the return differential reported by PES and confirmed in this paper. If these characteristics explain the return differential, the coefficient for the dummy variable for the readers' selection should be insignificantly different from zero. This finding would imply that individuals, using the criteria measured by the model to mimic the pros' selections, could achieve returns comparable to the pros' momentum investing returns. If these variables, collectively, provide no explanation for the return differential between the readers' and pros' selections, the value for β_1 ought to be negative and close to the difference of 19.98% reported in Table 2. This finding would indicate that one would need to search for other explanations for the superior performance of the pros relative to the readers. Below we discuss how the factors in Eq. (1) measure the variables described in Section 3.

We classify our total sample into three market regimes: the momentum period, the correction period, and the bear market period. Based on the findings of Cooper, Gutierrez and Hameed (2004), we expect returns to vary across market regimes. We identify the momentum period with a dummy variable, R_{1i}, which takes on a value of 1 if the security was selected in this period and is zero otherwise. We identify the correction period with a dummy variable, R_{2i}, which takes on a value of 1 if the security was selected in this period and is zero otherwise. We expect the coefficients of both of these variables, β_2 and β_3 to be positive. To the extent that these expectations are met and these variables explain the difference in returns between the pros' and the readers' selections, individual investors may be advised to use market timing to improve their momentum investing.

McKay (2005) argues that individual investors are not good at momentum investing because they are late to catch the momentum train. They purchase momentum securities that have experienced momentum for a longer period of time and, thus, are more inclined to experience a reversal. To measure McKay's hypothesis, we compare the age of the momentum cycle for the securities selected by the pros and the readers. For each security, we identify the decile position of its return in two six-month periods. As described above, we determine the decile placement of each security's return in the classification period, the six months just before the month of the contest (months -6 through months -1). Based on the decile placement in this classification period, we determine whether the security represents a momentum selection or not. To test McKay's hypothesis, we also identify the decile placement of the security's return in the six-month period before the classification period (months -12 through months -7). In this pre-classification period, according to McKay's hypothesis, the securities selected by the readers should show greater evidence of momentum than do the securities selected by the pros. The variable DD, in Eq. (1), is the decile ranking measure in the classification period minus the decile ranking in the pre-classification period. The smaller the value of DD, the longer the security has been experiencing momentum. Thus, if McKay's hypothesis holds, we would expect β_4 to be positive. Such a finding would indicate that individual investors could improve their momentum investing by measuring the time period that a security had displayed momentum returns.

Based on Lee and Swaminathan's (2000) finding, we expect momentum securities with high relative volume to experience lower returns in the contest period. We measure relative volume following Lee and Swaminathan by dividing average daily trading volume for a given month by the number of shares outstanding at the end of the month. We acquire both daily trading volume and shares outstanding from the CRSP database. We determine relative volume for each of the securities in the sample for each of the six months in the selection period. For each of these months, we also calculate relative volume for each security in the CRSP NYSE-AMEX-Nasdaq database with complete data for a given sample month. Given these calculations, we place each sample security in a decile ranking for each of the months in the sample period. We then average the decile ranking for each sample security in the appropriate classification period. The variable RV in our model represents this average; the higher the value of RV, the higher the relative value. Based on Lee and Swaminathan's finding, we would expect the coefficient for this variable, β_5, to be negative. If this hypothesis is supported, individual investors could improve their momentum profits by measuring relative volume for potential momentum purchases.

The final variables in our model seek to identify the influence of the well-known value premium and size premium. We measure the market value for each security in the sample and determine its natural log that we identify as S. The market value of the selected security is determined from Compustat and is given by the market value as of the end of the month in which the contest began. The coefficient for this variable, β_6, ought to be negative. We also

Table 3 Cross Sectional Analysis of Selection Returns

Variable	Coefficient	Edtimate	p-value
Constant	α	0.2405	[0.6192]
Di	β_1	−0.2127	[0.0612]
R_{1i}	β_2	0.4739	[0.0042]
R_{2i}	β_3	0.4463	[0.0070]
DD_i	β_4	0.0138	[0.2762]
RV_i	β_5	−0.0391	[0.3038]
S_i	β_6	0.0071	[0.8272]
BtM_i	β_7	0.4478	[0.0766]
Adjusted R^2	0.0862		
F	2.20		
N	90		

R_i measures the contest period return to selected security i; D_i is a dummy variable that takes on a value 1 if the security was selected by a reader and is 0 otherwise; R_{1i} is a dummy variable that takes on a value of 1 if the security was selected during the momentum market regime and is zero otherwise; R_{2i} is a dummy variable that takes on a value of 1 if the security was selected during the correction market regime and is zero otherwise; DD_i measures the influence of McKay's hypothesis by finding the difference between momentum decile ranking in the classification period and the pre-classification period; RV_i represents the average monthly decile rankings for relative volume for the security during the classification period; S_i tests for the influence of the size premium and represents the natural log of size for each selected security; BtM_i measures the impact of the value premium with the book to market ratio for each security; α and b_1 through b_7 represent OLS regression.

determine the value of the book to market ratio, BtM, of each variable in the sample selection. Similar to our measurement of the size variable, we identify the value of BtM as the book to market ratio for the security as of the end of the month in which the contest began. According to the value premium, the coefficient for the BtM ratio, β_7, ought to be positive. Significant findings for these securities would indicate that individual investors ought to consider size and value characteristics when selecting momentum securities.

4.3. Does the model explain relative performance?

The results from testing the model are shown in Table 3. The model does explain a significant portion of the return variations in the security selections as shown by an F value of 2.20, with a corresponding $p = 0.0425$. The crucial question for the model, however, is not its overall significance but whether it can explain the return difference between the selections of the pros and the readers. If the model explains the performance difference, the value for β_1, which measures the impact that the security was selected by a reader given all other variables, ought to be insignificantly different from zero. Because this result does not hold we conclude that the model does not explain the return differentials between the readers and the pros. Indeed, according to the model, after taking into consideration all of these factors, the readers under-perform the pros by 21.27% instead of the 19.98% reported in Table 2. After accounting for the influence of timing and other characteristics, the relative performance of the readers becomes worse.[9] Adopting the investment pattern of the pros as measured in this model, would reduce, not improve, the effectiveness of momentum investing for individual investors.

Although we have failed to explain the return differential between the selections of the readers and the pros, the variables included in the model explain a significant variability in total return variation. Perhaps examination of the individual variables within the model will provide guidance to an investor in making a momentum investment. For example, the readers may be correctly over-weighting low volume securities but incorrectly under-weighting value securities. To examine these possibilities, we examine the model results on a variable by variable basis. We examine each variable to determine the impact of the variable on the profitability of momentum investing and to determine the comparative behavior of the readers and the pros. This comparison may provide useful information for an individual investor seeking to purchase a momentum security.

4.4. Impact of variables on a case by case basis

4.4.1. Market regimes

As predicted, our model shows a strong influence from market regime to the profitability of a momentum strategy. The coefficient for the dummy variables, for the momentum period and the correction period, are both large and significant at the 1% level. Timing of momentum investing makes a significant impact on profitability. Although the overall model does not explain the inferior performance of individual investors, part of this difference could be because of timing considerations. The model does not indicate if pros concentrated their selections in these regimes, and, if the relative performance of the pros and the readers differ across regimes.

Table 4 reports the percentage of the investor groups' sample selections that were momentum selections, as measured by selections within the top three deciles and within the top decile across market regimes. The pros did not achieve higher returns by concentrating their momentum selection picks in the periods most advantageous to momentum investing. In the momentum market regime, over 70% of the total selections made by the readers were momentum selections and over one-third of their total selections were from the top decile of prior six-month returns for all securities. Corresponding values for the pros were 45% and 10%. For the pros, the selection percentage of the securities with the strongest momentum (Decile 9) was exactly equal to what would be expected by chance. Thus, the readers, not the pros, should benefit in the overall comparison from concentrating selections in the most advantageous period for momentum investing.

In the bear market regime, a disproportionate concentration of selections by the readers could influence their inferior performance. In this regime, again, the actual behavior of the readers and the pros is exactly opposite of what would help explain the return difference. In the bear market period, the pros were more likely to select momentum securities than were the readers, although again the readers concentrated their momentum picks in the top third of momentum securities. However, crucial to our market regime hypothesis, the shift away from momentum investing in the period least favorable to it, was a shift made by the readers to a much greater extent than by the pros. The readers, not the pros, appeared to have shifted their momentum investment strategy across the market regimes.

Because the readers concentrated their momentum picks in the momentum and correction periods, their overall results relative to the pros are biased upward. Thus, one may infer that

Table 4 Percentage of selections within specified deciles across market regime

Panel A: Top three deciles

	Market regimes		
	Momentum	Correction	Bear
Pros	45.0%	47.6%	37.8%
	$n = 9$	$n = 10$	$n = 34$
Readers	70.6%	40.0%	30.7%
	$n = 12$	$n = 8$	$n = 27$
Total	56.8%	43.9%	34.3%
	$n = 21$	$n = 18$	$n = 61$

Panel B: Top decile

	Market regimes		
	Momentum	Correction	Bear
Pros	10.0%	28.6%	12.2%
	$n = 2$	$n = 6$	$n = 11$
Readers	35.3%	25.0%	18.2%
	$n = 6$	$n = 5$	$n = 16$
Total	21.6%	26.8%	15.2%
	$n = 8$	$n = 11$	$n = 27$

In the six-month period before each monthly contest, which we refer to as the classification period, we determine cumulative six-month returns for the selected securities. We utilize these cumulative returns to place each of these sample securities into deciles based on cumulative returns for all securities included in the NYSE-AMEX-Nasdaq CRSP database. The percentages listed determine the proportion of the total selections made during the specified market regime that are momentum selections as defined by either the top three deciles (Panel A) or the top decile (Panel B). The value n captures the actual number of momentum selections within the given market regime.

individual investors are more disadvantaged in momentum investing than is suggested by the total sample results shown in Table 2. To investigate this conjecture, in Table 5 we report returns to momentum investing for the pros and readers across the three market regimes.

Panel A of Table 5 compares average returns for the pros' and the readers' selections for the momentum period where the technology bubble was at its height, and, where momentum investing was particularly profitable. Both the pros and the readers achieved average market-adjusted six-month returns of almost 50% during the contest period. These reported market-adjusted returns are made even more impressive by the fact that market returns were very high during this period. In these heady market conditions, momentum investing seems to be profitable for all investors over a short time period. In the post-contest period, the picks of the pros continued to outperform the market while the picks of the individual investors under-performed the market. For all of these picks, the post-contest period included the March 2000 crash. The pros picked momentum stocks that continued to outperform the market in a period that included a significant market correction. This result argues against the ability of individual investors to improve momentum investing profitability by merely using timing considerations followed by the pros.

Panel B reports the results for the correction period market regime. A priori, one would expect this market correction to be unkind to momentum investing. In contrast to this

Table 5 Top three deciles: Comparison of contest and post-contest performance—Market adjusted six-month cumulated returns for the pros and the readers

Panel A: Momentum market regime (May 1999 to September 1999)

	Contest period	Post-contest period
Pros	49.40%	16.48%
	$n = 9$	$n = 9$
Readers	48.64%	−18.54%
	$n = 12$	$n = 12$
Pros-readers	0.76%	35.02%
	(0.02)	(1.53)
	[0.4920]	[0.0797]
	$n = 9, 12$	$n = 9, 12$

Panel B: Correction market regime (October 1999 to March 2000)

	Contest period	Post-contest period
Pros	84.05%	0.29%
	$n = 10$	$n = 10$
Readers	22.11%	−48.83%
	$n = 8$	$n = 8$
Pros-readers	61.94%	49.12%
	(1.30)	(1.69)
	[0.1079]	[0.0601]
	$n = 10, 8$	$n = 10, 8$

Panel C: Bear market regime (April 2000 to March 2002)

	Contest period	Post-contest period
Pros	12.71%	4.59%
	$n = 34$	$n = 34$
Readers	−6.55%	−6.78%
	$n = 27$	$n = 27$
Pros-Readers	19.26%	11.37%
	(2.14)	(1.12)
	[0.0184]	[0.1342]
	$n = 34, 27$	$n = 34, 27$

Market-adjusted returns (security return minus the CRSP value-weighted index return) are determined on a monthly basis for each security and then cumulated over the two six-month periods following the security's selection. The t statistic ( ) in the third row results from a standard two-population test. The p-value [ ] results from a one-tail test, because it is assumed that Pros will be better at momentum investing than Readers.

expectation, the market-adjusted returns for the momentum picks of both the pros and the readers were positive. The returns for the pros were an average market-adjusted six-month return of 84.05%. This value was almost four times as high the return for the selections of the readers, but the difference was not statistically reliable given the small sample size. In the post-contest period, the selections of the pros kept pace with the market, but the readers' selections gave up the gains from the previous six-month period and more. The difference in this period is statistically reliable despite the small sample size. The results for the post-contest period suggest that the readers' picks may have earned a positive market-adjusted return during the contest period based on returns before the crash.[10]

The bear market regime, the longest sub-period, covers the contest selections that started in April 2000 and continued through March 2002. The average returns for momentum investing are substantially less in this period than for the earlier two periods. The most salient feature of the returns for this period, however, is the continued positive market-adjusted returns for the selections made by the pros. The pros continued to beat the market! Average six-month market-adjusted returns for the pros' selections are almost 20% higher than for the selections of the readers and this difference is statistically significant.[11] As with the other market regimes, in the post-contest period, the selections made by the pros continue to have positive market-adjusted returns and the selections made by the readers have negative market-adjusted returns. Thus, we present results that suggest a consistent basic difference in the ability of professional investment analysts and individual investors to conduct momentum investing. This difference in profitability does not appear to be related to timing, but still may be partially explained by the other variables in the model. These findings could still provide helpful indications to individual investors conducting momentum investing.

4.4.2. McKay's hypothesis

The variable DD shown in Eq. (1) measures the difference in momentum ranking between the classification and pre-classification periods for a particular security. If this difference is small, the selected security has a long period of momentum. The results from our model as reported in Table 3 indicate that, consistent with McKay's hypothesis, sample securities with shorter momentum runs have higher returns (β_4 is greater than zero). The difference is not statistically dependable, however. The model does not indicate whether the readers, consistent with McKay's argument, tend to pick securities with a longer momentum run. The implication from such a finding may still benefit the selection choice of an individual investor. Thus, we seek to determine if any differential exists between the selections of the readers and the pros in this section.

Although we find support for a relationship between length of momentum run and momentum return, we find no evidence to support McKay's hypothesis that individual investors pick securities that have a longer momentum run than do the selections of the pros. In Table 6, we report the average numerical decile ranking of the securities' returns in the classification period and the pre-classification period. A security that has a cumulative six-month return in the highest decile is provided a ranking value of 9. A security that has a cumulative six-month return in the lowest decile is provided a ranking value of 0. Thus, in the classification period all momentum securities will have rankings of 7, 8, or 9. As we report in Panel A of Table 6 for the overall sample, the readers tend to select securities with greater momentum than the pros in the classification period. PES argue that this outcome is consistent with McKay's hypothesis, in that longer running momentum securities would have higher decile rankings. Further analysis argues against their conclusion.

Our basic test of the McKay hypothesis concentrates on the pre-classification period. McKay's hypothesis implies that the readers' selections would show greater momentum both in the classification period and the pre-classification period. There is scant support for this hypothesis. The securities selected by both the readers and pros have average decile rankings that are within the neutral rankings in the pre-classification period, albeit slightly higher than a pure neutral selection of 4.5. Most critical to McKay's hypothesis, there is virtually no

Table 6 Comparison of pre-classification momentum: Mean six-month return deciles for the Pros and the Readers

Panel A: Full sample (May 1999 to March 2002)

	Pre-classification period	Classification period
Pros	5.793	8.151
	$n = 53$	$n = 53$
Readers	5.957	8.404
	$n = 47$	$n = 47$
Pros-Readers	−0.164	−0.253
	(−0.27)	(−1.67)
	[0.3943]	[0.0987]
	$n = 53, 47$	$n = 53, 47$

Panel B: Momentum market regime (May 1999 to September 1999)

	Pre-classification period	Classification period
Pros	7.556	8.000
	$n = 9$	$n = 9$
Readers	7.000	8.333
	$n = 12$	$n = 12$
Pros-Readers	0.556	−0.333
	(0.49)	(−1.02)
	[>0.5000]	[0.3195]
	$n = 9, 12$	$n = 9, 12$

Panel C: Correction market regime (October 1999 to March 2000)

	Pre-classification period	Classification period
Pros	6.500	8.400
	$n = 10$	$n = 10$
Readers	7.000	8.625
	$n = 8$	$n = 8$
Pros-Readers	−0.500	−0.225
	(−0.38)	(−0.70)
	[0.3555]	[0.4971]
	$n = 10, 8$	$n = 10, 8$

Panel D: Bear market regime (April 2000 to March 2002)

	Pre-classification period	Classification period
Pros	5.118	8.118
	$n = 34$	$n = 34$
Readers	5.185	8.370
	$n = 27$	$n = 27$
Pros-Readers	−0.067	−0.253
	(−0.08)	(−1.24)
	[0.4665]	[0.2214]
	$n = 34, 27$	$n = 34, 27$

The deciles are created from the pre-selection returns for every security in the CRSP NYSE-AMEX-Nasdaq database for both the six-month pre-classification period (months −12 through −7) and the six-month classification period (months −6 through −1) with 9 being the top decile. The t statistic ( ) results from a standard two-population test. The p-value [ ] results from a one-tail test, because McKay's hypothesis assumes that Readers select stocks which are longer in the momentum cycle than Pros' selections.

difference between the average decile value for the pros' and the readers' selections during this period. To further investigate McKay's hypothesis, we conduct analysis, with data segmented based on selection time, to determine if differences in the sub-periods may challenge our conclusion from the overall sample.

Panels B, C, and D of Table 6, report results from each of three market regimes. We find no evidence in any of the market regimes to support McKay's hypothesis. In all three periods, the strength of the momentum in the pre-classification period is very similar between the pros and the readers. In the momentum market regime, the pros appear to be picking securities with a longer momentum run, while in the last two market regimes, the readers pick securities with slightly longer momentum runs. In no case is the difference statistically significant. We do observe that, in the bear market regime, the length of the momentum period of the selections appears to be smaller, consistent with less momentum in the market during this bear period.

We recognize that the six-month periods that we use for classification, although having a basis in the methodology of the momentum literature, have little theoretical basis. Akhbari, Gressis and Kawosa (2006) suggest that momentum classification requires investigation of the pattern of momentum within the classification period. To examine the pattern within the six-month classification period, we divided the six-month classification period into two three-month periods. We examine whether, on this basis, the individual investors appear to be selecting securities longer into their momentum cycle as suggested by McKay's hypothesis. In results not reported here because of space considerations, we find substantially no difference in average decile rankings between the two three-month periods. Thus, using either a six-month or a three-month classification period, we are unable to provide support for McKay's hypothesis that individual investors buy momentum securities after a substantial run up in momentum.

4.4.3. Relative volume considerations

We measure relative volume in Eq. (1) by the variable RV. Consistent with the findings of Lee and Swaminathan (2000), the regression results indicate a negative relationship between security return and relative volume. These results are, however, statistically insignificant and do not provide any indication as to whether readers tend to buy high volume securities which might explain part of the difference in performance between the pros and the readers. To answer this question, we compare the relative volume of the securities selected by the readers and the pros. Table 7 reports the average relative volume decile ranking for the momentum securities selected by the pros and the readers. Decile rankings range from 0 to 9, with 9 showing the highest grouping by relative volume. Both the readers and the pros pick momentum securities with high volume relative to other securities. Although the readers, on average, selected securities with higher relative volume as measured by decile rankings, the difference is not statistically significant. Because testing shows that relative performance is affected by the level of momentum, we compare relative momentum between readers and pros with the data segmented by level of momentum. We find that for the top decile, contrary to the superior performance of the pros, the relative volume is slightly higher for the pros. In the case for the lower two deciles, the readers select securities with slightly higher relative volume. In neither case is the difference statistically significant. On an

Table 7 Comparison of classification period mean relative volume deciles for the Pros and Readers

	Momentum selections		
	Top three deciles	Top decile	Deciles 7 and 8
Pros	5.784	6.262	5.480
	$n = 54$	$n = 21$	$n = 33$
Readers	6.008	6.208	5.607
	$n = 42$	$n = 28$	$n = 14$
Pros-Readers	−0.224	0.054	−0.127
	(−1.13)	(0.20)	(−0.49)
	[0.1304]	[>0.5000]	[0.3260]
	$n = 54, 42$	$n = 21, 28$	$n = 33, 14$

The relative volume for each momentum selection is calculated and its appropriate decile ranking is determined using the relative volume decile rankings for every security in the CRSP NYSE-AMEX-Nasdaq database for each month in the six-month classification period (9 being the highest relative volume). The relative volume ranking for each selection is then averaged over the classification period. The t statistic ( ) results from a standard two-population test. The p-value [ ] results from a one-tail test, under the presumption that the readers select stocks with higher relative volume than the pros' selections.

individual basis, relative volume offers little explanation of the superior performance of the pros, and, little support for the proposition that individual investors can improve momentum investing by mimicking the selections of professional analysts.

4.4.4. Influence of the size and value premiums

We find no evidence to explain the pros' superior performance in momentum investing in an investigation, either collectively or individually, of three different hypotheses related to timing. We find that the pros do not concentrate their momentum selections within the periods most favorable to momentum investing. Nor do we find any evidence that pros are investing in momentum securities earlier in the securities' momentum cycle. In addition, we find no support for an explanation from a tendency for pros to pick momentum securities with lower relative volume. In this section, we investigate separately the influence of the value and size premiums.

Our model reports a positive and statistically significant value for β_7, indicating a significant value premium for the securities selected. The model does not indicate if the pros and the readers make different selections relative to value and growth securities. In contrast, our results indicate that a size premium is not present in this sample. β_6 is positive, indicating that securities of firms with higher market values tend to outperform. The result is not statistically dependable. Still, for sake of completion, we compare the market value of the securities selected by the pros and the readers.

According to Fama and French (1992, 1996), securities of firms that are smaller in size, as measured by the market value of equity, or that have a higher book-to-market ratio (value securities), historically exhibit higher returns. For each security, we obtain these two Fama and French factors, size and book-to-market ratio from the Standard and Poors Research Insight database. Utilizing the Fama and French U.S. Research Breakpoints,[12] we classify securities according to the characteristics of size and book-to-market ratio. Following standard methodology, we classify a firm as small if its market value of equity falls within

Table 8 Top three deciles: Comparison of security characteristics—Percentage of selections within Fama and French decile categories

Panel A: Size
Those selections having a market value of equity for month t in the bottom three deciles of all NYSE stocks included in the Fama and French breakpoints for month t are denoted as small firms, those selections in the middle four deciles are classified as neutral firms, and those selections in the top three deciles are classified as big firms

	Small	Neutral	Big	Total
Pros	11.8%	29.4%	58.8%	
	$n = 6$	$n = 15$	$n = 30$	n=51
Readers	22.2%	24.4%	53.3%	
	$n = 10$	$n = 11$	$n = 24$	n=45
Total	16.7%	27.1%	56.2%	
	$n = 16$	$n = 26$	$n = 54$	n=96

Panel B: Book to market
Those selections having a book to market ratio for year t in the bottom three deciles of all NYSE stocks included in the Fama and French breakpoints for year t are denoted as growth firms, those selections in the middle four deciles are classified as neutral firms, and those selections in the top three deciles are classified as value firms

	Growth	Neutral	Value	Total
Pros	82.4%	13.7%	3.9%	
	$n = 42$	$n = 7$	$n = 2$	$n = 51$
Readers	82.2%	15.6%	2.2%	
	$n = 37$	$n = 7$	$n = 1$	$n = 45$
Total	82.3%	14.6%	3.1%	
	$n = 79$	$n = 14$	$n = 3$	$n = 96$

We utilize the Fama and French U.S. Research Breakpoints for the market value of equity (size) and the book to market ratios to classify the sample securities into size and value groupings based on its respective security characteristics. The table reports the percentage of total momentum picks by the specified investor group that fall within the given characteristic classification.

the bottom three size deciles, and, as large if it falls within the top three deciles. We follow a similar procedure with the book-to-market ratio, denoting a firm as a growth firm if its book-to-market ratio falls in the bottom three deciles, and, as a value firm if it falls within the top three deciles.

Table 8 reports the classification of the selections by the contestants based upon firm size and book-to-market ratio. Not surprisingly, most of the selected momentum securities, 82.3%, had a low book-to-market ratio consistent with a rapid increase in market price for momentum securities. Only 3.1% of the selections had high book-to-market ratios. Less predictably, most of the momentum selections were big firm securities (56.2%). This preponderance of selections in the top three size deciles is consistent with market price momentum increasing market value.

The critical finding is that the superior performance of the pros is not explained by a systemic tendency to select either small firm securities or low book-to-market securities. A standard χ^2 test fails to reject the hypothesis of no difference in the classification of selections between the pros and the readers based either on size or book-to-market characteristics. The most notable difference is that the proportion of small firms selected by readers is almost twice as high as the proportion of small firm selections made by the pros. This difference in selection proportions is significant at the 0.01 level. Individual investors were much more likely to select small firm securities than were the pros. The propensity to select securities with low book-to-market ratios was almost identical. Hence, security characteristics of size and book-to-market ratio, individually, do not explain the performance difference between the pros and the readers. Based on these findings individual investors cannot expect to match the momentum investing performance of professional analysts by duplicating size and value considerations made by professional analysts.

4.5. Summary

We identify a number of variables that collectively explain a significant portion of the variation in returns among securities selected by both readers and pros in *The Wall Street Journal* Dartboard contest. These variables do not, however, explain why the pros outperform the readers in their momentum selections. Indeed, the extent to which the pros outperform the readers increases when these variables are taken into consideration. For instance, the pros make a higher percentage of their security selections in a bear market period in which momentum securities, in general, achieve lower returns than in bull market periods. Thus, we are unable to identify factors that individual investors ought to consider to match the momentum investing performance of the professional analysts. This result leads us to postulate that professional investment analysts select momentum securities whose pre-selection price increase is supported by fundamental factors that create post-selection superior performance. This investing advantage may result from access to superior information and/or a greater skill in analyzing information. This supposition is consistent with that part of the momentum literature that documents a connection between firm fundamentals and momentum, as evidenced by earnings growth (see for example Chan, Jegadeesh and Lakonishok, 1996; Hong, Lim and Stein, 2000). If the advantage of the pros in momentum investing is created either by superior information or a greater skill in analyzing information, mimicking the performance of successful momentum investing by professionals would prove difficult. Thus, our recommendation to individual investors concerning momentum investing is similar to that of PES: momentum investing can be profitable at times for individual investors, but it is a risky process that is perhaps best left to the pros.

5. Conclusion

Pettengill, Edwards and Schmitt (2006) find that, based on performance in the widely studied *The Wall Street Journal* Dartboard Contest, professional investment analysts outperform individual investors as momentum investors as measured by market-adjusted returns. In this paper we seek to determine if these return differentials can be explained by various security characteristics. If these characteristics are able to be identified individual investors could be more successful in momentum investing by duplicating the momentum selection criteria used by professional analysts.

We test three timing explanations of this return differential. We find that the observed superior performance is not because of the analysts concentrating their momentum selections in market regimes favorable to momentum investing. We also fail to find support for a timing hypothesis that the relative poor performance of readers is because of a tendency for individual investors to "be slow to catch the train" and invest in momentum securities only after these securities have exhausted most of the momentum run. Nor are the securities selected by the readers significantly higher in terms of relative volume. Finally, we find that the momentum selections of the professional analysts do not outperform on the basis of selecting securities with smaller market size or higher book-to-market value. When we apply a model to test these effects collectively, we find that the under-performance of the readers increases slightly. Further, none of these variables, when examined individually, provide a partial explanation of the superior performance of the pros. Thus, we are unable to reject the hypothesis that professional analysts are superior momentum investors because of superior analytical skills or the possession of superior information sets. If one were to accept this hypothesis one might conjecture that individual investors could benefit from the recommendations of professional investors concerning momentum securities.

This inference must be tempered by two salient facts. When we ascribe superior performance to the pros, we must do so in the face of significant evidence that professional investment analysts, such as mutual fund managers, are unable to beat the market. See, for example, Malkiel's (2005) study of the performance of mutual fund managers. A second disquieting finding for this inference is that in the dartboard contest the professional analysts outperformed the individual investors only with regard to momentum securities and not with regard to neutral and contrarian securities. If the pros use superior information sets or superior analytical ability to beat the market and the readers with regard to momentum selections, why would this skill not transfer to other types of securities? Thus, we conclude that individual investors may be wise to avoid momentum investing altogether.

Notes

1. A number of explanations have been offered for the existence of momentum in security returns. Chan, Jegadeesh and Lakonishok (1996) and Hong, Lim and Stein (2000) argue that momentum results from under-reaction to positive earnings announcements. Hong and Stein (1999) cite the interaction between various types of market participants as the cause of security momentum. Daniel, Hirshleifer and Subrahmanyam (1998) argue that behavioral biases on the part of investors create security momentum and eventual corrections. More recently, Zhang (2006) argues that firm-level uncertainty magnifies momentum profits and Arena, Haggard and Yan (2008) argue that momentum is influenced by idiosyncratic volatility.
2. The contest continues in a modified form in the online edition but is not reported in the printed version of the *Journal.*
3. For several reasons, we eliminate from our sample the five (four from the readers and one from the pros) selections that recommended shorting the stock pick. First, because discussion of momentum investing in both the practitioner literature and academic

literature centers on momentum of stocks earning a positive return, there is no clear reason to include the selections that recommended short sales. Second, if we were to include short-sell recommendations, it is not at all clear how we might classify such recommendations. One may argue that those recommendations to short stocks are seeking to purchase stocks that have experienced positive momentum that the short-seller perceives to have run its course. Alternatively, a momentum short-seller may purchase a stock on its way down expecting it to continue. Given this uncertainty and the lack of discussion in the literature relative to short behavior and stock momentum we simply exclude these securities from our sample.

4. PES follow standard practice in the Dartboard literature by identifying pre-selection and post-selection periods based on the announcement of the contest selections in *The Wall Street Journal.* On the basis that selections are made by the contestants, especially by the readers, some time before the contest selections are announced in the *Journal*, we find that this announcement date criteria to be inappropriate for our analysis. We move back the division date to be closer to the actual selection time. On this basis, and for sample convenience, we divided pre-selection and post-selection periods by the first trading day of the contest month.
5. Griffin, Ji and Martin (2005) report that a momentum portfolio long in winners and short in losers experiences higher returns in down markets than in up markets, supporting the conjecture that momentum securities achieve superior returns in both up and down markets.
6. Systematic risk measures contained in the CAPM or the Fama-French three-factor model are not the only available risk measures. As argued above, momentum securities and momentum strategies are uniquely subject to downside risk. However, risk adjusting using a variable such as Value at Risk (see Bali and Calcici, 2004) would be unlikely to provide an acceptable adjustment. Momentum securities may have large downside risk, however, by definition they would tend to have low Value at Risk. An alternative to measuring risk using systematic risk or downside risk, is to measure total risk. To examine total risk we determine the standard deviation of monthly returns for each security in our sample. Two questions are of particular concern. First, do momentum securities display higher total risk than neutral and contrarian selections? Second, critical to our conclusions presented later in the paper, do momentum securities selected by the pros have greater total risk than the momentum securities selected by the readers? If this were the case, superior returns achieved by the pros as measured by market-adjusted returns may be explained by risk. We use standard F-tests to compare total risk across the three classes of securities. In results not reported here, but available from the authors, we find no significant difference in total risk in comparing momentum securities to neutral or contrarian securities. In addition, we find no significant differences in the total risk of momentum securities selected by the pros and the readers. Hence, our results are robust to any risk adjustment using total risk measures.
7. In his analysis, Liang (1999) identifies a phenomenon that was first cited by Barber and Loeffler (1993) as influencing the performance of the pros in the dartboard contest. Both studies find that much of the return to the selections of the pros occurs

in the first several days following the announcement. Both of these authors attribute this phenomenon to herding by uniformed investors following *The Wall Street Journal* announcement. We acknowledge that the selections by individual investors will unlikely associate with a similar herding effect. In that sense, our comparisons could be viewed as unfair. Three factors ameliorate any concern over this effect. First, our primary comparisons are made for a six-month period. If the increase in returns of the pro's picks is due solely to herding, this effect ought to be reversed by the end of the contest. Further, our secondary comparisons using the post-contest period show an even stronger superior performance on the part of the performance of the securities selected by the pros relative to the securities selected by the readers. This comparison should not be influenced by a herding effect. Finally, Pettengill, Edwards and Schmitt (2006) directly test for this issue. They compare returns to the pros' selections with the returns to the readers' selections with the announcement period removed. They find superior performance on the part of the selections of the pros with the announcement period removed.

8. We check for multicollinearity following Neter, Wasserman and Kutner (1985) by variance inflation factors (VIF). According to these authors, if the VIF for any variable is equal to 1 it is not linearly related to any other variable, and, average mean VIF values considerably larger than 10 are indicative of serious multi-collinearity problems. For the several variables in our model the largest VIF value is 1.15 and the average VIF value is 1.08. Given these results we feel confident in concluding that our model is not seriously impacted by multi-collinearity.
9. We conduct this regression for the entire year following the sample selection and for the post-contest period. We find no material difference in our results. In all cases, the readers' performance was significantly lower than the pros' performance.
10. In results not reported here because of space consideration, we show that during the market correction period the returns of the readers and the pros were quite similar in the months before March 2000. During March 2000 and especially in the following months, the returns for the selections of the pros were substantially higher than the returns for the selections of the readers.
11. As our sample size is small in Tables 5 and 6, we replicate the parametric tests presented in these tables with the non-parametric, Mann-Whitney Comparison of Means test. In all cases, the non-parametric tests confirmed the results of our parametric tests.
12. The Fama and French U.S. Research Breakpoints (2007), available online, separate the market values of equity and the book-to-market ratio values into groupings based upon percentage of the values falling within each range for all NYSE firms meeting their data requirements.

References

Akhbari, M., Gressis, N., & Kawosa, B. (2006). Directional momentum strategies with no-load mutual funds. *Journal of Applied Business Research*, *22*, 67–88.

Arena, M., Haggard, K., & Xuemin, Y. (2008). Price momentum and idiosyncratic volatility. *The Financial Review*, *43*, 159–190.

Bali, T., & Cakici, N. (2004). Value at risk and expected stock returns. *Financial Analysts Journal*, *60*, 57–73.

Barber, B., & Loeffler, D. (1993). The 'dartboard' column: Second hand information and price pressure. *Journal of Financial and Quantitative Analysis*, *28*, 273–285.

Carhart, M. (1997). On persistence in mutual fund performance. *Journal of Finance*, *52*, 57–82.

Chan, L., Jegadeesh, N., & Lakonishok, J. (1996). Momentum strategies. *Journal of Finance*, *51*, 1681–1712.

Cooper, M., Gutierrez, R. Jr., & Hameed, A. (2004). Market states and momentum. *Journal of Finance*, 59, 1345–1365.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *Journal of Finance*, *53*, 1839–1886.

De Bondt, W., & Thaler, R. (1985). Does the stock market overreact? *Journal of Finance*, *40*, 793–805.

De Bondt, W., & Thaler, R. (1987). Further evidence on investor overreaction and stock market seasonality. *Journal of Finance*, *42*, 557–581.

Dickens, R., & Shelor, R. (2003). Pros Win! Pros Win! or Do They?: An analysis of the 'dartboard' contest using stochastic dominance. *Applied Financial Economics*, *13*, 573–579.

Fama, E., & French, K. (1992). The cross-section of expected stock returns. *Journal of Finance*, *47*, 427–465.

Fama, E., & French, K. (1996). Multifactor explanation of asset pricing anomalies. *Journal of Finance*, *51*, 55–84.

Fama and French U.S. Breakpoints. (2007) Retrieved February 21, 2007 (available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

Griffin, J., Ji, X., & Martin, J. (2005). Global momentum strategies. *Journal of Portfolio Management*, *31*, 23–39.

Hong, H., Lim, T., & Stein, J. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance*, *55*, 265–294.

Hong, H., & Stein, J. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance*, *54*, 2143–2184.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, *48*, 65–91.

Lee, C., & Swaminathan, B. (2000). Price momentum and trading volume. *Journal of Finance*, *55*, 2017–2069.

Liang, B. (1999). On the performance of hedge funds. *Financial Analysts Journal*, *55*, 72–85.

Malkiel, B. (2005). Reflections on the efficient market hypothesis: 30 years later. *Financial Review*, *40*, 1–9.

McKay, P. (2005). Forget chasing the money train. *The Wall Street Journal*, *246*, September 30:C1.

Neter, J., Wasserman, W., & and Kutner, M. (1985). *Applied Linear Statistical Models*, 2nd ed. Homewood, IL: Irwin.

Pettengill, G., & Clark, J. (2001). Estimating expected stock returns in an event study framework: Evidence from the dartboard column. *Quarterly Journal of Business and Economics*, *40*, 3–22.

Pettengill, G., Edwards, S., & Schmitt, D. (2006). Is momentum investing a viable strategy for individual investors? *Financial Services Review*, *15*, 181–197.

Swinkels, L. (2004). Momentum investing: A survey. *Journal of Asset Management*, *5*, 120–143.

Wright, D. (1994). Can prices be trusted? A test of the ability of experts to outperform or influence the market. *Journal of Accounting, Auditing, & Finance*, *9*, 307–323.

Zhang, X. (2006). Information uncertainty and stock returns. *Journal of Finance*, *61*, 105–137.