Seoul Journal of Business
Volume 4, Number 1 (June 1998)

Time-Varying Risk Premia and Profits from Portfolio Trading Strategies in the U.S. Stock Markets*

Bong-Chan Kho
College of Business Administration
Seoul National University

Abstract

This paper re-examines the profitability of two portfolio trading strategies that are currently the most controversial in financial research: the relative-strength strategy based on medium-term return continuation (3 to 12 months) and the contrarian strategy based on long-term return reversals (2 to 5 years). Using a sample of 1,500 stocks listed on the NYSE and AMEX from 1963 to 1989, the bootstrap test result shows that large parts of the profits to the relative-strength strategy can be explained by time-varying expected returns estimated from a bivariate GARCH model for the conditional CAPM. This result generally holds, even within subsamples classified by other measurees of risk such as firm sizes and market model betas, except for the medium- and large-size groups. However, profits to the contrarian strategy are shown to be the most difficult to reconcile with existing asset pricing models. The bootstrap distributions for the contrarian profits under any null models average significantly lower profits than the actual distributions at the 10% significance level. This indicates that the asset pricing models are incapable of explaining long-term mean reverting behavior of stock returns.

* I would like to thank Rene Stulz, Andrew Karolyi, K. C. Chan, Paul Schultz, Steve Buser, Dosoung Choi (the editor), and three anonymous referees for their comments and suggestions. Financial support from the Institute of Management Research at Seoul National University and the Dice Research Center at Ohio State University is gratefully acknowledged.

1. Introduction

The predictability of stock returns has been one of the most controversial issues in financial research for the last several decades. Unlike the early work surveyed by Fama (1970), many recent studies document evidence that stock returns are predictable simply from past returns and other variables, such as dividend yields and term premium. For example, DeBondt and Thaler (1985, 1987) and Chopra, Lakonishok, and Ritter (1992) provide evidence of return predictability over long horizons (3 to 5 years), whereas Lehmann (1990), Lo and MacKinlay (1990), Jegadeesh (1990), and Jegadeesh and Titman (1991, 1993) provide evidence over short or medium horizons (a week or months). These studies pose a serious challenge to the efficient market hypothesis. Yet, there is little consensus on the underlying reasons for the evidence of return predictability, which could be due to market overreaction/underreaction, rational time-variation in expected returns, or both.

This paper, using equilibrium models for time-varying expected returns, investigates the return-predictability question further by re-examining the profitability of two portfolio trading rules that are most controversial in the U.S. stock markets: the contrarian strategy and the relative-strength strategy. The contrarian strategy, as studied by DeBondt and Thaler (1985, 1987), is designed to profit from long-term return reversals: that is, loser stocks that performed poorly over the past 3 to 5 years tend to substantially outperform winner stocks over the next 3 to 5 years. Thus, buying losers and selling winners generate significant profits. However, there have been huge debates on the source of profits from the contrarian strategy: DeBondt and Thaler (1985, 1987) and Chopra, Lakonishok and Ritter (1992) interpret the results as evidence of an economically-important overreaction effect, whereas others attribute the results to systematic changes in the risk of losers and winners, to the size or January effect, and/or to biases in long-term cumulative returns (e.g., Chan, 1988; Ball and Kothari, 1989; Zarowin, 1990; and Conrad and Kaul, 1993).

In contrast to the contrarian strategy, Jegadeesh and Titman

(1993) devise a relative-strength strategy that is based on medium-term return continuation: that is, loser stocks that performed poorly over the past 3 to 12 months continue to significantly underperform winner stocks over the next 3 to 12 months. Although Jegadeesh and Titman (1993) attribute this result to the presence of positive feedback traders or to underreaction to information about the short-term prospects of firms (such as earnings forecasts), the debate on the source of the profits has not yet been completely settled.

To date, however, there exists little work attempting to resolve the question of whether and how much profits from the portfolio trading strategies mentioned above are explainable by rational time variation in expected returns. This question is especially important considering the copious literature in finance that shows time variation in the expected returns of common stocks, bonds and other securities.[1] In this regard, it is crucial to understand whether the profits represent fair compensation for time-varying risk assumed by investors following the trading strategies or whether the profits indicate market inefficiency. This paper, using equilibrium models for time-varying expected returns, attempts to answer the above question and examines whether the profits are consistent with a particular model of time-varying expected returns.

Using all stocks listed on the NYSE and AMEX from 1963 to 1989, I first replicate the portfolio trading strategies for various combinations of portfolio formation- and holding-periods. This is to confirm earlier evidence on the profitability of these trading strategies. Second, I estimate simple versions of the conditional Capital Asset Pricing Model (CAPM) for individual stocks with the CRSP (Center for Research in Security Prices) value-weighted index as the market portfolio. The conditional first and second moments of excess returns are allowed to vary over time with a bivariate generalized autoregressive conditionally heteroskedastic (GARCH) model, based on the work of Engle (1982) and Bollerslev (1986). These models have been proven to fit stock returns quite well (see, for example, Bollerslev, Chou,

1) Noteworthy papers in this area include Keim and Stambaugh (1986), Fama and French (1988a, 1988b, 1989), Conrad and Kaul (1988, 1989), Bollerslev, Engle and Wooldridge (1988), Harvey (1989, 1991), Bodurtha and Mark (1991), Ng (1991), and Turtle, Buse and Korkie (1994).

and Kroner, 1992). Third, I employ a robust inference procedure using bootstrap methodology, proposed by Efron (1979, 1982) and Freedman and Peters (1984), and applied to financial data sets by LeBaron (1991), Brock, Lakonishok, and LeBaron (1992), Levich and Thomas (1993), and Kho (1996). In this procedure, I compute empirical distributions for the trading-rule returns implied by the conditional CAPM, and compare the empirical distributions with the actual trading-rule returns; it can be judged from this whether the returns are fair compensation for time-varying risk. This testing procedure is robust in the sense that the bootstrap method effectively takes into account non-normality, autocorrelation, and conditional heteroskedasticity in returns by utilizing empirical error distributions from a null model. Thus, this procedure, by not relying on any particular distributional assumptions, possesses a great advantage over conventional statistical methods.

The rest of the paper consists of four sections. Section II describes the relative-strength strategy and the contrarian strategy, and provides evidence of their profitability. Section III introduces the bootstrap methodology with a random walk model as the null model. This establishes the simplest benchmark for comparison with the conditional CAPM model. Section IV presents estimation results and diagnostics for some versions of the conditional CAPM model. The bootstrap results under these models are presented for the overall sample and for beta- and size-based sub-samples. Section V concludes with a brief summary.

2. The Portfolio Trading Strategies

This paper considers two kinds of portfolio trading strategies on which current debate focuses: the relative-strength strategies based on medium-term (3- to 12-month) return continuation and the contrarian strategies based on long-term (2- to 5-year) return reversals.

2.1 Relative-Strength Strategies

The relative-strength strategies select stocks based on their return performance over the past 3, 6, 9, or 12 months, and hold the stocks for the next 3, 6, 9, or 12 months. Thus, a total of 16 different variations of this strategy can be considered, as in Jegadeesh and Titman (1993). At the beginning of each month, all stocks are ranked in ascending order based on their past J-month returns, and are assigned to one of 10 decile portfolios. The strategy then buys the winner portfolio (decile 10) and sells the loser portfolio (decile 1), holding this position for the next K months. I denote this strategy the "J-month/K-month" relative-strength strategy. In any given month, the strategy holds a series of portfolios that are formed at the beginning of the current month, as well as from the previous K-1 months, and each portfolio receives the weight, $1/K$, from the entire group of portfolios held in that month.

All stocks from the CRSP monthly tape with available return data for the J months preceding portfolio-formation month t are included in the sample. Monthly returns of each portfolio are computed as an equally-weighted average of the component stocks that are rebalanced monthly; thus, stocks dropping out of the sample, due to delisting, suspensions, mergers, or other reasons, do not affect the returns beyond the month that the stock is dropped. Since the 12-month/12-month strategy requires returns over a 23-month horizon, the month for portfolio evaluation starts from January 1965 and ends in December 1989, giving 300 monthly return observations for each of the 16 strategies.

2.2 Contrarian Strategies

Compared to the relative-strength strategies, the longer-term contrarian strategies rank stocks based on their returns performance over the past 2, 3, 4, or 5 years. The holding periods considered vary from 1 to 5 years, but are not longer than the ranking periods, resulting in a total of 14 strategies. For comparability with prior studies (e.g., Chopra, Lakonishok and Ritter, 1992; Ball and Kothari, 1989), I use all stocks contained in the CRSP monthly tape from January 1963 to December 1989, and use 20 portfolios in identifying losers and winners. At the beginning of each year, all stocks that have been continuously listed for the past X calendar years are ranked based on their X-year returns and assigned to one of the twenty portfolios. The strategy buys the loser portfolio (portfolio 1) and sells the winner portfolio (portfolio 20), holding this position for the next Y years. I denote this strategy the "X-year/Y-year" contrarian strategy. The starting year for portfolio evaluation is determined by the earliest full year in the sample (1963) and the length of the ranking period, X years. Similarly, the ending year is determined by the last year in the sample (1989) and the length of the holding period, Y years ($\leq X$ years). This procedure results in a time-series of 24, 22, 20, and 18 portfolio returns for strategies with 2-, 3-, 4-, and 5-year ranking periods, respectively.

The Y-year holding period return for each stock in a portfolio is computed by compounding the monthly CRSP returns for the period. These returns are then equally-weighted to get the portfolio's holding period return. If a stock is delisted within a calendar year, its annual return for that year is calculated using the CRSP equally-weighted index return for the remainder of that year. In subsequent years, the stock is deleted from the portfolio. This procedure is identical to Chopra, Lakonishok and Ritter (1992), but different from Ball and Kothari (1989). Ball and Kothari use stocks remaining listed on the NYSE for the entire Y-year holding period, which might create a survivorship bias.[2]

I use holding period returns (or equivalently buy-and-hold returns) for the contrarian strategies. Although these returns are not directly comparable with the cumulative abnormal returns used by DeBondt and Thaler (1985, 1987), nor with the average annual returns used by Ball and Kothari (1989) and Chopra, Lakonishok, and Ritter (1992), holding period returns are the returns that a long-term investor can actually receive. Moreover, as Conrad and Kaul (1993) demonstrate, the return to a typical long-term contrarian strategy implemented with the

2) In my sample of all eligible CRSP stocks from 1963 to 1989, approximately 25%, 31%, and 34% of the loser portfolio stocks are delisted by the end of the holding period for the 3-year/3-year, 4-year/4-year, and 5-year/5-year contrarian strategies, respectively, whereas 12% to 17% of the winner portfolio stocks are delisted for the strategies. These rates of delisting are somewhat higher than those of Chopra, Lakonishok and Ritter (22% for the losers and 8% for the winners) because the late 1960s and the 1970s, the era of takeover activities, account for larger parts of my sample period.

cumulative return measure is upward biased because the return is calculated by cumulating upward-biased single-period (monthly) returns over long intervals.[3] Conrad and Kaul show that, for non-January months, the loser-winner spreads over 36 months drop dramatically from 12.2% (when cumulative abnormal returns are used) to -1.7% (when holding period abnormal returns are used).

2.3 Profits from the Portfolio Trading Strategies

Panel A of Table 1 reports the mean monthly returns of the loser and winner portfolios, as well as of the zero-cost winner minus loser portfolio, for all 16 relative-strength strategies. The mean returns to all zero-cost portfolios are positive and statistically significant, except for the 3-month/3-month strategy. The most profitable zero-cost portfolio is for the 12-month/3-month strategy, yielding 1.31% per month with a t-statistic of 3.75. These results are virtually identical (within 2 basis points) to those reported in Jegadeesh and Titman (1993), confirming their conclusion that these strategies appear profitable. For example, the 6-month/6-month strategy here produces exactly the same return of 0.95% per month as in their Table 1. For comparison with their further analyses on the 6-month/6-month strategy, I also focus on the same strategy for the remainder of the paper.

Panel B of Table 1 presents the results for all 14 contrarian strategies. Consistent with the existing evidence, the results show that, over 3-year to 5-year holding periods, stocks that performed poorly during the previous 3 to 5 years (losers) tend to substantially outperform prior-period winners. This is not the case, however, for the 2-year/2-year contrarian strategy that produces positive but insignificant loser-winner spreads. This result, together with the significant winner-loser spreads for the relative-strength strategies shown in Panel A, implies that long-term return reversals occur gradually after 2 years from the start of the ranking period and materialize in 5 to 6 years from

3) Conrad and Kaul (1993) show that this upward bias is based on the work of Blume and Stambaugh (1983). That is, single-period returns are upwardly biased due to bid-ask errors, nonsynchronous trading, and/or price discreteness.

Table 1. Returns of Loser and Winner Portfolios

Panel A shows the mean monthly returns of the relative-strength portfolios, formed based on the past *J*-month lagged returns and held for the subsequent *K*-months, whereas Panel B shows the mean holding period returns of the contrarian portfolios, formed based on the past *X*-year lagged returns and held for the next *Y*-years. Ten equally-weighted portfolios are constructed for the relative-strength portfolios and twenty equally-weighted portfolios are constructed for the contrarian portfolios. The "Loser" portfolio denotes the lowest past return portfolio, the "Winner" portfolio denotes the highest past return portfolio, and the "W-L" or "L-W" portfolio refers to the zero-cost winner minus loser or loser minus winner portfolio, respectively. The *t*-statistics are in parentheses. The sample consists of all eligible CRSP stocks from January 1963 to December 1989.

Panel A. Mean Monthly Returns of Relative-Strength Portfolios

J		K=3	K=6	K=9	K=12
3	Loser	0.0110	0.0092	0.0093	0.0089
		(2.20)	(1.89)	(1.94)	(1.90)
3	Winner	0.0141	0.0149	0.0152	0.0156
		(3.58)	(3.77)	(3.82)	(3.88)
3	W-L	0.0031	0.0057	0.0059	0.0068
		(1.06)	(2.25)	(2.66)	(3.48)
6	Loser	0.0088	0.0079	0.0073	0.0081
		(1.69)	(1.58)	(1.50)	(1.68)
6	Winner	0.0171	0.0174	0.0174	0.0165
		(4.29)	(4.32)	(4.30)	(4.12)
6	W-L	0.0083	0.0095	0.0101	0.0085
		(2.43)	(3.06)	(3.74)	(3.33)
9	Loser	0.0077	0.0065	0.0071	0.0082
		(1.48)	(1.30)	(1.44)	(1.67)
9	Winner	0.0186	0.0186	0.0175	0.0163
		(4.56)	(4.52)	(4.29)	(4.02)
9	W-L	0.0109	0.0121	0.0104	0.0081
		(3.04)	(3.78)	(3.46)	(2.87)
12	Loser	0.0062	0.0067	0.0076	0.0089
		(1.20)	(1.32)	(1.51)	(1.77)
12	Winner	0.0193	0.0180	0.0168	0.0155
		(4.66)	(4.37)	(4.11)	(3.81)
12	W-L	0.0131	0.0113	0.0092	0.0066
		(3.75)	(3.39)	(2.93)	(2.22)

Panel B. Mean Holding Period Returns of Contrarian Portfolios

X		Y=1	Y=2	Y=3	Y=4	Y=5
2	Loser	0.1864	0.2556			
		(1.95)	(2.49)			
2	Winner	0.1851	0.1361			
		(2.81)	(2.15)			
2	L-W	0.0013	0.1195			
		(0.02)	(1.79)			
3	Loser	0.2158	0.3257	0.2221		
		(1.91)	(2.56)	(2.70)		
3	Winner	0.1580	0.1070	0.0870		
		(2.46)	(1.79)	(1.45)		
3	L-W	0.0578	0.2187	0.1351		
		(0.75)	(2.32)	(2.25)		
4	Loser	0.3067	0.2502	0.1743	0.1827	
		(2.31)	(2.86)	(2.22)	(3.12)	
4	Winner	0.1596	0.0585	0.0736	0.1092	
		(2.45)	(0.95)	(1.10)	(1.58)	
4	L-W	0.1471	0.1917	0.1007	0.0735	
		(1.44)	(2.80)	(2.01)	(1.96)	
5	Loser	0.2652	0.2025	0.2060	0.1991	0.1895
		(2.86)	(2.46)	(2.89)	(3.57)	(2.95)
5	Winner	0.1058	0.0690	0.1018	0.1256	0.1140
		(1.52)	(1.03)	(1.40)	(1.68)	(1.61)
5	L-W	0.1594	0.1335	0.1043	0.0736	0.0755
		(2.19)	(2.23)	(2.34)	(1.77)	(2.14)

the start of the ranking period. The holding period returns on the zero-cost 3-year/3-year, 4-year/4-year, and 5-year/5-year loser-winner portfolios are 13.5%, 7.4%, and 7.6%, respectively, and are all significant at the 5% level.[4] I choose to examine the 3-year/3-year strategy in detail for the remainder of the paper since the result for this strategy is representative of the results for the other strategies.

To facilitate further analyses with the bootstrap methodology,

4) However, these appear to be smaller than those reported in previous studies using the longer sample period from 1926 to 1986: Ball and Kothari (1989) and Chopra, Lakonishok and Ritter (1992), though not directly comparable, report approximately 14% of average annual returns on the 5-year/5-year loser-winner portfolio.

Table 2. Returns of Loser and Winner Portfolios: Random Subsample Results

Panel A shows the mean monthly returns of the relative-strength portfolios, formed based on the past *J*-month lagged returns and held for the subsequent *K*-months, whereas Panel B shows the mean holding period returns of the contrarian portfolios, formed based on the past *X*-year lagged returns and held for the next *Y*-years. Ten equally-weighted portfolios are constructed for the relative-strength portfolios and twenty equally-weighted portfolios are constructed for the contrarian portfolios. The "Loser" portfolio denote the lowest past return portfolio, the "Winner" portfolio denotes the highest past return portfolio, and the "W-L" or "L-W" portfolio refers to the zero cost, winner minus loser or loser minus winner portfolio. This table reports averages of the mean returns from 25 random subsamples of 1500 stocks out of all eligible CRSP stocks from January 1965 to December 1989. The average *t*-statistics are reported in parentheses.

Panel A. Mean Monthly Returns of Relative-Strength Portfolios

J		*K*=3	*K*=6	*K*=9	*K*=12
3	Loser	0.0108	0.0091	0.0092	0.0088
		(2.16)	(1.88)	(1.94)	(1.89)
3	Winner	0.0139	0.0148	0.0151	0.0156
		(3.50)	(3.71)	(3.78)	(3.86)
3	W-L	0.0031	0.0056	0.0059	0.0067
		(1.01)	(2.15)	(2.54)	(3.36)
6	Loser	0.0087	0.0078	0.0072	0.0080
		(1.67)	(1.56)	(1.49)	(1.67)
6	Winner	0.0170	0.0173	0.0174	0.0166
		(4.21)	(4.28)	(4.27)	(4.11)
6	W-L	0.0083	0.0094	0.0101	0.0085
		(2.32)	(2.95)	(3.61)	(3.25)
9	Loser	0.0078	0.0065	0.0072	0.0082
		(1.48)	(1.30)	(1.44)	(1.66)
9	Winner	0.0186	0.0185	0.0176	0.0164
		(4.50)	(4.48)	(4.27)	(4.02)
9	W-L	0.0108	0.0120	0.0104	0.0082
		(2.89)	(3.62)	(3.34)	(2.80)
12	Loser	0.0063	0.0067	0.0076	0.0089
		(1.21)	(1.31)	(1.51)	(1.76)
12	Winner	0.0192	0.0180	0.0169	0.0156
		(4.60)	(4.35)	(4.11)	(3.82)
12	W-L	0.0130	0.0114	0.0093	0.0068
		(3.55)	(3.28)	(2.85)	(2.18)

Panel B. Mean Holding Period Returns of Contrarian Portfolios

X		Y=1	Y=2	Y=3	Y=4	Y=5
2	Loser	0.1767	0.2480			
		(1.88)	(2.39)			
2	Winner	0.1822	0.1314			
		(2.75)	(2.02)			
2	L-W	-0.0055	0.1167			
		(-0.15)	(1.58)			
3	Loser	0.2124	0.3263	0.2121		
		(1.89)	(2.54)	(2.50)		
3	Winner	0.1564	0.1094	0.0825		
		(2.40)	(1.79)	(1.34)		
3	L-W	0.0559	0.2169	0.1297		
		(0.67)	(2.20)	(2.02)		
4	Loser	0.3105	0.2485	0.1705	0.1689	
		(2.33)	(2.83)	(2.10)	(2.63)	
4	Winner	0.1604	0.0540	0.0705	0.1055	
		(2.39)	(0.87)	(1.01)	(1.48)	
4	L-W	0.1501	0.1945	0.1000	0.0635	
		(1.40)	(2.80)	(1.82)	(1.39)	
5	Loser	0.2615	0.2058	0.2030	0.1887	0.2003
		(2.78)	(2.41)	(2.70)	(3.12)	(2.78)
5	Winner	0.1072	0.0633	0.1019	0.1257	0.1052
		(1.48)	(0.90)	(1.35)	(1.63)	(1.46)
5	L-W	0.1542	0.1425	0.1011	0.0631	0.0951
		(2.06)	(2.21)	(1.88)	(1.25)	(2.06)

which requires estimation of large numbers of stocks and hundreds of simulations of individual stock-returns series, I am forced by capacity limitations to focus on a subsample of all the CRSP stocks. To ensure that this subsample is representative of the population, I use a random re-sampling procedure based on Efron (1982, Chapters 8 and 9) in which a number of equal-sized samples of stocks are randomly drawn from the population. I arbitrarily choose the size of the subsample to be 1500 stocks and repeat 25 different random drawings from the population. Table 2, Panel A, presents the mean monthly returns for the loser, winner, and zero-cost portfolios for each of the 16 different relative-strength strategies. The reported returns are the averages across the 25 random subsamples of 1500 stocks. Similarly, Panel B shows the results for the contrarian portfolios. The results in both panels are remarkably similar to those of Table 1 and confirm that subsequent results based on one of these random subsamples would not be biased.

3. Bootstrap Methodology

The bootstrap methodology, inspired by Efron (1979, 1982), has been recently applied to many areas of finance to augment conventional statistical tests and inference procedures. For example, LeBaron (1991) and Levich and Thomas (1993) have examined simple moving-average rules for currency spot and currency futures markets using bootstrap methods and have confirmed the profitability of the technical trading rules. In addition, Brock, Lakonishok, and LeBaron (1992) have applied bootstrap methods to evaluating profits from moving-average rules under various null models, using daily returns of the Dow Jones Industrial Average stock index from 1897 to 1986. Their results also provide strong support for the technical trading rules.

There are several benefits from using bootstrap methodology. First, the bootstrap method allows us to construct empirical distributions of complex tests across various trading rules that are not independent. Second, the conventional t-statistics reported in Tables 1 and 2 assume normal, stationary, and independent distributions; however, it is well-known that individual stock returns often deviate from these properties due to autocorrelation, conditional heteroskedasticity, skewness, and leptokurtosis. The bootstrap method can address these problems effectively by utilizing empirical error distributions generated from a null model that account for such deviations reasonably well.[5] Third, hundreds of simulated returns series for individual stocks are generated under a null model; thus, one can perform

5) The bootstrap method used in this study is the parametric one in the sense that the properties of stock returns such as autocorrelation, heteroskedasticity, skewness, and leptokurtosis are estimated under a given returns-generating model. Therefore, it could be that the bootstrap results are sensitive to the assumed model and the sample period as well, although I do not claim that the assumed model is the best representation of expected returns and risks.

hundreds of out-of-sample tests on whether the profits are the result of time-varying expected returns or market inefficiency.

The bootstrap method used in this paper is implemented as follows. Following the parametric bootstrap approach proposed by Freedman and Peters (1984), I first estimate null models to obtain parameter estimates and residuals. The residuals are standardized using their standard deviations, and then are redrawn with replacement to form a scrambled standardized residuals series. The scrambled residual series, together with the parameter estimates, is then used to construct a simulated return series representative of the null model. I then evaluate the profitability of trading rules by comparing the actual mean returns with those from the simulated return series. This procedure is repeated 500 times for each null model, and the fraction of the 500 replications that generates a return larger than that from the actual series is considered the simulated *p*-value.[6)]

3.1 Random Walk Bootstrap Results

In order to provide a simple benchmark case for comparison with the conditional CAPM in Section IV, I use a random walk model as the first null model. Specifically, the driftless random walk model for each stock i is expressed as:

$$r_{it} = \varepsilon_{it}, \tag{1}$$

and assumes that the returns are independently and identically distributed. The random walk model is simulated for each individual stock by randomly drawing from the original returns with replacement.[7)] By construction, the simulated series has

6) A useful reference is Chapter 5 and 10 of Efron (1982), which is summarized for a stock return application in the Appendix of Brock, Lakonishok and LeBaron (1992).

7) I handle the problem of missing months in the "scrambling" algorithm by preserving these months in their actual order. For example, if the returns are continuously available for 120 months except for two missings in months 60 and 61, the remaining returns are reordered unrestrictively, but months 60 and 61 are still declared missing. If firms are newly-listed or delisted from the CRSP files for whatever reason, I similarly preserve this history in the bootstrap algorithm.

Table 3. Bootstrap Tests for Random Walk Model

The return series for each stock is resampled with replacement to generate a simulated return series. The 6-month/6-month strategy is then applied to the simulated return series and its mean monthly returns for each portfolio are reported in Panel A ("L" denotes the lowest past 6-month return decile; "W" denotes the highest past 6-month return decile; P2 through P9 denote the other portfolios in ascending order). In Panel B, the 3-year/3-year contrarian strategy is applied to the same set of the simulated return series and its holding period returns are reported ("L3/1" denotes the lowest past 3-year return portfolio held for the subsequent 1-year, "W3/1" denotes the highest past 3-year return portfolio held for the subsequent 1-year, and so on). "W-L" or "L-W" denotes the zero cost, winner minus loser or loser minus winner portfolio. The simulated mean returns are from 500 simulations. The *p*-value denotes the fraction of the 500 simulations that generate returns larger than the actual returns. The 5% and 95% fractiles from the empirical distributions for each portfolio's returns are reported.

Panel A. 6-month/6-month Relative-Strength Strategy

	Actual		Simulation			
Portfolio	Return	(*t*-stat)	Return	(*p*-val)	5%	95%
			(1) All CRSP stocks			
L	0.0079	(1.58)	0.0084	(0.976)	0.0080	0.0093
P2	0.0113	(2.80)	0.0117	(0.972)	0.0114	0.0122
P3	0.0124	(3.38)	0.0122	(0.182)	0.0120	0.0126
P4	0.0125	(3.60)	0.0124	(0.274)	0.0122	0.0128
P5	0.0129	(3.87)	0.0126	(0.124)	0.0124	0.0130
P6	0.0134	(4.14)	0.0131	(0.014)	0.0127	0.0133
P7	0.0137	(4.22)	0.0133	(0.046)	0.0130	0.0136
P8	0.0143	(4.30)	0.0139	(0.024)	0.0136	0.0141
P9	0.0154	(4.37)	0.0144	(0.000)	0.0141	0.0147
W	0.0174	(4.33)	0.0160	(0.000)	0.0152	0.0166
W-L	0.0095	(3.06)	0.0076	(0.000)	0.0059	0.0086
			(2) 1500-stock subsample			
L	0.0076	(1.52)	0.0087	(0.850)	0.0069	0.0103
P2	0.0108	(2.65)	0.0117	(0.938)	0.0107	0.0126
P3	0.0125	(3.37)	0.0122	(0.308)	0.0114	0.0131
P4	0.0125	(3.56)	0.0124	(0.404)	0.0116	0.0132
P5	0.0133	(3.95)	0.0127	(0.068)	0.0119	0.0131
P6	0.0133	(4.09)	0.0129	(0.196)	0.0122	0.0136
P7	0.0132	(4.01)	0.0133	(0.522)	0.0125	0.0138
P8	0.0137	(4.09)	0.0137	(0.494)	0.0129	0.0145
P9	0.0150	(4.20)	0.0144	(0.142)	0.0134	0.0152
W	0.0176	(4.35)	0.0153	(0.008)	0.0138	0.0164
W-L	0.0100	(3.21)	0.0066	(0.006)	0.0048	0.0085

Panel B. 3-year/3-year Contrarian Strategy

	Actual		Simulation			
Portfolio	Return	(*t*-stat)	Return	(*p*-val)	5%	95%
			(1) All CRSP stocks			
L3/1	0.2158	(1.91)	0.1043	(0.000)	0.0784	0.1301
L3/2	0.3257	(2.56)	0.1116	(0.000)	0.0847	0.1381
L3/3	0.2221	(2.70)	0.1155	(0.000)	0.0861	0.1431
W3/1	0.1580	(2.46)	0.2428	(1.000)	0.2201	0.2688
W3/2	0.1070	(1.79)	0.2371	(1.000)	0.2144	0.2609
W3/3	0.0871	(1.45)	0.2302	(1.000)	0.2057	0.2569
L-W3/1	0.0578	(0.75)	-0.1385	(0.000)	-0.1751	-0.1047
L-W3/2	0.2187	(2.32)	-0.1255	(0.000)	-0.1638	-0.0924
L-W3/3	0.1351	(2.25)	-0.1147	(0.000)	-0.1539	-0.0761
			(2) 1500-stock subsample			
L3/1	0.2247	(1.62)	0.1048	(0.000)	0.0574	0.1555
L3/2	0.3444	(2.33)	0.1118	(0.000)	0.0625	0.1671
L3/3	0.2202	(2.59)	0.1182	(0.002)	0.0677	0.1757
W3/1	0.1847	(2.62)	0.2399	(0.974)	0.1920	0.2925
W3/2	0.1148	(1.89)	0.2360	(1.000)	0.1873	0.2867
W3/3	0.0947	(1.48)	0.2315	(1.000)	0.1862	0.2786
L-W3/1	0.0400	(0.41)	-0.1351	(0.000)	-0.2000	-0.0625
L-W3/2	0.2295	(1.89)	-0.1242	(0.000)	-0.1999	-0.0510
L-W3/3	0.1255	(2.63)	-0.1133	(0.000)	-0.1865	-0.0378

the same unconditional moments as the original series. The same trading rules are applied to the simulated series, and the empirical distributions of the trading rule returns are derived from the 500 replications. Table 3, Panel A, presents the random walk bootstrap results for the 6-month/6-month relative-strength strategy, and Panel B shows the results for the 3-year/3-year contrarian strategy. Each panel presents the results obtained from all CRSP stocks and the random subsample of 1500 stocks. In Panel A, I report the actual mean monthly returns to the decile portfolios (L is the loser portfolio; W is the winner portfolio; and P2 through P9 are the in-betweens in ascending order) and to the zero-cost winner-loser portfolio (W-L), as well as the *t*-statistics associated with these returns. Additionally, the average of the simulated mean monthly returns across the 500 replications under the random walk model is reported for each portfolio. The simulated *p*-value is the number of replications for which the simulated returns exceed the actual returns. I also report the 5% and 95% fractiles from the empirical distributions of the trading-rule returns.

The results confirm that the actual mean returns are positive and statistically significant according to the *t*-statistics. The simulated mean returns are also positive, but not comparable to the actual mean returns as indicated by their simulated *p*-values. For example, the simulated mean return for the loser portfolio is 0.84% per month, which is too high compared to the actual mean return of 0.79% per month with a simulated *p*-value of 97.6%. The simulated winner return is 1.6% per month, which is too low compared to the actual return of 1.74% with a simulated *p*-value of 0.0%. As a result, the simulated winner-loser spread of 0.76% per month is significantly lower than the actual spread of 0.95% per month with a simulated *p*-value of 0.0%. In the lower part of Panel A, I obtain similar results using the random subsample of 1500 stocks; that is, compared to the actual mean returns, the simulated loser return is too high, and the simulated winner return is too low, and thus the simulated winner-loser spread is too low.

Panel B of Table 3 presents the results for the 3-year/3-year contrarian strategy applied to the same set of simulated returns series used in Panel A. This panel reports the holding period returns to each portfolio (e.g., L3/1 is the loser portfolio held for the subsequent 1 year; W3/1 is the winner portfolio held for the subsequent 1 year; and L-W3/1 is the zero-cost loser-winner portfolio held for 1 year.) The actual holding period return to the loser-winner portfolio turns significant from year 2 for all CRSP stocks and for the random subsample of 1500 stocks. This is due to the rise in loser portfolio returns in the second year and the fall in winner portfolio returns in the second and third years. However, the simulated loser-winner spreads are all negative and never comparable to the actual spreads. For example, using all CRSP stocks, the simulated loser-winner spread over the 3-year holding period is -11.5%, which is significantly lower than the actual spread of 13.5% with a simulated *p*-value of 0.0%. In sum, the results in both Panels A and B suggest that the random walk model cannot explain any of the profits of either

Table 4. Bootstrap Tests for Random Walk Model: Size and Beta Subsample Results

The return series for each stock in the subsample of 1500 stocks are resampled with replacement to generate a simulated return series. The 6-month/6-month strategy is then applied for the simulated return series for the size-based and beta-based subsamples from the 1500 stocks and its mean monthly returns for each portfolio are reported in Panel A ("L" denotes the lowest past 6-month return decile; "W" denotes the highest past 6-month return decile; P2 through P9 denote the other portfolios in ascending order). In Panel B, the 3-year/3-year contrarian strategy is applied for the same set of the simulated return series and its holding period returns are reported ("L3/1" denotes the lowest past 3-year return portfolio held for the subsequent 1-year, "W3/1" denotes the highest past 3-year return portfolio held for the subsequent 1-year, and so on). "W-L" or "L-W" denotes the zero cost, winner minus loser or loser minus winner portfolio. The simulated mean returns are from 500 simulations. The *p*-value denotes the fraction of the 500 simulations that generate returns larger than the actual returns. The 5% and 95% fractiles from the empirical distributions for each portfolio's return are reported.

Panel A. 6-month/6-month Relative-Strength Strategy

	Size 1		Size 2		Size 3	
Portfolio	Actual Ret (*t*-stat)	Simulation Ret (*p*-val)	Actual Ret (*t*-stat)	Simulation Ret (*p*-val)	Actual Ret (*t*-stat)	Simulation Ret (*p*-val)
L	.0089(1.59)	.0069(.104)	.0039(0.76)	.0096(1.00)	.0075(1.71)	.0126(1.00)
P2	.0137(2.85)	.0100(.000)	.0087(2.04)	.0125(1.00)	.0086(2.39)	.0131(1.00)
P3	.0155(3.45)	.0106(.000)	.0124(3.14)	.0131(.758)	.0105(3.22)	.0128(.998)
P4	.0161(3.59)	.0111(.000)	.0131(3.55)	.0132(.524)	.0103(3.33)	.0126(1.00)
P5	.0169(3.92)	.0114(.000)	.0136(3.81)	.0135(.468)	.0111(3.69)	.0127(.998)
P6	.0168(4.00)	.0118(.000)	.0136(3.95)	.0137(.550)	.0109(3.72)	.0128(1.00)
P7	.0169(3.90)	.0121(.000)	.0135(3.83)	.0141(.756)	.0109(3.70)	.0131(1.00)
P8	.0163(3.87)	.0124(.002)	.0139(3.86)	.0147(.778)	.0112(3.78)	.0137(1.00)
P9	.0184(4.19)	.0129(.000)	.0152(3.90)	.0153(.518)	.0124(3.85)	.0144(.990)
W	.0164(3.51)	.0136(.048)	.0180(4.17)	.0164(.100)	.0178(4.53)	.0160(.088)
W-L	.0075(2.41)	.0067(.356)	.0141(4.29)	.0068(.000)	.0103(3.14)	.0033(.000)

	Beta 1		Beta 2		Beta 3	
Portfolio	Actual Ret (*t*-stat)	Simulation Ret (*p*-val)	Actual Ret (*t*-stat)	Simulation Ret (*p*-val)	Actual Ret (*t*-stat)	Simulation Ret (*p*-val)
L	.0080(1.48)	.0083(.532)	.0075(1.51)	.0086(.774)	.0033(0.72)	.0086(.996)
P2	.0124(2.68)	.0116(.190)	.0103(2.44)	.0118(.922)	.0091(2.53)	.0116(.994)
P3	.0133(3.05)	.0121(.080)	.0132(3.33)	.0124(.212)	.0109(3.50)	.0122(.940)
P4	.0126(2.91)	.0123(.380)	.0136(3.54)	.0126(.136)	.0118(3.93)	.0123(.748)
P5	.0144(3.49)	.0125(.002)	.0144(3.93)	.0129(.042)	.0118(4.04)	.0126(.848)
P6	.0150(3.67)	.0128(.000)	.0140(3.94)	.0132(.182)	.0121(4.29)	.0128(.842)
P7	.0150(3.68)	.0131(.010)	.0136(3.70)	.0134(.392)	.0120(4.29)	.0132(.944)
P8	.0149(3.65)	.0137(.068)	.0145(4.03)	.0138(.236)	.0123(4.29)	.0137(.950)
P9	.0164(3.93)	.0144(.022)	.0154(4.16)	.0143(.158)	.0142(4.57)	.0144(.586)
W	.0172(3.89)	.0153(.122)	.0187(4.68)	.0153(.010)	.0153(4.39)	.0154(.522)
W-L	.0091(2.97)	.0071(.188)	.0112(3.39)	.0066(.012)	.0120(3.19)	.0068(.012)

Panel B. 3-year/3-year Contrarian Strategy

	Size 1		Size 2		Size 3	
Portfolio	Actual Ret (t-stat)	Simulation Ret (p-val)	Actual Ret (t-stat)	Simulation Ret (p-val)	Actual Ret (t-stat)	Simulation Ret (p-val)
L3/1	.2620(1.62)	.0960(.000)	.1538(1.52)	.1137(.214)	.0895(1.38)	.1305(.706)
L3/2	.3601(2.08)	.1049(.000)	.2344(2.28)	.1121(.026)	.1424(2.25)	.1328(.428)
L3/3	.1924(2.05)	.1150(.048)	.2519(2.91)	.1133(.008)	.1223(1.88)	.1306(.528)
W3/1	.2373(2.17)	.2255(.398)	.1763(2.22)	.2493(.942)	.1258(2.53)	.2396(.994)
W3/2	.1485(1.46)	.2208(.894)	.1335(1.92)	.2504(.996)	.0488(0.97)	.2312(1.00)
W3/3	.1619(1.83)	.2193(.830)	.0979(1.16)	.2456(1.00)	.0810(1.33)	.2266(1.00)
L-W3/1	.0247(0.22)	-.1295(.014)	-.0226(-0.4)	-.1356(.062)	-.0363(-0.5)	-.1092(.202)
L-W3/2	.2116(1.64)	-.1159(.000)	.1009(1.52)	-.1383(.002)	.0936(1.26)	-.0984(.024)
L-W3/3	.0304(0.36)	-.1044(.048)	.1540(2.14)	-.1324(.000)	.0413(0.54)	-.0960(.068)

	Beta 1		Beta 2		Beta 3	
Portfolio	Actual Ret (t-stat)	Simulation Ret (p-val)	Actual Ret (t-stat)	Simulation Ret (p-val)	Actual Ret (t-stat)	Simulation Ret (p-val)
L3/1	.2411(1.54)	.1049(.018)	.2030(1.76)	.1033(.044)	.1260(1.63)	.1068(.332)
L3/2	.3683(1.99)	.1139(.004)	.2689(2.35)	.1063(.006)	.1357(1.84)	.1180(.358)
L3/3	.2202(2.21)	.1185(.058)	.1419(1.68)	.1190(.304)	.1208(2.12)	.1189(.458)
W3/1	.2004(2.47)	.2349(.738)	.1386(2.28)	.2470(.988)	.1679(2.73)	.2329(.900)
W3/2	.1476(1.92)	.2292(.938)	.0866(1.77)	.2419(1.00)	.0472(0.79)	.2335(1.00)
W3/3	.1284(1.75)	.2288(.974)	.1003(1.43)	.2330(1.00)	.0622(0.88)	.2313(.998)
L-W3/1	.0407(0.38)	-.1300(.016)	.0643(0.61)	-.1437(.008)	-.0420(-0.6)	-.1261(.124)
L-W3/2	.2207(1.45)	-.1153(.002)	.1823(1.76)	-.1356(.000)	.0885(0.85)	-.1155(.012)
L-W3/3	.0918(1.57)	-.1103(.002)	.0416(0.50)	-.1140(.026)	.0586(0.65)	-.1124(.032)

the relative-strength strategies or the contrarian strategies.

3.2 Random Walk Bootstrap Results: Size- and Beta-based Subsamples

In this subsection, I repeat the random walk bootstrap tests within subsamples based on firm sizes and market model betas. Specifically, I implement the tests for three size-based subsamples (small-, medium-, and large-size stocks) and three beta-based subsamples (low-, medium-, and high-beta stocks). These supplementary tests check the robustness of the profitability of the portfolio trading strategies across firms with different types of risk exposure. Classic studies of the unconditional CAPM, such as Black, Jensen, and Scholes (1972), Fama and MacBeth (1973), and Banz (1981), indicate that expected returns are linearly-related to their betas and firm size.[8] Thus, it is interesting to see whether the cross-sectional dispersion in mean returns across losers and winners shrinks within subsamples that control for these important attributes of expected returns.

Panel A of Table 4 reports the results for the 6-month/6-month relative-strength strategy. At the beginning of each evaluation month, all stocks in the random subsample of 1500 stocks are assigned to one of three size groups. Then, the relative-strength strategy is applied to each size group separately. First, the upper part of Panel A shows that the actual mean returns to decile portfolios within each size group are all positive and significant, except for extreme loser portfolios, and the winner-loser spreads are significant for all size groups with t-statistics of 2.41, 4.29 and 3.14. Second, the simulation results also accord with the significant t-statistics for the actual winner-loser spreads, except for the small-size group. For the medium- and large-size groups, the simulated spreads are 0.68% and 0.33%, respectively, which are significantly lower than their actual counterparts, 1.41% and 1.03%.

In the lower part of Panel A of Table 4, the results for the beta subsamples are reported. At the beginning of each evaluation month, I estimate market model betas for all 1500 stocks using past 12 months of the actual returns (or simulated returns in each simulation run). Then, the relative-strength strategy is applied to each beta subsample separately. The market model beta, β_i, is estimated from the regression

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \varepsilon_{it} \tag{2}$$

where r_{it} is the return on stock i, r_{mt} is the return on the CRSP value-weighted index, r_{ft} is the one-month Treasury bill yield, and ε_{it} is the idiosyncratic residual. The results show that the actual mean returns to decile portfolios within each beta group

8) Many recent studies, most notably, Fama and French (1992), have re-examined this linear relationship and found much weaker results for beta after controlling for firm size.

are all positive and significant, except for the extreme losers, resulting in significant winner-loser spreads for all beta groups with t-statistics of 2.97, 3.39 and 3.19. The actual winner-loser spreads are also significantly higher than the simulated spreads, except for the low-beta group. For the medium- and high-beta groups, the random walk model generates simulated winner-loser spreads as large as the actual ones in only 6 out of 500 replications (simulated p-value of 1.2%). In sum, the profits from buying winners and selling losers based on the 6-month/6-month strategy appear profitable, even after controlling for risk associated with size and beta, except for the small-size and/or low-beta groups.

Panel B of Table 4 reports the results for the 3-year/3-year contrarian strategy by size- and beta-based subsamples. For all subsamples, the actual loser portfolio returns rise rapidly in 2 years, whereas the winner-portfolio returns continue to fall over 3 years. Consequently, the actual loser-winner spreads are highest at the 2-year holding period. Note also that some of the t-statistics are seriously understated compared to the simulated p-values. For example, the actual spread, 21.2%, for the portfolio L-W3/2 in the size 1 group has a t-statistic of only 1.64, whereas its simulated p-value is 0.0%. The simulated spreads are negative for all size and beta subsamples, and are significantly lower than the actual spreads as indicated by the simulated p-values, with a few exceptions in size 1, size 2, and beta 3 groups for the L-W3/1 portfolio. In sum, the random walk model cannot possibly explain the profits to the long-term contrarian strategy, even after controlling for risk associated with both size and beta.

4. Time-Varying Risk Premia and the Portfolio Trading Profits

In this section, I introduce asset-pricing models for time-varying expected returns in order to see whether and how much the time-varying expected returns can explain portfolio trading-rule profits. In fact, the conditional version of the CAPM implies that expected returns should vary according to changes in the information set available at each time t; that is,

$$E(r_{it} - r_{ft} | \Omega_{t-1}) = \frac{E(r_{mt} - r_{ft} | \Omega_{t-1})}{Var(r_{mt} - r_{ft} | \Omega_{t-1})} Cov(r_{it} - r_{ft}, r_{mt} - r_{ft} | \Omega_{t-1}), \quad (3)$$

where $E(\cdot | \Omega_{t-1})$, $Var(\cdot | \Omega_{t-1})$, and $Cov(\cdot | \Omega_{t-1})$ denote the conditional expected return, variance, and covariance given the information set at time $t-1$, Ω_{t-1}. A common restriction applied in tests of the CAPM is that the price of covariance risk, defined as the ratio of the conditional expected excess returns on the market portfolio to the conditional variance of the market, is assumed to be a constant λ:

$$E(r_{it} - r_{ft} | \Omega_{t-1}) = \lambda Cov(r_{it} - r_{ft}, r_{mt} - r_{ft} | \Omega_{t-1}). \quad (4)$$

I denote this constrained version of the model the "constant price of risk (CPR)" model, whereas the more general version in equation (3) is referred to as the "time-varying price of risk (TPR)" model.[9)]

4.1 GARCH-M Models for the Conditional CAPM

The multivariate autoregressive conditionally heteroskedastic (ARCH) model developed by Engle (1982) and Bollerslev (1986) has been extensively used in estimating the conditional models of asset returns as shown in equations (3) and (4) above (see Bollerslev, Engle, and Wooldridge, 1988; Bodurtha and Mark, 1991; Ng, 1991; McCurdy and Morgan, 1992; and Turtle, Buse and Korkie, 1994). For the TPR version of the conditional CAPM in equation (3), I replace rational expectations with realized values and forecast errors, and then obtain the following system of equations,

$$r_{it} - r_{ft} = \gamma_{0i} + \mu_i \frac{h_{imt}}{h_{mt}} (\gamma_m' \mathbf{Z}_{t-1} + \theta_m \varepsilon_{mt-1}) + \theta_i \varepsilon_{it-1} + \varepsilon_{it}, \quad (5)$$

$$r_{mt} - r_{ft} = \gamma_m' \mathbf{Z}_{t-1} + \theta_m \varepsilon_{mt-1} + \varepsilon_{mt}, \quad (6)$$

9) Empirical tests of the conditional CAPM often allow for more general time-varying patterns in expected returns, betas, the price of covariance risk, or even all three: for example, Harvey (1989, 1991), Bollerslev, Engle and Wooldridge (1988), Bodurtha and Mark (1991), Ng (1991), McCurdy and Morgan (1992), and Turtle, Buse and Korkie (1994).

$$\text{and } \varepsilon_t | \mathbf{Z}_{t-1} \sim \mathbf{N}(0, \mathbf{H}_t), \tag{7}$$

where the error term vector, ε_t, for the excess returns on stock i and the market portfolio m is assumed to be conditionally normally distributed with variance-covariance matrix $\mathbf{H}_t$. The unrestricted multiplicative parameter μ_i is used as a way of positing a general alternative specification, following the work of McCurdy and Morgan (1992). The instrument vector $\mathbf{Z}_{t-1}$, which is a subset of the information set available at time t-1, Ω_{t-1}, consists of a constant, the spread between yields on Moody's Baa- or lower-rated bonds and Moody's AAA-rated bonds (PREM_{t-1}), the term spread between 10-year Treasury bonds and 1-month Treasury bill yields (TERM_{t-1}), the 12-month-trailing dividend yield on the CRSP value-weighted stock index (DIV_{t-1}), the one-month Treasury bill yield (r_{ft}), and the conditional variance of the market excess returns (h_{mt}). Given existing evidence that these instruments have predictive power for market-excess returns, the following linear combination of the instruments is used to predict market excess returns:

$$\begin{aligned} \gamma_m' \mathbf{Z}_{t-1} = \gamma_{0m} + \gamma_{1m}\text{PREM}_{t-1} + \gamma_{2m}\text{TERM}_{t-1} \\ + \gamma_{3m}\text{DIV}_{t-1} + \gamma_{4m}r_{ft} + \gamma_{5m}h_{mt}. \end{aligned} \tag{8}$$

For the CPR version of the model in equation (4), I replace equation (5) with the following equation:[10]

$$r_{it} - r_{ft} = \gamma_{0i} + \lambda_i h_{imt} + \theta_i \varepsilon_{it-1} + \varepsilon_{it}. \tag{9}$$

In this model, any potential effect of time variation in the price of risk on variation in the individual stock's expected returns is purged away.

The specification for the conditional variance and covariance follows that of Baba, Engle, Kraft and Kroner (1989) to ensure a positive definite covariance matrix,

---

10) The price of covariance risk, of course, must be the same across all assets according to the CAPM. However, it is computationally impossible to impose this cross-sectional restriction in a single system for a large number of assets. So, I choose to estimate the bivariate system of equations for each stock separately. Alternatively, one could use a multi-factor model that can handle the cross-sectional covariances in returns.

$$\mathbf{H}_t = \begin{bmatrix} h_{it} & h_{imt} \\ h_{imt} & h_{mt} \end{bmatrix}$$
$$= \mathbf{C}'\,\mathbf{C} + \mathbf{A}'\,\varepsilon_{t\text{-}1}\varepsilon_{t\text{-}1}\mathbf{A} + \mathbf{B}'\,\mathbf{H}_{t\text{-}1}\mathbf{B} + \mathbf{D}'\,\mathbf{u}_{t\text{-}1}\mathbf{u}'_{\;t\text{-}1}\mathbf{D} + \mathbf{F}_{t\text{-}1} + \mathbf{G}_{t\text{-}1}. \quad (10)$$

I impose that the coefficient matrices **A**, **B**, and **D** be symmetric and that **C** be upper triangular. Following the work of Engle and Ng (1993) and Glosten, Jagannathan and Runkle (1993), I allow asymmetric variance responses to past shocks via $\mathbf{u}_t$= Max $(\mathbf{0}, \varepsilon_t)$, and include the one-month Treasury bill yield, r_{ft}, in the diagonal matrix $\mathbf{F}_{t\text{-}1}$. Finally, the diagonal matrix $\mathbf{G}_{t\text{-}1}$ consists of an indicator variable for the month of the October 1987 market crash. The model parameters are estimated using the maximum likelihood method with the numerical algorithm of Berndt et. al. (1974). For inferences, robust standard errors in the presence of non-normality in residuals are computed following the quasi-maximum likelihood methods of Bollerslev and Wooldridge (1990).

Optimally, one should estimate both the CPR and TPR versions of the model for all 1500 stocks using their monthly returns. This approach, however, is prohibitively difficult in terms of computation. As a compromise, I classify all 1500 stocks into ten size groups based on their average size across months for which market capitalization is available (rounded up to the nearest integer), and estimate each model for 30 stocks randomly-selected from each size decile. I then average the parameter estimates across the 30 stocks in each size decile and assign them to each stock in the decile.[11)]

Although the parameter estimates are not reported (available upon request), the estimation results and model diagnostics are summarized as follows. First, for the market excess returns, the coefficient of the dividend yield, γ_{3m}, is significant for all size deciles in the TPR model and for most of the size deciles in the CPR model. This is consistent with the findings of Fama and French (1988, 1989). The junk bond spread, γ_{1m}, is also significant for some of the size deciles in the TPR model, but for

11) This second-best estimation approach is similar in spirit to the adjustment behavior of shrinkage estimators pioneered by James and Stein (1961) and popularized by Efron and Morris (1975). The understanding is that the structure of individual stock returns in the context of an equilibrium model is generally similar, at least within the size group to which the stock belongs.

none of the size deciles in the CPR model [see Campbell (1987) and Harvey (1989, 1991) for similar results]. In terms of R^2 and RMSE, the TPR model explains more of the market excess returns than the CPR model. Second, for the individual stocks' expected returns, the constant price of risk in the CPR model, λ_i, is insignificantly different from zero, implying that the CPR model fails to detect time-varying risk premia. For the TPR model, where the constant λ_i is replaced with the conditionally-expected market excess returns divided by their conditional variances, I obtain strong evidence of time-varying risk premia: the multiplicative parameter μ_i is significantly different from zero for most of the size deciles at the 10% level. In terms of R^2 and RMSE, the TPR model does better than the CPR model in explaining the individual stock returns. The R^2s for individual stocks range from 4.8% to 7%, which is similar to those of previous studies using monthly data, e.g., Keim and Stambaugh (1986), and Harvey (1989, 1991). Finally, residual diagnostics performed on the bivariate series of the standardized residuals for stocks with more than 12 observations show that the excess kurtosis is significant on average, although the Portmanteau tests up to the 12th order suggest that the model captures most of the serial dependence in the raw and squared residuals.

4.2 Bootstrap Results for the Conditional CAPM

The estimation results in the last subsection provide evidence of time-varying expected returns in individual stocks when the price of risk is allowed to vary over time. This evidence suggests that the trading rule returns should be evaluated in excess of the time-varying expected returns. Of course, the expected return for an individual stock is estimated from data; thus, it is random by nature and only one of many possible summary measures of the return distribution. Moreover, it is difficult to devise an analytical test for trading rule returns in excess of the time-varying expected returns.[12] I therefore use the bootstrap

---

12) This is especially true when the time-varying expected returns are specified using a GARCH-M model whose asymptotic distributions are not yet well-known. In contrast, it is relatively easy to develop a test for significance of trading rule excess returns when the expected returns are assumed to be constant. See, for instance, Sweeney (1986, 1988).

method that can generate full simulated distributions of trading rule returns under the null model of the conditional CAPM. If the actual returns lie within some confidence intervals of the simulated distributions, then the trading rule returns can be interpreted as fair compensation for the time-varying risk assumed by investors following the trading rules.

The bootstrap test under the null model of the conditional CAPM is somewhat different from that under the random walk model. Specifically, the procedure is as follows:

(1) The model parameters for the conditional CAPM are estimated for 30 stocks randomly-selected from each size decile. The parameters are averaged across the 30 stocks in each size decile and assigned to each of the stocks in the size decile.

(2) Using these parameters, I estimate a time series of the standardized residual vectors for each stock using $\hat{\mathbf{z}}_t = \hat{\mathbf{H}}_t^{-1/2}\varepsilon_t$, where $\hat{\mathbf{H}}_t^{-1/2}$ is the inverse of the Cholesky factor of the estimated variance-covariance matrix $\hat{\mathbf{H}}_t$.

(3) I scramble the estimated standardized residual vectors $\hat{\mathbf{z}}_t$ with replacement.

(4) The evolution of the simulated $\hat{\mathbf{H}}_t$, observations on the individual stock returns, and the market returns are generated recursively using the scrambled residual series and the estimated parameters.

(5) Trading rules are applied to these new return series and the empirical distributions of the trading rule returns are computed by repeating steps (3) through (5) 500 times.

Table 5 presents the bootstrap results for the 6-month/6-month relative-strength strategy in Panel A and for the 3-year/3-year contrarian strategy in Panel B. The actual returns to both trading strategies, with associated t-statistics, are reproduced from Table 3 for comparison with the simulated returns. Recall from Table 3 that both the winner-loser spreads over the 6 months and the loser-winner spreads over the 3 years are all statistically significant in terms of both conventional t-statistics and simulated p-values, suggesting that these strategies appear profitable. However, the simulated returns under the TPR model in the lower part of Panel A is 1.07% per month, which is higher than the actual profit of 1.0% per month. Its simulated p-value is 70.2%, suggesting that the actual return of 1.0% per month is not unusual under the TPR model and, thus, explainable by the

Table 5. Bootstrap Tests for Conditional CAPM

The standardized residual vectors for each stock and market excess returns are resampled with replacement and used along with the estimated parameters to generate the bivariate GARCH-M simulated series. The 6-month/6-month strategy is then applied to the simulated return series for the 1500 stocks. Its mean monthly returns for each portfolio are reported in Panel A ("L" denotes the lowest past 6-month return decile; "W" denotes the highest past 6-month return decile; P2 through P9 denote the other portfolios in ascending order). In Panel B, the 3-year/3-year contrarian strategy is applied to the same set of the simulated return series and its holding period returns are reported ("L3/1" denotes the lowest past 3-year return portfolio held for the subsequent 1-year, "W3/1" denotes the highest past 3-year return portfolio held for the subsequent 1-year, and so on). "W-L" or "L-W" denotes the zero cost, winner minus loser or loser minus winner portfolio. The simulated mean returns are from 500 simulations. The *p*-value denotes the fraction of the 500 simulations that generate returns larger than the actual ones. The 5% and 95% fractiles from the empirical distributions for each portfolio's returns are reported.

Panel A. 6-month/6-month Relative-Strength Strategy

	Actual		Simulation			
Portfolio	Return	(*t*-stat)	Return	(*p*-val)	5%	95%
			(1) Constant price of risk model			
L	0.0076	(1.52)	0.0080	(0.674)	0.0064	0.0095
P2	0.0108	(2.65)	0.0112	(0.784)	0.0103	0.0122
P3	0.0125	(3.37)	0.0117	(0.074)	0.0109	0.0126
P4	0.0125	(3.56)	0.0119	(0.090)	0.0111	0.0126
P5	0.0133	(3.95)	0.0120	(0.002)	0.0113	0.0128
P6	0.0133	(4.09)	0.0122	(0.010)	0.0116	0.0129
P7	0.0132	(4.01)	0.0126	(0.086)	0.0119	0.0134
P8	0.0137	(4.09)	0.0130	(0.076)	0.0122	0.0138
P9	0.0150	(4.20)	0.0136	(0.008)	0.0128	0.0145
W	0.0176	(4.35)	0.0147	(0.002)	0.0133	0.0161
W-L	0.0100	(3.21)	0.0067	(0.008)	0.0046	0.0086
			(2) Time-varying price of risk model			
L	0.0076	(1.52)	0.0050	(0.000)	0.0035	0.0064
P2	0.0108	(2.65)	0.0097	(0.032)	0.0087	0.0106
P3	0.0125	(3.37)	0.0109	(0.000)	0.0100	0.0117
P4	0.0125	(3.56)	0.0115	(0.034)	0.0108	0.0124
P5	0.0133	(3.95)	0.0121	(0.004)	0.0113	0.0128
P6	0.0133	(4.09)	0.0126	(0.048)	0.0119	0.0133
P7	0.0132	(4.01)	0.0132	(0.434)	0.0124	0.0139
P8	0.0137	(4.09)	0.0139	(0.618)	0.0131	0.0147
P9	0.0150	(4.20)	0.0147	(0.286)	0.0138	0.0155
W	0.0176	(4.35)	0.0157	(0.012)	0.0143	0.0170
W-L	0.0100	(3.21)	0.0107	(0.702)	0.0086	0.0129

Panel B. 3-year/3-year Contrarian Strategy

	Actual		Simulation			
Portfolio	Return	(*t*-stat)	Return	(*p*-val)	5%	95%
			(1) Constant price of risk model			
L3/1	0.2247	(1.62)	0.1164	(0.000)	0.0650	0.1681
L3/2	0.3444	(2.33)	0.1189	(0.000)	0.0651	0.1752
L3/3	0.2202	(2.59)	0.1249	(0.002)	0.0661	0.1883
W3/1	0.1847	(2.62)	0.2629	(0.992)	0.2191	0.3165
W3/2	0.1148	(1.89)	0.2568	(1.000)	0.2032	0.3093
W3/3	0.0947	(1.48)	0.2482	(1.000)	0.1892	0.3102
L-W3/1	0.0400	(0.41)	-0.1465	(0.000)	-0.2223	-0.0776
L-W3/2	0.2295	(1.89)	-0.1379	(0.000)	-0.2210	-0.0663
L-W3/3	0.1255	(2.63)	-0.1234	(0.000)	-0.2119	-0.0462
			(2) Time-varying price of risk model			
L3/1	0.2247	(1.62)	0.1481	(0.010)	0.0950	0.2005
L3/2	0.3444	(2.33)	0.1805	(0.000)	0.1249	0.2403
L3/3	0.2202	(2.59)	0.1695	(0.084)	0.1115	0.2306
W3/1	0.1847	(2.62)	0.2652	(0.998)	0.2187	0.3128
W3/2	0.1148	(1.89)	0.2663	(1.000)	0.2158	0.3139
W3/3	0.0947	(1.48)	0.2527	(1.000)	0.1965	0.3058
L-W3/1	0.0400	(0.41)	-0.1172	(0.000)	-0.1889	-0.0509
L-W3/2	0.2295	(1.89)	-0.0858	(0.000)	-0.1612	-0.0113
L-W3/3	0.1255	(2.63)	-0.0832	(0.000)	-0.1599	-0.0007

expected returns implied by the model. In contrast, the CPR model in the upper part of Panel A implies winner-loser spreads of only 0.67% per month, which are significantly lower than the actual spreads of 1.0% per month (*p*-value of 0.8%). This result demonstrates that the TPR model with a time-varying price of risk implies much broader winner-loser spreads (1.07% versus 0.67%) than the CPR model with a constant price of risk. This finding emphasizes the importance of modeling time-variation in the price of risk as a source of variation in the individual stock's expected returns.

The bootstrap results for the long-term contrarian strategy are presented in Panel B of Table 5. Unlike the case of the medium-term relative-strength strategy, simulated contrarian profits (loser-winner spreads) under both CPR and TPR models are negative (-12.34% and -8.32% for three years, respectively) and are not comparable to the actual profits (12.55% for three years) with simulated p-values of 0.0%. Rather, both CPR and TPR models imply that prior winners continue to outperform prior losers, thus failing to capture the pattern of long-term return reversals. In sum, profits from the medium-term relative-strength strategy can be successfully explained by the TPR version of the conditional CAPM, whereas profits from the long-term contrarian strategy are difficult to reconcile with existing asset pricing models.

4.3 Bootstrap Results for the Conditional CAPM: Size- and Beta-based Subsamples

In this subsection, I perform further analyses of the bootstrap tests using subsamples based on firm sizes and market model betas: three size-based subsamples (small-, medium-, and large-size stocks) and three beta-based subsamples (low-, medium-, and high-beta stocks). These supplementary tests check the robustness of the results presented in the last subsection across subsamples with different degrees of size- and market model beta-related risk exposure.

Table 6 presents the bootstrap test results for the size-based subsamples. The actual returns to both trading strategies, with associated t-statistics, are reproduced from Table 4 for comparison with the simulated returns. For the relative-strength strategy in Panel A, simulated winner-loser spreads for the small-size subsample are 0.72% and 1.17% per month for the CPR and TPR models, respectively, and are not significantly different from the actual spreads of 0.75% per month as indicated by the simulated p-values. However, for the medium- and large-size subsamples, the simulated winner-loser spreads are significantly lower than the actual spreads for both CPR and TPR models, indicating that the zero-cost strategy of buying winners and selling losers within these subsamples generates profits greater than the asset pricing model implies.

Panel B of Table 6 presents the size subsample results for the 3-year/3-year contrarian strategy. The zero-cost strategy of buying losers, selling winners, and holding the resulting position for 3 years generates negative returns for all size subsamples for

Table 6. Bootstrap Tests for Conditional CAPM: Size-Subsample Results

The standardized residual vectors for each stock and market excess returns are resampled with replacement and used along with the estimated parameters to generate the bivariate GARCH-M simulated series. The 6-month/6-month strategy is then applied to the simulated return series for the size-based subsample from the 1500 stocks and its mean monthly returns for each portfolio are reported in Panel A ("L" denotes the lowest past 6-month return decile; "W" denotes the highest past 6-month return decile; P2 through P9 denote the other portfolios in ascending order). In Panel B, the 3-year/3-year contrarian strategy is applied to the same set of the simulated return series and its holding period returns are reported ("L3/1" denotes the lowest past 3-year return portfolio held for the subsequent 1-year, "W3/1" denotes the highest past 3-year return portfolio held for the subsequent 1-year, and so on). "W-L" or "L-W" denotes the zero cost, winner minus loser or loser minus winner portfolio. The simulated mean returns are from 500 simulations. The *p*-value denotes the fraction of the 500 simulations that generate returns larger than the actual ones. The 5% and 95% fractiles from the empirical distributions for each portfolio's returns are reported.

Panel A. 6-month/6-month Relative-Strength Strategy

	Size 1		Size 2		Size 3	
Portfolio	Actual Ret (*t*-stat)	Simulation Ret (*p*-val)	Actual Ret (*t*-stat)	Simulation Ret (*p*-val)	Actual Ret (*t*-stat)	Simulation Ret (*p*-val)
			(1) Constant price of risk model			
L	.0089(1.59)	.0051(.004)	.0039(0.76)	.0091(1.00)	.0075(1.71)	.0142(1.00)
P2	.0137(2.85)	.0087(.000)	.0087(2.04)	.0120(1.00)	.0086(2.39)	.0134(1.00)
P3	.0155(3.45)	.0095(.000)	.0124(3.14)	.0125(.538)	.0105(3.22)	.0128(1.00)
P4	.0161(3.59)	.0099(.000)	.0131(3.55)	.0127(.292)	.0103(3.33)	.0124(1.00)
P5	.0169(3.92)	.0102(.000)	.0136(3.81)	.0129(.200)	.0111(3.69)	.0123(.988)
P6	.0168(4.00)	.0107(.000)	.0136(3.95)	.0132(.278)	.0109(3.72)	.0124(.992)
P7	.0169(3.90)	.0109(.000)	.0135(3.83)	.0136(.516)	.0109(3.70)	.0127(1.00)
P8	.0163(3.87)	.0112(.000)	.0139(3.86)	.0141(.574)	.0112(3.78)	.0131(.998)
P9	.0184(4.19)	.0117(.000)	.0152(3.90)	.0146(.262)	.0124(3.85)	.0140(.978)
W	.0164(3.51)	.0123(.002)	.0180(4.17)	.0158(.038)	.0178(4.53)	.0162(.128)
W-L	.0075(2.41)	.0072(.436)	.0141(4.29)	.0067(.000)	.0103(3.14)	.0020(.000)
			(2) Time-varying price of risk model			
L	.0089(1.59)	.0029(.000)	.0039(0.76)	.0067(.962)	.0075(1.71)	.0097(.898)
P2	.0137(2.85)	.0081(.000)	.0087(2.04)	.0113(.996)	.0086(2.39)	.0116(1.00)
P3	.0155(3.45)	.0096(.000)	.0124(3.14)	.0123(.438)	.0105(3.22)	.0117(.950)
P4	.0161(3.59)	.0105(.000)	.0131(3.55)	.0128(.330)	.0103(3.33)	.0119(.998)
P5	.0169(3.92)	.0112(.000)	.0136(3.81)	.0133(.354)	.0111(3.69)	.0121(.966)
P6	.0168(4.00)	.0118(.000)	.0136(3.95)	.0136(.472)	.0109(3.72)	.0124(.994)
P7	.0169(3.90)	.0125(.002)	.0135(3.83)	.0140(.762)	.0109(3.70)	.0127(1.00)
P8	.0163(3.87)	.0132(.000)	.0139(3.86)	.0146(.776)	.0112(3.78)	.0132(1.00)
P9	.0184(4.19)	.0140(.000)	.0152(3.90)	.0151(.462)	.0124(3.85)	.0137(.948)
W	.0164(3.51)	.0146(.098)	.0180(4.17)	.0161(.058)	.0178(4.53)	.0143(.004)
W-L	.0075(2.41)	.0117(.976)	.0141(4.29)	.0094(.010)	.0103(3.14)	.0045(.004)

Panel B. 3-year/3-year Contrarian Strategy

Portfolio	Size 1 Actual Ret (*t*-stat)	Size 1 Simulation Ret (*p*-val)	Size 2 Actual Ret (*t*-stat)	Size 2 Simulation Ret (*p*-val)	Size 3 Actual Ret (*t*-stat)	Size 3 Simulation Ret (*p*-val)
			(1) Constant price of risk model			
L3/1	.2620(1.62)	.1096(.004)	.1538(1.52)	.1090(.162)	.0895(1.38)	.1467(.814)
L3/2	.3601(2.08)	.1210(.000)	.2344(2.28)	.1070(.014)	.1424(2.25)	.1420(.468)
L3/3	.1924(2.05)	.1325(.200)	.2519(2.91)	.1071(.014)	.1223(1.88)	.1431(.590)
W3/1	.2373(2.17)	.2942(.786)	.1763(2.22)	.2556(.942)	.1258(2.53)	.2307(.986)
W3/2	.1485(1.46)	.2847(.980)	.1335(1.92)	.2516(.986)	.0488(0.97)	.2232(1.00)
W3/3	.1619(1.83)	.2702(.906)	.0979(1.16)	.2461(1.00)	.0810(1.33)	.2195(.994)
L-W3/1	.0247(0.22)	-.1846(.010)	-.0226(-0.4)	-.1465(.052)	-.0363(-0.5)	-.0840(.280)
L-W3/2	.2116(1.64)	-.1637(.000)	.1009(1.52)	-.1446(.000)	.0936(1.26)	-.0812(.034)
L-W3/3	.0304(0.36)	-.1377(.062)	.1540(2.14)	-.1390(.002)	.0413(0.54)	-.0764(.090)
			(2) Time-varying price of risk model			
L3/1	.2620(1.62)	.1366(.022)	.1538(1.52)	.1508(.480)	.0895(1.38)	.1274(.686)
L3/2	.3601(2.08)	.1854(.006)	.2344(2.28)	.1707(.138)	.1424(2.25)	.1407(.466)
L3/3	.1924(2.05)	.1753(.376)	.2519(2.91)	.1501(.086)	.1223(1.88)	.1398(.558)
W3/1	.2373(2.17)	.2569(.574)	.1763(2.22)	.2722(.984)	.1258(2.53)	.2421(.992)
W3/2	.1485(1.46)	.2573(.934)	.1335(1.92)	.2845(1.00)	.0488(0.97)	.2494(1.00)
W3/3	.1619(1.83)	.2390(.840)	.0979(1.16)	.2697(1.00)	.0810(1.33)	.2340(100)
L-W3/1	.0247(0.22)	-.1202(.056)	-.0226(-0.4)	-.1214(.100)	-.0363(-0.5)	-.1147(.178)
L-W3/2	.2116(1.64)	-.0719(.006)	.1009(1.52)	-.1138(.006)	.0936(1.26)	-.1087(.018)
L-W3/3	.0304(0.36)	-.0637(.174)	.1540(2.14)	-.1196(.002)	.0413(0.54)	-.0942(.072)

both CPR and TPR models. For example, under the TPR model, the simulated loser-winner spreads are all negative and are never comparable in magnitude to actual spreads, though the simulated *p*-values are insignificant for small- and large-size subsamples (17.4% and 7.2%, respectively). In sum, both CPR and TPR models fail to replicate long-term contrarian profits as high as the actual ones within size subsamples.

Table 7 presents the results for the beta-based subsamples. The results for the relative-strength strategy in Panel A generally conform to those of the overall sample presented in Panel A of Table 5. That is, in all beta subsamples under the TPR model, we observe simulated winner-loser spreads as high as the actual spreads with insignificant simulated *p*-values ranging from

Table 7. Bootstrap Tests for Conditional CAPM: Beta-Subsample Results

The standardized residual vectors for each stock and market excess returns are resampled with replacement and used along with the estimated parameters to generate the bivariate GARCH-M simulated series. The 6-month/6-month strategy is then applied to the simulated return series for the beta-based subsample from the 1500 stocks. Its mean monthly returns for each portfolio are reported in Panel A ("L" denotes the lowest past 6-month return decile; "W" denotes the highest past 6-month return decile; P2 through P9 denote the other portfolios in ascending order). In Panel B, the 3-year/3-year contrarian strategy is applied to the same set of the simulated return series and its holding period returns are reported ("L3/1" denotes the lowest past 3-year return portfolio held for the subsequent 1-year, "W3/1" denotes the highest past 3-year return portfolio held for the subsequent 1-year, and so on). "W-L" or "L-W" denotes the zero cost, winner minus loser or loser minus winner portfolio. The simulated mean returns are from 500 simulations. The *p*-value denotes the fraction of the 500 simulations that generate returns larger than the actual ones. The 5% and 95% fractiles from the empirical distributions for each portfolio's returns are reported.

Panel A. 6-month/6-month Relative-Strength Strategy

	Beta 1		Beta 2		Beta 3	
Portfolio	Actual Ret (*t*-stat)	Simulation Ret (*p*-val)	Actual Ret (*t*-stat)	Simulation Ret (*p*-val)	Actual Ret (*t*-stat)	Simulation Ret (*p*-val)
			(1) Constant price of risk model			
L	.0080(1.48)	.0079(.470)	.0075(1.51)	.0077(.552)	.0033(0.72)	.0080(.996)
P2	.0124(2.68)	.0112(.114)	.0103(2.44)	.0111(.780)	.0091(2.53)	.0113(.988)
P3	.0133(3.05)	.0117(.026)	.0132(3.33)	.0117(.064)	.0109(3.50)	.0117(.844)
P4	.0126(2.91)	.0118(.132)	.0136(3.54)	.0120(.022)	.0118(3.93)	.0119(.524)
P5	.0144(3.49)	.0119(.000)	.0144(3.93)	.0122(.010)	.0118(4.04)	.0120(.598)
P6	.0150(3.67)	.0122(.000)	.0140(3.94)	.0124(.020)	.0121(4.29)	.0122(.594)
P7	.0150(3.68)	.0126(.000)	.0136(3.70)	.0127(.142)	.0120(4.29)	.0125(.742)
P8	.0149(3.65)	.0130(.002)	.0145(4.03)	.0131(.036)	.0123(4.29)	.0131(.860)
P9	.0164(3.93)	.0137(.008)	.0154(4.16)	.0136(.018)	.0142(4.57)	.0138(.306)
W	.0172(3.89)	.0150(.064)	.0187(4.68)	.0144(.002)	.0153(4.39)	.0150(.460)
W-L	.0091(2.97)	.0072(.182)	.0112(3.39)	.0067(.012)	.0120(3.19)	.0070(.010)
			(2) Time-varying price of risk model			
L	.0080(1.48)	.0048(.024)	.0075(1.51)	.0048(.030)	.0033(0.72)	.0051(.870)
P2	.0124(2.68)	.0097(.008)	.0103(2.44)	.0098(.274)	.0091(2.53)	.0096(.700)
P3	.0133(3.05)	.0109(.004)	.0132(3.33)	.0110(.004)	.0109(3.50)	.0107(.408)
P4	.0126(2.91)	.0116(.086)	.0136(3.54)	.0117(.010)	.0118(3.93)	.0114(.286)
P5	.0144(3.49)	.0121(.000)	.0144(3.93)	.0123(.008)	.0118(4.04)	.0119(.556)
P6	.0150(3.67)	.0126(.000)	.0140(3.94)	.0127(.046)	.0121(4.29)	.0125(.716)
P7	.0150(3.68)	.0131(.012)	.0136(3.70)	.0133(.366)	.0120(4.29)	.0131(.958)
P8	.0149(3.65)	.0138(.096)	.0145(4.03)	.0139(.212)	.0123(4.29)	.0139(.990)
P9	.0164(3.93)	.0145(.012)	.0154(4.16)	.0146(.220)	.0142(4.57)	.0150(.822)
W	.0172(3.89)	.0153(.088)	.0187(4.68)	.0155(.012)	.0153(4.39)	.0169(.872)
W-L	.0091(2.97)	.0105(.738)	.0112(3.39)	.0106(.374)	.0120(3.19)	.0117(.452)

Panel B. 3-year/3-year Contrarian Strategy

	Beta 1		Beta 2		Beta 3	
Portfolio	Actual Ret (*t*-stat)	Simulation Ret (*p*-val)	Actual Ret (*t*-stat)	Simulation Ret (*p*-val)	Actual Ret (*t*-stat)	Simulation Ret (*p*-val)
			(1) Constant price of risk model			
L3/1	.2411(1.54)	.1216(.040)	.2030(1.76)	.1122(.028)	.1260(1.63)	.1183(.414)
L3/2	.3683(1.99)	.1214(.000)	.2689(2.35)	.1135(.006)	.1357(1.84)	.1221(.388)
L3/3	.2202(2.21)	.1315(.124)	.1419(1.68)	.1215(.362)	.1208(2.12)	.1236(.490)
W3/1	.2004(2.47)	.2561(.804)	.1386(2.28)	.2689(1.00)	.1679(2.73)	.2572(.950)
W3/2	.1476(1.92)	.2476(.948)	.0866(1.77)	.2633(1.00)	.0472(0.79)	.2524(1.00)
W3/3	.1284(1.75)	.2454(.972)	.1003(1.43)	.2494(.998)	.0622(0.88)	.2448(.996)
L-W3/1	.0407(0.38)	-.1346(.028)	.0643(0.61)	-.1567(.000)	-.0420(-0.6)	-.1390(.116)
L-W3/2	.2207(1.45)	-.1262(.002)	.1823(1.76)	-.1498(.000)	.0885(0.85)	-.1302(.018)
L-W3/3	.0918(1.57)	-.1139(.032)	.0416(0.50)	-.1279(.022)	.0586(0.65)	-.1212(.028)
			(2) Time-varying price of risk model			
L3/1	.2411(1.54)	.1376(.050)	.2030(1.76)	.1463(.140)	.1260(1.63)	.1662(.716)
L3/2	.3683(1.99)	.1694(.000)	.2689(2.35)	.1802(.060)	.1357(1.84)	.1932(.764)
L3/3	.2202(2.21)	.1592(.174)	.1419(1.68)	.1664(.610)	.1208(2.12)	.1743(.736)
W3/1	.2004(2.47)	.2582(.860)	.1386(2.28)	.2724(.998)	.1679(2.73)	.2664(.958)
W3/2	.1476(1.92)	.2642(.992)	.0866(1.77)	.2708(1.00)	.0472(0.79)	.2609(1.00)
W3/3	.1284(1.75)	.2511(.994)	.1003(1.43)	.2564(.998)	.0622(0.88)	.2468(1.00)
L-W3/1	.0407(0.38)	-.1206(.018)	.0643(0.61)	-.1261(.006)	-.0420(-0.6)	-.1002(.246)
L-W3/2	.2207(1.45)	-.0948(.000)	.1823(1.76)	-.0905(.002)	.0885(0.85)	-.0677(.060)
L-W3/3	.0918(1.57)	-.0919(.030)	.0416(0.50)	-.0900(.056)	.0586(0.65)	-.0725(.104)

37.4% to 73.8%. For the CPR model, however, simulated spreads are significantly lower than the actual ones, except for the low-beta group. In terms of the magnitude of the spreads, the TPR model generates spreads much closer to the actual spreads than the CPR model: for example, for the actual spreads of 0.91%, 1.12%, and 1.2% per month for the low-, medium-, and high-beta groups, the corresponding simulated spreads are 1.05%, 1.06%, and 1.17%, respectively, whereas those under the CPR model are only 0.72%, 0.67%, and 0.7%, respectively.

Panel B of Table 7 presents the beta subsample results for the contrarian strategy. The results are also similar to those of the overall sample presented in Panel B of Table 5 in the sense that the simulated loser-winner spreads are all negative and not comparable to the actual ones: for example, the actual spreads over 3 years are 9.18%, 4.16%, and 5.86% for the low-, medium-, and high-beta groups, respectively, whereas the TPR model generates negative simulated spreads of -9.19%, -9.0%, and -7.25%, respectively. Although some of the simulated *p*-values for the loser-winner spreads appear insignificant (e.g., 5.6% and 10.4% for the medium- and high-beta groups under the TPR model), their simulated spreads are still not comparable to the actual ones. In sum, the TPR version of the conditional CAPM generates time-varying expected returns that are inconsistent with long-term return reversals, even within size- and beta-based subsamples. However, the profits from the medium-term relative-strength strategy are quite consistent with the TPR model, even after controlling for other measures of risk such as size and market model beta (except for the medium- and large-size subsamples).

5. Summary and Conclusions

This paper investigates the profitability of two kinds of portfolio trading strategies that are currently the most controversial in financial research: the relative-strength strategy based on medium-term return continuation (3 to 12 months) and the contrarian strategy based on long-term return reversals (2 to 5 years). Consistent with previous studies, I confirm that these trading rules generate significant profits, using stocks listed in the NYSE and AMEX from 1963 to 1989. For example, when applied to a random subsample of 1500 stocks, the 6-month/6-month relative-strength strategy that buys past winners, sells past losers, and holds the resulting position for 6 months generates a mean monthly excess return (winner-loser spread) of 1.0%. Similarly, the 3-year/3-year contrarian strategy that buys past losers, sells past winners, and holds the resulting position for 3 years generates a mean 3-year excess return (loser-winner spread) of 12.6%.

The statistical significance of these excess returns is reinforced by the random walk bootstrap tests, suggesting that the profits do not occur by chance. However, since the random walk bootstrap, by definition, destroys all the important time-series and cross-sectional dependence in stock returns, it does not properly account for risk-return relationships implicit in the measured profits. Further bootstrap analyses with conditional asset pricing models indicate that the time-varying expected returns are systematically related to profits for the relative-strength strategy but not for the contrarian strategy. Specifically, when the model allows the price of risk to vary over time, the model-implied winner-loser spread for the relative-strength strategy averages 1.07% per month, which is insignificantly different from the actual profits of 1.0% per month. Similar results hold even after controlling for other measures of risk such as an individual stock's beta and size, except for the medium- and large-size subsamples. This result implies that a large portion of the returns to the relative-strength strategy is a consequence of time-varying risk premia, and thus represents fair compensation for the time-varying risk assumed by investors following the trading strategy. This result is in sharp contrast to Jegadeesh and Titman's (1993) conjecture on the presence of positive feedback traders or the underreaction effect as possible explanations for the returns.

On the other hand, profits from the long-term contrarian strategy are shown to be most difficult to reconcile with existing asset pricing models. Even with a general model for time-varying risk, the model-implied loser-winner spread is negative (-8.32% for 3 years) and is never comparable to the actual profits (12.6% for 3 years). The same result holds for all size and beta subsamples. The reason for this contradictory result for the two trading strategies is that asset pricing models examined in this paper naturally build a structure of expected returns that are positively autocorrelated in the medium-term, but fail to capture the pattern of return reversals in the long-term. Thus, alternative asset pricing models that account for the return reversals or regime-switches in conditional variances, together with efficient methods of estimation for individual stock returns, may be more effective. The potential importance of these alternatives in explaining trading-rule profits is worth investigation in future research.

References

Baba, Y., R. Engle, D. Kraft, and K. Kroner, 1989, Multivariate simultaneous generalized ARCH, Working paper, University of California at San Diego.

Ball, R., and S. P. Kothari, 1989, Nonstationary expected returns: Implications for tests of market efficiency and serial correlation in returns, *Journal of Financial Economics* 25, 51-74.

Banz, R., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3-18.

Berndt, E., J. Hall, S. Hall, and J. Hausman, 1974, Estimation and inference in nonlinear structural models, *Annals of Economic and Social Measurement* 3, 653-665.

Black, F., M. Jensen, and M. Scholes, 1972, The capital asset pricing model: Some empirical tests, In M. Jensen (ed.), *Studies in the Theory of Capital Markets* (Praeger Press, New York, NY).

Blume, M., and R. Stambaugh, 1983, Biases in computed returns: An application to the size effect, *Journal of Financial Economics* 12, 387-404.

Bodurtha, J., and N. Mark, 1991, Testing the CAPM with time-varying risks and returns, *Journal of Finance* 46, 1485-1505.

Bollerslev, T., 1986, Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics* 31, 307-327.

Bollerslev, T., R. Chou, and K. Kroner, 1992, ARCH modeling in finance: A review of the theory and empirical evidence, *Journal of Econometrics* 52, 5-59.

Bollerslev, T., R. Engle, and J. Wooldridge, 1988, A capital asset pricing model with time-varying covariances, *Journal of Political Economy* 96, 116-131.

Bollerslev, T., and J. Wooldridge, 1990, Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances, *Econometric Reviews* 11, 143-172.

Brock, W., J. Lakonishok, and B. LeBaron, 1992, Simple technical trading rules and the stochastic properties of stock returns, *Journal of Finance* 47, 1731-1764.

Campbell, J., 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, 373-400.

Chan, K. C., 1988, On the contrarian investment strategy, *Journal of Business* 61, 147-163.

Chopra, N., J. Lakonishok, and J. Ritter, 1992, Measuring abnormal returns: Do stocks overreact? *Journal of Financial Economics* 31, 235-268.

Conrad, J., and G. Kaul, 1988, Time-variation in expected returns, *Journal of Business* 61, 409-425.

Conrad, J., and G. Kaul, 1989, Mean reversion in short-horizon expected returns, *Review of Financial Studies* 2, 225-240.

Conrad, J., and G. Kaul, 1993, Long-term market overreaction or biases in computed returns? *Journal of Finance* 48, 39-63.

DeBondt, W., and R. Thaler, 1985, Does the stock market overreact? *Journal of Finance* 40, 793-805.

DeBondt, W., and R. Thaler, 1987, Further evidence of investor overreaction and stock market seasonality, *Journal of Finance* 42, 557-581.

Efron, B., 1979, Bootstrap methods: Another look at the jackknife, *The Annals of Statistics* 7, 1-26.

Efron, B., 1982, The Jackknife, The Bootstrap and Other Resampling Plans, *Society for Industrial and Applied Mathematics* (Philadelphia, PA).

Efron, B., and C. Morris, 1975, Data analysis using Stein's estimator and its generalization, *Journal of American Statistical Association* 70, 311-319.

Engle, R., 1982, Autoregressive conditional heteroskedasticity with estimates of the variance of U.K. inflation, *Econometrica* 50, 987-1008.

Engle, R., and V. Ng., 1993, Measuring and testing the impact of news on volatility, *Journal of Finance* 48, 1749-1778.

Fama, E., 1970, Efficient capital markets: A review of theory and empirical work, *Journal of Finance* 25, 383-417.

Fama, E., and J. MacBeth, 1973, Risk, return and equilibrium: Empirical test, *Journal of Political Economy* 81, 607-636.

Fama, E., and K. French, 1988, Dividend yields and expected stock returns, *Journal of Financial Economics* 22, 3-26.

Fama, E., and K. French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23-49.

Fama, E., and K. French, 1992, The Cross-section of expected returns, *Journal of Finance* 47, 427-465.

Freedman, D., and S. Peters, 1984, Bootstrapping an econometric model: Some empirical results, *Journal of Business and Economic Statistics* 2, 150-158.

Glosten, L., R. Jagannathan, and D. Runkle, 1993, On the relationship between the expected value and the volatility of the nominal excess returns on stocks, *Journal of Finance* 48, 1779-1802.

Harvey, C., 1989, Time-varying conditional covariances in tests of asset pricing models, *Journal of Financial Economics* 24, 289-317.

Harvey, C., 1991, The world price of covariance risk, *Journal of Finance* 46, 111-157.

James, W., and C. Stein, 1961, Estimation with quadratic loss, *Proceedings of the Fourth Berkeley Symposium on Mathematical Statistics and Probability* 1, 361-379, Berkeley Press.

Jegadeesh, N., 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881-898.

Jegadeesh, N., and S. Titman, 1991, Short horizon return reversals and the bid-ask spread, Working paper, University of California at Los Angeles.

Jegadeesh, N., and S. Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48, 65-91.

Keim, D., and R. Stambaugh, 1986, Predicting returns in the stock and bond markets, *Journal of Financial Economics* 17, 357-390.

Kho, B. C., 1996, Time-varying risk premia, volatility, and technical trading rule profits: Evidence from foreign currency futures markets, *Journal of Financial Economics* 41, 249-290.

LeBaron, B., 1991, Technical trading rules and regime shifts in foreign exchange, Working paper, University of Wisconsin.

Lehmann, B., 1990, Fads, martingales and market efficiency, *Quarterly Journal of Economics* 105, 1-28.

Levich, R., and L. R. Thomas, 1993, The significance of technical trading-rule profits in the foreign exchange market: a bootstrap approach, *Journal of International Money and Finance* 12, 451-474.

Lo, A., and C. MacKinlay, 1990, When are contrarian profits due to stock market overreaction? *Review of Financial Studies* 3, 175-206.

McCurdy, T., and I. Morgan, 1992, Evidence of risk premiums in foreign currency futures markets, *Review of Financial Studies* 5, 65-83.

Ng, L., 1991, Tests of the CAPM with time-varying covariances: A multivariate GARCH approach, *Journal of Finance* 46, 1507-1521.

Sweeney, R. J., 1986, Beating the foreign exchange market, *Journal of Finance* 41, 163-182.

Sweeney, R. J., 1988, Some new filter rule tests: Methods and results, *Journal of Financial and Quantitative Analysis* 23, 285-300.

Turtle, H., A. Buse, and R. Korkie, 1994, Tests of Conditional Asset Pricing with time-varying moments and risk prices, *Journal of Financial and Quantitative Analysis* 29, 15-29.

Zarowin, P., 1990, Size, seasonality and stock market over-reaction, *Journal of Financial and Quantitative Analysis* 25, 113-125.