Journal of Business and Economic Studies, Vol. 14, No. 2, Fall 2008

Value and Momentum Strategies: Returns From Risk-Controlled Portfolios

*Philip S. Russel, Philadelphia University**
Karthik Sankaran, Duke Solutions

Abstract

Two popular techniques for managing equity portfolio are value and momentum based investment strategies. Several researchers have examined and found that such investment strategies provide superior returns. There is, however, a lack of consensus on the source of such abnormal returns. We investigate an alternate explanation by modeling the risk of portfolios using the Arbitrage Pricing Theory. Our results suggest that the superior returns observed in prior studies can be attributed to risk premium.

Keywords: Arbitrage Pricing Theory
JEL Classification: G120/G140

INTRODUCTION

Many researchers have demonstrated that value and momentum based investment strategies are effective in predicting stock returns [Jegadeesh et al (1993), Fama and French (1992 & 1993), Lakonishok et al (1994)]. Asness (1997) notes that there is no universally accepted explanation for the success of these strategies. We propose that a meaningful explanation can be found once the risks of the portfolios are controlled relative to the risks of a benchmark portfolio. We posit that once exposure to factor risks are accounted for, returns from combining value and momentum stocks will not be significantly different across portfolios as assets that have equivalent risk characteristics can be expected to provide equivalent returns. Furthermore, returns from such risk-neutral portfolios should not significantly differ from benchmark returns.

We test our hypotheses by first clustering stocks according to their value and momentum characteristics. Each group of stocks is then converted to portfolios by assigning equal weights (group A), and optimal weights (group B). In group B, the portfolios are formed by controlling for several risk factors that were found to be priced in the market by previous studies. We analyze the excess returns from these portfolios relative to return from benchmark S&P 500.

It is plausible that other factors may have explanatory power as well. For example, Hong et. al (1999) suggests that size (i.e. market capitalization) and analyst coverage may explain abnormal returns to momentum strategies. To explore that possibility we use the weights from groups A and B to estimate average size and average number of analysts' coverage. These variables are then used in regressions of returns from the portfolios as independent variables to test their explanatory power.

The contribution of this paper is twofold with useful implications for investors: (1) Clearer understanding of returns from value and momentum strategies, and (2) Identification of sources of excess returns observed in previous studies. If the excess returns reported in previous studies are merely a premium for risk, it should force investors to evaluate risks inherent in portfolios constructed using value or momentum strategies. Furthermore, investors should calculate risk-adjusted returns from value and momentum strategies against risk-adjusted returns from other quantitative and non-quantitative strategies.

PRIOR RESEARCH

Mutual funds have grown in popularity as the preferred investment vehicle. The number of mutual funds has increased to nearly 15,000 with assets under management of $8.496 trillion (Investment Company Institute, 2005). With the growing popularity of mutual funds, investigations over its economic implications have also correspondingly increased. In this paper, we investigate two popular portfolio management styles – value based and momentum based.

Value and Momentum Trading Strategies

Value investment style involves investing in stocks of firms that are underpriced relative to their fundamentals. It is argued that investors frequently react irrationally to information resulting in distorted prices that can be exploited to generate superior returns. Several researchers have investigated and documented the superior performance of value based investment strategies. Fama and French (1992) found that stocks with high earnings-price (E/P) ratio produced higher returns during the 1963-1990 period. They further observe that the positive relationship between firms with positive E/P ratios and average returns can be attributed to the positive correlation between E/P and book-to-market value equity (BV/MV) ratios. Their results suggest that value investment strategies based on a firm's BV/MV can be used to form superior portfolios. Corroborating evidence is provided by Basu (1973) and Chan, Hamao and Lakonishok (1991).

Lakonishok, Shleifer, and Vishny (1994) investigated a contrarian investment strategy by comparing the performance of value stocks and glamour stocks.[1] They report that value stocks significantly outperformed the glamour stocks, generating an average annual return of 19.8% compared to 10.5% for glamour stocks. The authors note that the superior returns are due to the ability of the contrarian investment strategy to exploit the

---

[1] Glamour stocks are defined as stocks that have done very well in the past and are overpriced due to increased demand by naïve investors. These stocks will be characterized by low book-to-market value of equity (B/M), low cash flow-to-market value of equity (C/P), low earnings-to-market value of equity (E/P), and high growth rate of sales (GS). Value stocks are stocks that are underpriced due to investors over-discounting bad information about a stock. These stocks will be characterized by high book-to-market value of equity (B/M), high cash flow-to-market value of equity (C/P), high earnings-to-market value of equity (E/P), and low growth rate of sales (GS).

suboptimal behavior of investors rather than due to relatively higher systematic risk as argued by Fama and French (1992).

There is extant evidence on the superior performance of momentum strategies as well. While value investors try to "buy low and sell high", momentum investors tend to chase the trend by "buying high and selling higher". Momentum strategies are based on the assumption that investors tend to overreact to information. Thus, a strategy of investing in recent losers and shorting recent winners should generate positive returns if investors tend to be irrationally optimistic about the future prospects of "good stocks" and overly pessimistic about the future prospects of "poor stocks." For instance, Jagdeesh and Titman (1993) posit that a contrarian strategy should generate significant abnormal returns if market prices do not adjust appropriately to information. They find that a portfolio formed by buying stocks that performed well and selling stocks that underperformed over the previous 6 months generated an annual abnormal return of 12.01% when held for six months.[2] They report similar results around earnings announcements wherein past losers realize higher returns than past winners. Their evidence supports a delayed stock market reaction to firm-specific information.

More recently, Asness (1997) investigates the interaction of value and momentum strategies on a sample of NYSE, Amex and NASDAQ firms for the period July 1963 through December 1994. Asness measures value using the traditional book-to-market ratio (log BV/MV) and dividend yield (D/P) and proxies momentum using average monthly return on stock over the past twelve months (past (2, 12)). Univariate tests reveal that the three variables used for measuring value and momentum strategies are positively associated with future expected return. The difference in average returns between the lowest and highest quintile when the portfolio was sorted by past (2, 12), log (BV/MV), and D/P was .87%, .51% and .31% respectively. Furthermore, value and momentum strategies were found to be negatively associated with each other suggesting interaction effects. Further analysis reveals that value strategy is relatively superior among firms with weak momentum (and weaker among firms with strong momentum). Similarly, momentum strategy produces superior return among firms with poor values (relative to firms with high value). For empirical analysis of value and momentum strategies in international markets see Capul, Rowley and Sharpe (1993), Schiereck, De Bondt, and Martin Weber (1999) Rouwenhorst (1997), Scott, Stump and Xu (2003) and Bird and Whitaker (2003).

Taken together, the empirical evidence suggests that both value and momentum strategies can be used to predict stock returns and generate abnormal returns. However, there is a lack of consensus about the source of such returns. Several explanations have been offered for the ability of value and momentum investment strategies to outperform the market. One school of thought argues that naïve investors tend to be guided by irrational optimism and pessimism. As a result, investors bid up the prices of stocks when

[2] They also consider trading strategies based on stock returns over the past 1, 3, or 4 quarters and holding periods of 1 to 4 quarters. They examined the returns for (a) buy and hold portfolios and (b) portfolios that were rebalanced monthly to maintain equal weights. Thus, there were a total of 32 trading strategies.

they are overly optimistic (such as during the dot com boom) and depress the prices of stocks on other occasions due to panic selling (such as post 911). By trading against naïve investors, it will be possible for contrarian investors to generate superior returns. Writings on volatility tests (Shiller, 1981), noise nraders (Shleifer and Summers, 1990), social psychology (Shiller, 1984) fad variable (Summers, 1986), heuristic decision making (Kahneman and Tversky, 1986) predictability of stock returns (Jegadeesh, 1990) and short-run speculative motive of investors (Keynes, 1936) suggest market inefficiencies or irrationalities in investor behavior, at least in the short-run. Fama (1992), on the other hand, argues that the higher returns are a compensation for the higher fundamental risk involved in such portfolios. A third explanation for excess returns or predictive ability is the possibility of methodological flaws such as data mining, survivorship bias, and inappropriate modeling (Kleidon, 1986; Black, 1993).

In this paper, we contribute to the understanding the source of abnormal returns by investigating if it is possible to find explanation to the observed superior returns once the risks of the portfolios are controlled using the Arbitrage Pricing Theory.

DATA AND RESEARCH METHODOLOGY

Value and Momentum Stocks

In the literature value stocks have been classified based on dividend yield and the ratio of book value to market value. We use the latter as dividend yield does not, in our opinion, accurately capture the true value. Any test of using dividend yield as an indicator of value is a test of affirmation of market expectations and not of abnormal returns. This can be understood by considering the constant dividend growth model for equity valuation.[3] Using dividend growth model, dividend yield can be expressed as the spread between the required rate of return on the equity and the growth rate. As the spread widens, due to increase in the required rate of return or decrease in growth rate or both, the price falls and the dividend yield increases. Conversely, as the spread narrows, the price increases and the dividend yield falls. However, at equilibrium, required rate of return should equal expected rate of return. In other words, when the dividend yield is higher the market expects higher return and vice versa. *Ex ante* we should expect the returns that the studies have confirmed. It follows that dividend yield is neither a contrarian nor an abnormal return indicator.

The ratio of book value to market value is not subject to such criticism since there is no established relationship between the two values that would lead to any ex ante expectations. Consequently, the ratio does not necessarily indicate whether a stock is "expensive" or "cheap". However, for lack of a better term the ratio is equated with "value". *Ex poste*, as studies have shown, the ratio seems to predict abnormal returns and is an indicator of value of the stock to an investor. For these reasons we chose the ratio of book value to market value (hereafter denoted by B/M) as an indicator of value.

[3] The argument that follows is applicable even if there are multiple growth rates.

Specifically, we use year-end book value per share to calculate the B/M ratio.[4] Momentum characteristic of a stock is measured as the average of past twelve month returns. Both value and momentum characteristics are calculated at the end of every month during the testing period. Return for each characteristic is measured at the end of the following month.

Sample

The sample data was collected for the period July 1989 to December 1997 from Center for Research on Security Prices (CRSP). The value and momentum characteristics were measured using monthly returns from July 1988 along with month end market price starting from June 1989 and year-end book value per share data beginning from June 1988. The final sample consists of 1029 stocks that meet the above requirement and other criteria (discussed later).

Once a stock's value characteristic is measured, it is classified as a high value (HV) or medium value (MV) or low value (LV) stock according to whether its value measure falls in the top third or middle third or bottom third, respectively, of value measures of all stocks for that month. Similarly, each stock is classified as a high momentum (HM) or medium momentum (MM) or a low momentum (LM) stock at the end of each month. Equal weighted portfolios of stocks in each classification of value and momentum characteristics are then formed. In other words, each month three equal-weighted value portfolios and three equal-weighted momentum portfolios are constructed. Characteristic measurement, classification, and portfolio construction are done at the end of each month while return for the portfolios are measured at the end of the following month. Results reported are average of these monthly returns.

We also sort the stocks by interaction between the two characteristics. Thus, given three classifications for each of the two characteristics, there will be a total of nine groups: HM-HV, HM-MV, HM-LV, MM-HV, MM-MV, MM-LV, LM-HV, LM-MV, and LM-LV.[5] This classification scheme allows us to construct nine portfolios every month. We construct the portfolios by assigning (a) equal weights to stocks and (b) optimal weights based on an optimization model. The purpose of constructing optimal portfolios is to make all nine portfolios risk equivalent with one another as well as with the benchmark portfolio, S&P 500 index. To the extent that we are successful in making the portfolios risk equivalent, and assuming that the risk factor(s) that were controlled completely explain the returns, *ex ante* we should not expect to see any significant

[4] For example, year-end 1988 book value per share and 1989 June-end market price per share are used to calculate the ratio to classify the stock as of 1989 June end. The 1988 year-end book value per share will continue to be used until 1990 May end. For calculation at 1990 June end we use 1989 year-end book value per share, and so on. In other words, we allow for lag in availability of year-end data and thus avoid "look-ahead bias"

[5] Each of these groups is an intersection of the respective value and momentum classifications. For example, HM-HV is the intersection of stocks in HM and HV classifications.

differential among the returns of the portfolios or between the returns of the portfolios and the return from S&P 500. The results of our analysis can be found in Table 7.

We also used the following additional data obtained from in-house data base of Duke Solutions: Monthly data from January 1970 to December 1997 on Consumer Price Index (CPI), industrial production index (INDUS), three-month T-bill rate (3MO), thirty-year t-bond yield (30Y), spread between ten-year t-bond yield and yield on BBB rated bond (PREMIUM), and NAPM Purchasing Managers Index (PMI). First, expected value of each of these series was constructed using data from January 1970 to December 1988. Second, unexpected component of each of these series was estimated from January 1989 to June 1997. Finally, the unexpected components were used in regressions of S&P 500 returns as well as all returns from 1029 stocks in the sample in order to obtain factor exposures to these risk factors.

Portfolio Optimization Problem Statement

Solve $\sum_I \alpha_i = 1$

subject to following constraints:

C1. $\beta_k = \sum_i \alpha_i \beta_{ik} = \beta_k \ \forall k$
C2. $-1 \le \alpha_i \le 1 \ \forall i$.

Constraint C1 requires that a portfolio's total exposure to any factor should equal index exposure to that factor. Constraint C2 sets limits on the weights for stocks in the portfolio.

α_i is the weight for ith stock, β_{ik} is the ith stock's exposure to factor k, and β_k is the S&P 500 index exposure to factor k.

Using the factor exposures, we constructed optimal portfolios for each value and momentum combination, i.e. HM-HV, HM-MV, etc., following the optimization problem stated in the box below. The optimization model makes each portfolio's exposure to each risk factor equal to that of the S&P 500 index. Note that the constraint on the stock weights is quite liberal. This is done in order to ensure feasible solution to the optimization problem. While admittedly such weights are unrealistic, it does not detract from the focus of this study as we are interested in understanding the reason behind observed abnormal returns rather than proposing realistic portfolio construction approaches. Alternatively, since the optimization problem allows short positions, one can view the optimization problem solved here as stretching the well-known long-short investment strategy beyond reasonable limits. Finally, each portfolio's average size, i.e. market capitalization, and average analyst coverage are calculated, where we assign equal weights to each stock in the portfolio. Assigning equal weight for the purpose of calculating average size and average coverage is necessary since assigning weights from the solution of the optimization problem will result in assigning negative size or negative coverage to some stocks, which is not meaningful. We assign a score of one to a stock that belongs to the lowest size group, and a score of two to a stock that belongs to the second lowest group, and so on. For analyst coverage, a score of one is given if one analyst covers it, a score of two if two analysts cover it, and so on. Portfolios are formed at the end of a month and returns are measured at the end of the next month. This process is repeated for each month during the testing period.

RESULTS

Results are presented in Tables 1 and 2. First, high value stocks provide lower return than low value stocks. Second, relative to momentum stocks value stocks provide lower returns. These results affirm the superiority of momentum stocks over value stocks during the 1990s. Previous studies had covered earlier periods and reached opposite conclusion. We do not analyze the returns any further as our focus is on understanding the returns for combination of value and momentum characteristics.

Table 1: **Average Returns from Momentum Portfolios** (Equal-Weighted)

	High Momentum (HM)	Medium Momentum (MM)	Low Momentum (LM)	HM - MM	HM - LM	MM - LM
Monthly Return	9.08%	1.24%	-5.53%	7.84%	14.6%	6.77%
t-statistic	49.87#	14.53#	-31.96#	39.03#	58.16#	35.09#

Test for Average Monthly Return= 0. Significant at 1%. N = 102.

Table 2: Average Returns from Value Portfolios (Equal-Weighted)

	High Value (HV)	Medium Value (MV)	Low Value (LV)	HV - MV	HV - LV	MV - LV
Monthly Return	1.3	1.33	1.66	-0.024	-0.35	-0.33
t-statistic	3.57#	4.19#	4.46#	-0.049	-0.68	-0.68

Test for Average Monthly Return= 0. Significant at 1%. N = 102.

Results in Table 3 for equal-weighted portfolios are similar to Asness (1997). First, certain combination of value and momentum stocks produces superior returns. Second, these combinations also produce significant excess returns relative to the S&P

500 index. Finally, a long-short strategy involving different combinations produces superior returns.

Table 3: Average Returns from Value + Momentum Portfolios (Equal-Weighted)

	HM	MM	LM
HV			
Monthly Return	10.09%	1.23%	-5.82%
t-statistic	40.37#	14.09#	-28.82#
MV			
Monthly Return	8.11%	1.24%	-4.91%
t-statistic	51.75#	14.62#	-29.17#
LV			
Monthly Return	8.92%	1.24%	-5.79%
t-statistic	49.59#	14.62#	-34.94#

Test for Average Monthly Return= 0. Significant at 1%. N = 102.

HM: High Momentum MM: Medium Momentum LM: Low Momentum
HV: High Value MV: Medium Value LV: Low Value

However, with risk-controlled portfolios as shown in Table 4, we observe that the superiority of the value and momentum combinations disappears. As seen in Table 5 for equal-weighted portfolios the excess returns to value+momentum portfolios are, on average, both statistically and economically significant, but for the risk-controlled portfolios the excess returns are almost insignificant. This is not surprising given the raw results in Table 4. Table 4 suggests that when risks are controlled returns from following a strategy of combining value and momentum stocks will not be profitable.

Another strategy of interest is the returns from following long-short combination with different portfolios. For example, going long on high value stocks while shorting low value stocks or going long on high momentum stocks and going short on low momentum stocks. Results from such strategies are presented in Table 6. We observe that returns for risk-controlled portfolios are much lower (in fact, economically insignificant) compared to the returns for equal-weighted portfolios. Finally, Table 7 presents results from regression of returns against average size and average analyst coverage. We find that size is a significant explanatory variable for all but medium momentum portfolios whereas analyst coverage explains only returns for some of the low momentum portfolios. One reason for not finding significant explanatory power to analyst coverage could be that more than half of the stocks in our sample did not have any analyst coverage. Given the significant explanatory power of size it is possible to conjecture that additional firm-specific factors will be useful in explaining the returns from the portfolios.

Table 4: Average Returns from Value + Momentum Portfolios (Risk-Controlled)

	HM	MM	LM
HV			
Monthly Return	-0.36	NA	0.15
t-statistic	-5.71#		5.83#
MV			
Monthly Return	-0.194	NA	0.119
t-statistic	-4.11#		4.55#
LV			
Monthly Return	-0.18	NA	0.132
t-statistic	-3.75#		4.14#

Test for Average Monthly Return= 0. Significant at 1%. N = 102.

NA: Not Available

HM: High Momentum MM: Medium Momentum LM: Low Momentum
HV: High Value MV: Medium Value LV: Low Value

Table 5: Excess Returns (Portfolios vs S&P 500)

(a) Equal-Weighted Portfolios

	HMHV – S&P	HMMV – S&P	HMLV – S&P	MMHV – S&P	MMMV – S&P	MMLV – S&P	LMHV – S&P	LMMV – S&P	LMLV – S&P
Average	8.92%	6.93%	7.74%	0.05%	0.06%	0.06%	-7.00%	-6.09%	-6.97%
t-statistic	22.78#	22.04#	25.49#	0.15	0.17	0.16	-20.09#	-19.53#	-22.21#

Test for Average = 0. Significant at 1%. N = 102.

(b) Risk-Controlled Portfolios

	HMHV – S&P	HMMV – S&P	HMLV – S&P	MMHV – S&P	MMMV – S&P	MMLV – S&P	LMHV – S&P	LMMV – S&P	LMLV – S&P
Average	-1.54%	-1.37%	-1.34%	NA	NA	NA	-1.03%	-1.06%	-1.05%
t-statistic	-4.44#	-3.87#	-3.7#				-2.91#	-2.99#	-2.99#

Test for Average = 0. Significant at 1%. N = 102.

HMHV: High Momentum High Value HMMV: High Momentum Medium Value
HMLV: High Momentum Low Value MMHV: Medium Momentum High Value
MMMV: Medium Momentum Medium Value MMLV: Medium Momentum Low Value
LMHV: Low Momentum High Value LMMV: Low Momentum Medium Value
LMLV: Low Momentum Low Value

Table 6: Return Differential between Properties

(a) Equal-Weighted Portfolios

	Expensive Vs Cheap		Winner Vs Loser	
	HMHV - HMLV	LMHV - LMLV	HMHV - LMHV	HMLV - LMLV
Average	1.18%	-0.035%	15.92%	14.7%
t-statistic	6.56#	-0.31	53.31#	82.12#

, # Test for Average = 0. Significant at 1%. N = 102.

(b) Risk-Controlled Portfolios

	Expensive Vs Cheap		Winner Vs Loser	
	HMHV - HMLV	LMHV - LMLV	HMHV - LMHV	HMLV - LMLV
Average	-0.202	0.018	-0.508	-0.288
t-statistic	-2.41#	0.448	-7.366#	-5.616#

Test for Average = 0. Significant at 1%. N = 102.

HMHV: High Momentum High Value HMMV: High Momentum Medium Value
HMLV: High Momentum Low Value MMHV: Medium Momentum High Value
MMMV: Medium Momentum Medium Value MMLV: Medium Momentum Low Value
LMHV: Low Momentum High Value LMMV: Low Momentum Medium Value
LMLV: Low Momentum Low Value

Table 7: Regression Results

(a) Equal-Weighted Portfolios

	HMHV – S&P	HMMV – S&P	HMLV – S&P	MMHV – S&P	MMMV – S&P	MMLV – S&P	LMHV – S&P	LMMV – S&P	LMLV – S&P
Average Size									
Coefficient	-15.49	-12.65	-10.11	0.224	0.894	-1.14	16.36	10.46	2.89
t-statistic	-7.91#	-7.85#	-9.95#	0.125	0.454	-0.528	7.45#	6.25#	1.52#
Average Coverage									
Coefficient	0.879	0.268	-0.214	0.216	-0.05	0.297	-0.739	0.318	1.08
t-statistic	1.94	1.04	-1.74	0.624	-0.176	1.46	-1.39	0.882	4.27#
F statistic	51.22#	50.69#	72.46#	0.45	0.11	1.22	64.58#	77.81#	79.43#
Adjusted R^2	49.9%	49.6%	58.6%	0	0	0.43%	55.7%	60.3%	60.8%

Test for coefficient is zero. Significant at 1%. N = 102.

HMHV: High Momentum High Value HMMV: High Momentum Medium Value
HMLV: High Momentum Low Value MMHV: Medium Momentum High Value
MMMV: Medium Momentum Medium Value MMLV: Medium Momentum Low Value
LMHV: Low Momentum High Value LMMV: Low Momentum Medium Value
LMLV: Low Momentum Low Value

(b) Risk-Controlled Portfolios

	HMHV – S&P	HMMV – S&P	HMLV – S&P	MMHV – S&P	MMMV – S&P	MMLV – S&P	LMHV – S&P	LMMV – S&P	LMLV – S&P
Average Size				NA	NA	NA			
Coefficient	-9.33	-13.09	-11.12				10.58	7.3	2.02
t-statistic	-4.86#	-6.31#	-8.13#				4.58#	3.23#	0.796
Average Coverage				NA	NA	NA			
Coefficient	-0.195	0.548	-0.165				0.891	1.00	1.13
t-statistic	-0.44	1.65	-0.995				1.59	2.06#	3.37#
F statistic	32.31#	27.56	45.81#				57.03	40.87#	41.47
Adjusted R^2	38.27	34.47	47.01				52.6	44.11	44.48

Test for coefficient is zero. Significant at 1%. N = 102.

NA: Not Available

HMHV: High Momentum High Value HMMV: High Momentum Medium Value
HMLV: High Momentum Low Value MMHV: Medium Momentum High Value
MMMV: Medium Momentum Medium Value MMLV: Medium Momentum Low Value
LMHV: Low Momentum High Value LMMV: Low Momentum Medium Value
LMLV: Low Momentum Low Value

CONCLUSION

The success of value and momentum strategies is now well documented. However, there is lack of consensus among researchers on the source of success for these strategies. Our study contributes to the extant literature by offering an alternate explanation. The results suggest that risk factors, as modeled along APT framework, can be used to explain the superior returns from value and momentum strategies documented in earlier studies. Accordingly, we recommend that investors should not use value and/or momentum strategies indiscriminately without understanding the risk inherent in such portfolios. It is critical to examine if these strategies produce superior returns in proportion to the inherent risks. We believe that an approach that takes into consideration risk exposures, as is done in the present study, and uses a more realistic optimization model will lead to better trading strategies.

REFERENCES

Asness, C. (1997), The interaction of value and momentum strategies." *Financial Analysts Journal*, (March/April): 29-36.

Basu, S. (1973) "Investment performance of common stocks in relation to their price earning ratios: A test of efficient market hypothesis," *Journal of Finance*, 663.

Bird, R. and J. Whitaker (2003) "The performance of value and momentum investment portfolios: Recent experience in the major European markets," *Journal of Asset Management*, 221-231.

Black, F. (1993) "Beta and return," *Journal of Portfolio Management*, Fall 1993, 8-18.

Capaul, C., Rowley, I. and W. F. Sharpe (1993) "International value and growth stock returns," *Financial Analysts Journal*, 27-36.

Chan, L. K.C., Jegadeesh, N. and J. Lakonishok (1996), "Momentum strategies," *Journal of Finance*, 1681-1713.

Fama, E. (1970) "Efficient capital market: A review of theory and empirical work," *Journal of Finance*, 383-417.

______ [1991] "Efficient capital markets: II", *Journal of Finance* 46, 1575-1617.

Fama, E. and K. French (1992), " The cross-section of expected returns," *Journal of Finance*, vol. 47, no. 2 (June): 427-465.

______ and ______ (1993), "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics*, vol. 33, no. 1 (February): 3-56.

Hong, H., Lim, T., and J. C. Stein (1999), "Bad bews travels slowly: Size, analyst coverage, and the profitability of momentum strategies." <u>Working Paper</u>.

Jegadeesh, N. (1990) "Evidence of predictable behavior of security returns," *Journal of Finance*, 881-898.

Jegadeesh, N. and S. Titman (1993), "Returns to buying winners and selling losers: Implications for Stock Market Efficiency." *Journal of Finance*, 65-91.

Kahneman, D. and A. Tversky (1986) "Choices, values, and frames," *American Psychologist*, 341-350.

Keynes, J.M. [1936] *The General Theory of Employment, Interest, and Money*. Cambridge University Press.
Kleidon, A.W. [1986] "Variance bounds tests and stock price valuation models," *Journal of Political Economy* 94, 953-1001.
Lakonishok, J., A. Shleifer and R. W. Vishny (1994), "Contrarian investment, extrapolation, and risk." *Journal of Finance*, 1541-1578.
LeRoy, S.F. and R.D. Porter (1981) "Stock price volatility: Tests based on implied variance bounds," *Econometrica*, 97-113.
Rouwenhorst, K. (1997), "International momentum strategies." Working Paper.
Scott, J., M. Stumpp, and P.Xu (2003) "Overconfidence bias in international stock prices," *Journal of Portfolio Management*, 80.
Shiller, R, I. (1981) "Do stock prices move too much to be justified by subsequent changes in dividends?," *American Economic Review*, 421-435.
_________ (1981) "Use of volatility measure in assessing market efficiency," *Journal of Finance*, 291-304.
________ [1984] "Stock prices and social dynamics," *Brookings Papers on Economic Activity* 2, 457-498.
_________ (1988) "The problem of gross violations of the present value invariance inequality," *Journal of Political Economics*, 1089-1092.
Schiereck, *D.*, De Bondt, W. and M. Weber (1999) "Contrarian and momentum strategies in Germany," *Financial Analysts Journal*. 104-117.
Shilling, G. A. (1992) "Market timing: Better than buy-and-hold strategy," *Financial Analysts Journal*, March/April, 46-50.
Shleifer and L.H. Summers (1990) "The noise trader approach to finance," *Journal of Economic Perspectives*, 19-33.
Summers, L.H. [1986] "Does the stock market rationally reflect fundamental values?," *Journal of Finance* 41, 591-601.

[*] We are grateful to Bruno Solnik and anonymous referee for their suggestions to an earlier version of this paper. The usual disclaimer applies. The author names are in no order of preference.

Mark Khojasteh, Ph.D., is Professor of Management in the School of Business and Economics at Winston Salem University , NC. Dr. Khojasteh, earned his B.S. in Management in 1975 from Gilan College of Management in Iran, his MBA from Iowa State University in 1979 and his DBA from United States International University-San Diego California in 1983. He has published a text book along with a dozen refereed journal articles and over 70 proceedings. His areas of interests are CEO compensation, work commitment and performance.

Malik Lasgari, Ph.D., **CFA,** is Professor of Finance at the Barney School of Business at Hartford University. He received his Ph.D., and M.Phil., degrees in Business Administration from the Graduate School of Business, New York University in 1978, currently named Stern Schools of Business. He is a Chartered Financial Analyst (CFA). His name has appeared in the 1998 edition of *Who's Who Among America's Teachers; The Best Teachers in America Selected by the Best Students,* as well as in *Who's Who in Finance and Industry, 2000-2001.* His research interests include portfolio pension planning and assessment, U.S. treasury inflation-indexed bonds, corporate governance, and financial planning for college.

Francisco Ramon-Ballester is an advisor at the European Central Bank's representative office at the International Monetary Fund. He previously worked as a senior economist at the European Central Bank, specializing in the analysis of Latin American economies. Before joining the ECB in 2000, he was an economist at Oxford Economic Forecasting. He holds a master's degree in International Economics from the Institute of World Economics in Kiel, Germany and a bachelor's degree in economics and political science from Georgetown University, Washington D.C.

Philip Samuel Russel, Ph.D., is an Associate Professor of Finance at Philadelphia University. He earned his doctorate in Finance from the University of Massachusetts-Amherst following an MBA from Morgan State University and a MA in Business Economics and BBA (Honors) from University of Delhi - India. Dr. Russel's main research interests are in the areas of corporate bankruptcy and managed portfolios. His work has been published in several journals, such as *Journal of Business and Economic Studies*, *Quarterly Journal of Business and Economics*, *International Journal of Finance*, *Managerial Finance*, *Risk Management Association Journal*, *Journal of Alternative Investments*, *Journal of Insurance and Risk Management,* and others.

Daniel Singer, Ph.D., received his degree in Economics from the University of Colorado and is a Professor in the Department of Finance at Towson University. His scholarly activities include numerous books, such as *The Real Estate Investment Handbook* and *Successful Web Portals in Retail Banking* as well as academic journals, such as the *Journal of Internet Bus*iness and the *Business and Society Review.* Dr. Singer consults in the area of web site design, portfolio management, and real estate investing.

David Steward, Ph.D., is currently Chair of the Department of Business Administration and Economics at Winston-Salem State University. He received his doctorate in finance from the University of Tennesse and has published in journals including, *Economic Systems*, *American Economist,*and the *International Journal of Finance.*