Extrapolation of Volatility Persistence in Stock Returns Based on Momentum and Price Reversal Strategies

Pradosh Simlai
University of North Dakota

In this paper we re-examine the influence of common risk factors in momentum and price reversal based portfolios and extrapolate the role of volatility persistence. We show that accounting for conditional heteroskedasticity increases the evidence that common risk factor misses the continuation of size and momentum based portfolio returns. We also provide a characterization of predictable heteroskedasticity in the variability of portfolio returns formed on various past-return behaviors and demonstrate that accounting for conditional heteroskedasticity increases the evidence that a three factor model captures the reversal for the post-formation returns of long-term losers (smaller distressed stocks) and winners (strong stocks). The interesting aspect of our result is that various classes of firms react differently to volatility risk and both the average size and book-to-market equity of firms are important sources of potential risk loading even under the presence of strong volatility persistence.

INTRODUCTION

A growing body of empirical research documents many patterns in average stock returns that are not explained by the traditional capital asset pricing model (CAPM) of Sharpe (1964) and Linter (1965), popularly known as average-return anomalies. Potential explanations (outside of CAPM domain) for the predictability of the average returns on common stocks fall, primarily into two areas: (1) some form of firm characteristics such as size, earnings/price, cash flow/price, book-to-market equity, past sales growth or (2) some forms of part return behavior that can be either long-term or short-term. For example, Stattman (1980), Banz (1981), Rosenberg, Reid, and Lanstein (1985), and Lakonishok, Shleifer and Vishny (1994) showed that a firm’s average stock return is related to its size (ME = stock price × number of shares), book-to-market equity (BE/ME = book value of common equity/market value of common equity), PE ratio (E/P = earnings/price), CP ratio (C/P = cash flow/price), and past sales growth. DeBondt and Thaler (1985) find a reversal in long-term returns; stocks that experienced poor performance over 3-5 year horizons tended to outperform prior-period winners during the subsequent 3-5 years. Jegadeesh and Titman (1993) find a continuation in short-term returns; stocks with higher returns over 3-12 months holding period tend to have higher future returns and on average short-term past winners continue to outperform short-term past-losers.

In a series of seminal papers, Fama and French (1992a, 1992b) demonstrated the joint roles of market beta and various firm characteristics such as size, earnings/price, leverage and book-to-market equity in the cross–section of average stock returns. In other related papers, Fama and French (1993, 1995, 1996) argued that many of the average-return anomalies are related and they are captured by a three-factor model. Fama and French uses time series approach to identify five common risk factors in the returns to stocks and bonds and showed that stock returns have shared variation due to both stock-market factors and bond-market factors. In addition, they showed that the three factor model do not fail to capture the returns to portfolios formed on E/P, C/P, and sales growth. In the present paper, we investigate a similar relationship between the common stock market risk factors and stock return variability of different investment strategies by using generalized autoregressive conditional heteroskedastic (GARCH) model. Our presentation assumes that there are three stock-market factors: an overall market factor and factors related to firm size and the ratio of book-to-market value of equity. As Durack, Durand and Maller (2004) noted, the Fama-French three factor model has succeeded CAPM as the paradigm within which asset prices are analyzed. Therefore it is critical to study if the support for three factor model is sensitive to model specification when we want to justify its explanatory power for the continuation of short-term returns and reversal of long-term returns. More specifically, we show if the portfolios constructed to mimic risk factors related to size and momentum still captures strong common variation in short-term and long-term stock returns when the asset pricing model is intrinsically conditionally heteroskedastic. Even though researchers have made considerable amount of progress [e.g., see French, Schwert and Stambaugh (1987), Bollerslev, Engle and Wooldridge (1988), and Jegannathan and Wang (1996)] in identifying various conditionally heteroskedastic CAPM models with better explanatory powers, for some reason there is absolutely no work on the role and characterization of underlying volatility in explaining average-return anomalies.

Throughout the paper we examine the effect of volatility persistence on some common empirical tests. We show if the existence of volatility persistence can alter explanatory power of three factor model for the continuations of short-term and reversal of long-term average returns. The persistence of volatility predicted by our model is similar to those that can be estimated by more complex GARCH procedures. Our study is unique in some important aspects. First, it provides a more realistic measure of market betas and common risk factors for momentum and price reversal based portfolios when the underlying conditional variance is not constant over time and is predicted by past forecast errors. Second, by not employing an arbitrary exogenous variable to explain heteroskedasticity it captures some of the effects of omitted variables and nonnormality problems of the regression disturbance term.

In the following section we first describe the data set and methodology used throughout the paper. Then we present the main empirical results in two parts. First we outline our findings regarding the performance of various portfolios based on size and momentum. In the second part, we describe the results by comparing various momentum and simple price reversal strategies. The final section concludes the paper.

DATA AND METHODOLOGY

We use the procedure described in Fama and French (1993) to construct mimicking risk factors and excess returns. The mimicking risk factors in returns relating to size and BE/ME are based on the intersection of 2 sizes (market equity) and 3 momentum groups and the excess returns are based on 25 size-momentum stock portfolios. The returns on all the portfolios formed on size and momentum equity are obtained from Kenneth French[1]. The results are based on the period from July, 1926 to June, 2007. We utilize median NYSE size (price time's shares) to break all NYSE, Amex and NASDAQ stocks into two groups, small and big. We also divide NYSE, Amex and NASDAQ stocks into three book-to-market equity groups based on the NYSE stocks ranked values of BE/ME. Following Fama and French (1992a, 1993), the intersection portfolios of the 2 size and 3 momentum groups gives us 6 portfolios. The risk factor in returns mimicking size is the difference, each month, between average returns on the 3 small stock portfolios and the average of the 3 big stock portfolios. The risk factor in returns mimicking BE/ME is the difference, each month, between the average of the returns on the 2 high-BE/ME portfolios and 2 low-BE/ME portfolios.

For dependent variable, we use two sets of portfolio for our analysis. First, we utilize the excess returns of 25 portfolios at the end of each June which are the intersections of 5 portfolios formed on size and 5 portfolios formed on the ratio of book-to-market equity. The size breakpoints for year t are the NYSE market equity quintiles at the end of June of year t. BE/ME for June of year t is the book equity for the last fiscal year end in t-1 divided by ME for December of t-1. The BE/ME breakpoints are NYSE quintiles. Small (S) and Big (B) stands for the smallest and biggest size quintiles; Low (L) and High (H) stands for the lowest and highest book-to-market quintiles. Our dependent variable is based on R_t which denotes the return on each of the 25 portfolios from July, 1926 to June, 2007. Among other variables used in the regression model, RM_t is the return of CRSP's value-weighted index on all NYSE, AMEX, and NASDAQ stocks, and RF_t is the 1-month T-bill rate obtained from Ibbotson and Associates.

For the second set of dependent variable, we utilize the excess-return of portfolios formed on three types of past returns of all NYSE firms on CRSP: short-run (t-12 to t-2), medium-term (t-20 to t-2), and long-term (t-60 to t-13). Similar to Fama and French (1996), our portfolios are formed monthly, and equal-weight simple returns in excess of the one-month bill rate are calculated for each month. That is, all 10 equal-weighted portfolios formed monthly on short-term (11 months), medium-term (18 months) and long-term (up to five years of) past returns of all NYSE firms on CRSP. At the beginning of each month firms with returns for month *t-x* and *t-y* for all NYSE firms are allocated to deciles based on their continually compounded returns between *t-x* and *t-y*. For example, decile 1 contains the NYSE stocks with the lowest continuously compounded past returns and decile 10 contains the NYSE stocks with the highest continuously compounded past returns.

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research.

TABLE 1: DESCRIPTIVE STATISTICS FOR 25 STOCK PORTFOLIOS FORMED ON SIZE AND MOMENTUM; JULY 1926 TO JUNE 2007, 960 OBSERVATIONS

Size	Momentum Quintile				
Quintile	Low	2	3	4	High
	Average of annual averages of firm size				
Small	20.84	26.49	28.13	29.16	29.99
2	129.18	132.31	133.59	133.52	133.75
3	299.62	306.22	308.46	308.65	302.52
4	746.73	768.87	769.43	765.21	759.78
Big	4555.26	5495.86	5551.5	5362.89	4824.43
	Average of annual number of firms in portfolio				
Small	563.67	246.75	194.03	190.88	318.18
2	84.31	75.27	71.6	73.60	105.49
3	49.81	58.15	60.51	61.84	76.63
4	37.59	51.18	55.46	58.10	61.84
Big	28.26	47.75	55.95	59.43	52.10

EMPIRICAL RESULTS

We first present average characteristics for twenty five portfolios to summarize our data. Average of annual averages of firm size and averages of annual number of firms for the twenty five portfolios are reported in Table 1. The various panel of Table 1 shows that portfolios in the largest size quintile have the biggest annual averages of firm size (i.e., fewest stocks but largest fractions of value) and the portfolios in the smallest size quintile have the most number of firms on average (i.e., largest stocks but smallest fractions of value). The panels also shows that as we move from lower to higher momentum portfolios, both average annual number of firms and average firm size increases, suggesting a positive correlation between those two variables.

Table 2 contains the summary statistics for the monthly dependent and explanatory returns (in percent) used in the time series regression. The first explanatory variable (RM-RF) is the excess return of CRSP's value-weighted index on all NYSE, AMEX, and NASDAQ stocks. The second variable SMB (small minus big) is the difference each month between the simple average of the percent returns on the three small-stock portfolios and the simple average of the returns on the three big-stock portfolios. The third regressor HML (high minus low) is the difference each month between the simple average of the returns on the two high-BE/ME portfolios and the average of the returns on the two low-BE/ME portfolios. From the second panel on the dependent variable we can see that for 25 portfolios formed on size and momentum the range of average excess returns varies from 0.23% to 1.67% per month. Except for the lowest momentum quintiles, the significant t-statistics justifies the robustness of the average excess returns.

TABLE 2: SUMMARY STATISTICS FOR THE MONTHLY DEPENDENT AND EXPLANATORY RETURNS (IN PERCENT) IN THE REGRESSION; JULY 1926 TO JUNE 2007, 960 OBSERVATIONS

				Autocorrelation for lag			Correlations		
Name	Mean	s.d	t	1	2	12			
				Explanatory returns					
RM-RF	0.64	5.43	3.66	0.10	-0.01	0.00	1.00		
SMB	0.16	3.36	1.53	0.14	0.08	0.10	0.31	1.00	
HML	0.51	3.57	4.43	0.16	0.00	0.03	0.19	0.09	1.00

Dependent variable: Excess returns on 25 stock portfolios formed on size and momentum quintiles

Size					Momentum Quintile					
Quintile	Low	2	3	4	High	Low	2	3	4	High
			Means					**Standard deviations**		
Small	0.67	1.13	1.36	1.44	1.67	11.09	9.69	9.00	9.30	8.95
2	0.32	0.88	0.96	1.19	1.49	9.88	8.33	7.30	7.39	8.01
3	0.33	0.72	0.83	0.96	1.37	9.55	7.68	6.90	6.32	7.04
4	0.38	0.59	0.75	0.92	1.31	9.45	7.28	6.42	6.15	6.50
Big	0.23	0.47	0.54	0.74	0.95	10.14	6.54	5.82	5.37	5.89

		t-statistics for means			
Small	1.88	3.62	4.70	4.80	5.78
2	1.00	3.30	4.09	4.98	5.79
3	1.09	2.90	3.73	4.70	6.03
4	1.25	2.51	3.62	4.65	6.27
Big	0.70	2.23	2.91	4.29	5.02

Note: RM is the return of CRSP's value-weighted index on all NYSE, AMEX, and NASDAQ stocks, and RF is the 1-month T-bill rate obtained from Ibbotson and Associates. SMB (small minus big) is the difference each month between the simple average of the percent returns on the three small-stock portfolios and the simple average of the returns on the three bog-stock portfolios. HML (high minus low) is the difference each month between the simple average of the returns on the two high-BE/ME portfolios and the average of the returns on the two low-BE/ME portfolios.

The Performance of Momentum based Portfolios and the Role of Common Risk Factors

Once we combine the evidence on the dependent variable with descriptive statistics from Table 1, it is evident that for all portfolios, average returns tend to increase with momentum quintiles whereas average annual number of firms tends to go down as we move from small to big size portfolios. The relationship is opposite as we compare the average of annual average firm size for different portfolios. In other words, both excess returns and annual average firm size tend to increase with the momentum quintiles suggesting a positive correlation between these two variables. Regarding explanatory variables, the average value of the market premium (RM-RF) is quite high 0.64% per month and statistically significant. Among other two variables, size related factor premium (average SMB returns) is 0.16% with an insignificant t-statistics of 1.53 and book-to-market factor premium (average HML returns) is 0.51% per month with a significant t-statistics of 4.43. Therefore, our preliminary investigation suggests a statistically robust role for only market premium and book-to-market factor premium. Also very low correlations across re-

TABLE 3: REGRESSIONS OF EXCESS STOCK RETURNS (IN PERCENT) ON THE EXCESS MARKET RETURN (RM-RF) AND THE MIMICKING RETURNS FOR THE SIZE (SMB) AND BOOK-TO-MARKET (HML) FACTORS; JULY 1926 TO JUNE 2007, 960 OBSERVATIONS,

$$R_t - RF_t = a + b\,[RM_t - RF_t] + s\,SMB_t + h\,HML_t + e_t$$

Dependent variable: Excess returns on 25 stock portfolios formed on size and Momentum

Size Quintile	Momentum Quintile Low	2	3	4	High	Low	2	3	4	High
			a					**t(a)**		
Small	-0.71	-0.14	0.16	0.28	0.66	-5.50	-1.51	1.99	2.86	5.48
2	-0.93	-0.20	0.01	0.27	0.59	-8.78	-2.92	0.13	4.35	6.80
3	-0.89	-0.32	-0.07	0.16	0.64	-7.47	-4.65	-1.29	2.87	7.26
4	-0.79	-0.35	-0.09	0.17	0.66	-6.08	-4.69	-1.64	3.08	7.41
Big	-1.02	-0.32	-0.16	0.15	0.43	-4.14	-3.87	-3.10	2.92	5.14
			b					**t(b)**		
Small	1.20	1.04	0.99	1.02	1.02	29.58	32.75	34.49	17.05	19.56
2	1.30	1.08	0.99	0.98	1.08	36.85	50.19	43.69	43.55	27.53
3	1.34	1.11	1.01	0.94	1.04	29.61	43.73	50.37	41.38	28.42
4	1.38	1.15	1.02	1.00	1.02	24.23	38.73	35.76	35.56	32.44
Big	1.17	1.07	1.00	0.96	1.00	14.53	29.62	41.69	49.93	37.59
			s					**t(s)**		
Small	1.48	1.29	1.18	1.19	1.13	14.27	9.43	10.29	6.86	7.21
2	1.01	0.91	0.71	0.81	0.80	12.68	10.46	16.48	6.72	6.40
3	0.67	0.54	0.50	0.45	0.50	9.66	13.84	17.00	10.31	5.21
4	0.36	0.22	0.24	0.21	0.24	3.95	4.37	6.49	6.05	3.07
Big	0.21	-0.08	-0.09	-0.16	-0.08	1.82	-1.31	-1.97	-4.11	-2.33
			h					**t(h)**		
Small	0.71	0.77	0.71	0.59	0.29	7.52	11.31	10.68	5.65	2.65
2	0.46	0.49	0.40	0.29	0.12	6.80	10.37	9.17	5.36	1.51
3	0.44	0.44	0.34	-0.08	0.20	4.81	10.34	9.88	4.06	-0.67
4	0.40	0.29	0.26	0.13	-0.09	3.56	7.16	7.02	3.11	-1.52
Big	0.31	0.21	0.15	-.002	-0.18	2.88	3.95	3.55	-0.10	-3.97
			R^2				**Test for ARCH effects**			
Small	0.85	0.88	0.89	0.84	0.79	25.5	9.73	4.78	155	8.12
2	0.88	0.92	0.91	0.90	0.84	51.0	68.7	10.0	2.36	0.70
3	0.84	0.92	0.93	0.90	0.82	61.5	19.6	66.5	84.7	2.68
4	0.80	0.88	0.91	0.90	0.80	22.2	102	35.0	44.0	14.6
Big	0.47	0.83	0.90	0.89	0.80	114	34.6	6.63	11.15	67.9

Note: For excess returns the 25 portfolios constructed at the end of each June, are the intersections of 5 portfolios formed on size (ME) and 5 portfolios formed on the ratio of book equity to market equity. R(t) denotes the return on each of the 25 portfolios from July, 1926 to June, 2007, RM(t) is the return of CRSP's value-weighted index on all NYSE, AMEX, and NASDAQ stocks, and RF(t) is the 1-month T-bill rate obtained from Ibbotson and Associates. SMB (small minus big) is the difference each month between the simple average of the percent returns on the three small-stock portfolios and the simple average of the returns on the three bog-stock portfolios. HML (high minus low) is the difference each month between the simple average of the returns on the two high-BE/ME portfolios and the average of the returns on the two low-BE/ME portfolios. All t-values are corrected for autocorrelation (with lag=3) and heteroskedasticity as suggested by Newey and West (1987). The null and alternative hypotheses for the tests for ARCH effects are no ARCH effects and ARCH(1) disturbance respectively.

gressors suggest the absence of multicollinearity and further influence their effectiveness as independent variable.

In Table 3 we report monthly time-series regression results of excess returns of CRSP's 25 size and momentum stock portfolios on two market factors and excess market returns. More specifically, it summarizes estimates of the following three-factor regression:

$$R_t - RF_t = a + b\,[RM_t - RF_t] + s\,SMB_t + h\,HML_t + e_t\,,\ E(e_t) = 0,\ V(e_t) = \sigma^2 \qquad (1)$$

In equation (1), RM_t is the return of CRSP's value-weighted index on all NYSE, Amex, and NASDAQ stocks, RF_t is the 1-month T-bill rate obtained from Ibbotson and Associates, SMB_t (small minus big) is the difference each month between the simple average of the percent returns on the three small-stock portfolios and the simple average of the returns on the three big-stock portfolios, and HML_t (high minus low) is the difference each month between the simple average of the returns on the two high-BE/ME portfolios and the average of the returns on the two low-BE/ME portfolios. The model says that the return on a portfolio in excess of the risk-free rate ($R_t - RF_t$) is explained by three factors: the excess return on a broad market portfolio ($RM_t - RF_t$), SMB and HML. All t-values are corrected for autocorrelation with lag 3 and heteroskedasticity as suggested by Newey and West (1987). The OLS estimates of model (1) supports the evidence from Banz (1981) that portfolio beta coefficients are monotonically decreasing in firm size. It is also consistent with the Fama and French (1993) results that low market value firms stocks (i.e., stocks with high book-to-equity ratios) earns average returns that are larger than the higher market value firms represented by low book-to-equity ratios. Overall, the result shows that all three independent variable captures strong variation in stock returns. The slope on the market premium varies between 0.94 and 1.38 and always significant in statistical terms. The slope coefficient of SMB, the mimicking return for the size factor, produces a wide range of estimates from -0.09 to 1.48. Except for big size quintile the SMB variable has a positive effect on the excess returns of various stock portfolios. Also the SMB slope coefficient is statistically significant in all but 3 portfolios. Overall, the SMB slope coefficients are higher for lower momentum quintile portfolios and lower for bigger size quintile portfolios.

The estimates of the HML coefficients, the mimicking return for the book-to-market factor, vary between -0.18 to 0.77 and are statistically significant in all but 4 stock portfolios. The empirical evidence on HML slope estimates suggests that returns on lower momentum and smaller size stocks are more sensitive to the risk captured by HML than the returns on higher momentum or bigger size stocks. On the other hand, the pattern on SMB slope estimates suggests that returns on bigger size or higher momentum stocks are less sensitive to the risk captured by the SMB than the returns on smaller size or lower momentum stocks. Interestingly for almost all momentum quintiles, both the HML and SMB slope shows a declining trend as we move from smaller to bigger size quintiles. The negative slope on SMB for four biggest size stocks corresponds to the pattern observed by Fama and French (1993). The value of R^2, a measure of overall performance of model fit, also shows persistent patterns. Except for the big size-low momentum portfolio all the portfolios has a value greater than 0.80. The precision of the model is highest for median size-momentum portfolios.

TABLE 4: REGRESSIONS OF EXCESS STOCK RETURNS (IN PERCENT) ON THE EXCESS MARKET RETURN (RM-RF) AND THE MIMICKING RETURNS FOR THE SIZE (SMB) AND BOOK-TO-MARKET (HML) FACTORS WITH CONDITIONAL HETEROSKEDASTICITY; JULY 1926 TO JUNE 2007, 960 OBSERVATIONS

$$R_t - RF_t = a + b\,[RM_t - RF_t] + s\,SMB_t + h\,HML_t + e_t\,,$$

$$e_t|F_{t-1} \sim N(0, q_t),\ q_t = d_0 + d_1\,(e_{t-1})^2 + d_2\,q_{t-1}$$

Dependent variable: Excess returns on 25 stock portfolios formed on size and momentum

Size	Momentum Quintile									
Quintile	Low	2	3	4	High	Low	2	3	4	High
			a					**t(a)**		
Small	-0.76	-0.10	0.15	0.26	0.35	-6.93	-1.42	1.88	4.35	3.73
2	-0.73	-0.10	0.00	0.29	0.33	-6.74	-1.69	0.02	3.91	4.07
3	-0.68	-0.20	-0.01	0.16	0.45	-7.29	-3.45	-0.10	3.11	6.18
4	-0.52	-0.20	-0.01	0.12	0.41	-5.00	-3.24	-0.18	2.62	4.67
Big	-0.52	-0.13	-0.05	0.10	0.29	-2.20	-1.91	-1.26	2.39	4.04
			b					**t(b)**		
Small	1.13	0.91	0.91	0.95	1.06	25.84	37.66	51.05	42.16	35.24
2	1.19	0.98	0.94	0.99	1.13	29.97	57.77	62.94	54.45	42.83
3	1.12	1.00	0.96	0.95	1.11	27.07	48.06	65.58	42.51	44.52
4	1.10	1.03	0.99	1.03	1.08	24.42	41.90	38.20	74.22	41.07
Big	0.98	0.95	0.96	0.98	1.05	21.82	34.13	61.90	57.88	46.21
			s					**t(s)**		
Small	1.50	1.14	1.03	0.96	1.19	15.88	22.74	33.90	29.22	24.46
2	1.07	0.90	0.75	0.76	0.76	18.79	28.38	33.57	24.16	10.11
3	0.74	0.61	0.52	0.50	0.50	11.69	20.36	23.16	14.38	7.05
4	0.40	0.26	0.22	0.22	0.20	7.28	9.02	4.72	9.29	2.61
Big	-0.10	-0.14	-0.15	-0.22	-0.16	-1.08	-4.25	-5.82	-8.03	-4.77
			h					**t(h)**		
Small	0.63	0.49	0.45	0.42	0.28	6.94	9.50	14.28	13.43	4.34
2	0.30	0.30	0.31	0.23	0.13	5.11	9.62	10.67	6.69	1.88
3	0.33	0.30	0.25	0.17	0.03	5.35	8.85	9.40	4.50	0.56
4	0.20	0.17	0.16	0.13	0.02	3.59	5.79	2.03	5.34	0.28
Big	0.14	0.06	0.08	0.01	-0.17	1.72	1.59	3.58	0.48	-4.67
			d_1					**t(d_1)**		
Small	0.12	0.12	0.14	0.23	0.22	1.54	2.37	2.87	2.02	3.09
2	0.14	0.17	0.16	0.15	0.28	2.39	4.37	2.86	2.91	2.07
3	0.18	0.18	0.14	0.09	0.26	2.52	2.60	3.33	2.32	3.58
4	0.21	0.24	0.30	0.12	0.17	5.16	3.64	0.09	4.89	2.99
Big	0.32	0.31	0.16	0.16	0.14	2.57	1.55	3.91	3.56	4.18
			d_2					**t(d_2)**		
Small	0.86	0.86	0.85	0.75	0.73	12.45	20.96	24.11	8.83	12.37
2	0.82	0.81	0.82	0.84	0.64	13.99	24.04	22.59	34.82	5.34
3	0.80	0.76	0.82	0.88	0.72	10.70	8.85	19.02	4.50	15.54
4	0.78	0.70	0.67	0.83	0.81	23.30	9.18	0.19	33.60	18.27
Big	0.56	0.66	0.82	0.79	0.81	4.06	3.09	17.70	17.15	20.08

TABLE 4 (CONTINUED)

Size Quintile	Low	Momentum Quintile 2	3	4	High
			R^2		
Small	0.46	0.69	0.82	0.84	0.69
2	0.60	0.80	0.87	0.83	0.70
3	0.44	0.73	0.84	0.67	0.69
4	0.40	0.66	0.81	0.88	0.64
Big	0.30	0.57	0.81	0.81	0.70

Note: For excess returns the 25 portfolios constructed at the end of each June, are the intersections of 5 portfolios formed on size (ME) and 5 portfolios formed on the momentum factor. R_t denotes the return on each of the 25 portfolios from July, 1926 to June, 2007, RM_t is the return of CRSP's value-weighted index on all NYSE, AMEX, and NASDAQ stocks, and RF_t is the 1-month T-bill rate obtained from Ibbotson and Associates. SMB (small minus big) is the difference each month between the simple average of the percent returns on the three small-stock portfolios and the simple average of the returns on the three bog-stock portfolios. HML (high minus low) is the difference each month between the simple average of the returns on the two high-BE/ME portfolios and the average of the returns on the two low-BE/ME portfolios. F_{t-1} is the information set and q_t is the conditional variance of the residual of the three factor regression.

To investigate the dependence structure of the disturbance term, we evaluate various summary statistics (not reported) about the sample moments and test for dependence of the residuals and their squares for our basic equation (1). The sample skewness and kurtosis for all 25 stock portfolios formed on size and momentum and the Jarque-Bera normality tests statistics indicate high level of non-normality. In addition, the Ljung-Box Q-statistics for residuals and squared residuals indicates significant temporal dependence and clustering of high volatility. The autocorrelation and partial autocorrelation also shows that there is persistence in the second moments for at least 8-10 lags for all the portfolios. The test for ARCH effects in Table 3 supports the existent of conditional heteroskedasticity in all but 24 stock portfolios. In other words, it justifies the estimation of all of our models with time varying conditional variance. We also employed the Augmented Dicky-Fuller unit root test to test for nonstationarity for all models investigated in Table 3 and do not find any evidence of nonstationarity. Finally, although not reported, in order to select an appropriate GARCH model, we test different p and q values for the standard symmetric GARCH(p,q) model using four different forecast measures. These measures, presented by Brooks (1997), are mean squared error, median squared error, mean absolute error and adjusted mean absolute percentage error. Based on various models ability to produce forecasts the selection procedure shows that GARCH(1,1) model performs best in almost all cases.

Table 4 reports our main results concerning monthly time-series regressions of the following model that incorporate conditional heteroskedasticity:

$$R_t - RF_t = a + b\,[RM_t - RF_t] + s\,SMB_t + h\,HML_t + e_t\,,\quad e_t|F_{t-1} \sim N(0, q_t),$$
$$q_t = d_0 + d_1\,(e_{t-1})^2 + d_2\,q_{t-1} \qquad (2)$$

Here mean part of the model is same as in equation (1), but the conditional variance (q_t) is a function of an intercept (d_0), a shock from the prior period (with a coefficient d_1) and the variance from last period (with a coefficient d_2). If $d_1=d_2=0$, the conditional variance is constant and e_t is conditionally homoskedastic as in Fama-French model (1). It is well known in the literature that GARCH procedure such as given by (2) indirectly takes account of the mutual dependence and nonnormality of the regression errors whereas the simple OLS procedure fails to acknowledge it.

The vital gain from the inclusion of conditionally heteroskedastic errors is clearly reflected in the improved standard errors of market betas and two common risk factors coefficients. Moreover, the autoregressive specification in (2) can capture any persistence in volatility and the sum of d_1 and d_2 measures the degree of that persistence in the conditional variance process. If $d_1, d_2 \geq 0$, a large shock to the current period variance will increase the next periods variance. Therefore, as $d_1 + d_2$ becomes close to one, the impact of shocks becomes more persistent. In addition, a GARCH specification such as given by equation (2) can also captures the tendency for volatility clustering; originally identified by Fama (1965) and Mandelbrot (1963).

From the results of Table 4 it is clear that even though there are no substantial differences in point estimates of slope coefficients the efficiency of all the model coefficients is markedly improved. The estimate of the intercepts suggests that both model (1) and (2) leaves a negative unexplained return for the portfolio of stocks in the lowest momentum quintiles, and a large positive unexplained return for the highest momentum quintiles. However, the number of intercepts that are close to zero has gone up from 4 in model (1) to 8 in model (2). Not to our surprise, the two stock market factors – SMB and HML – still captures strong common variation in average stock returns for momentum based portfolios. Among 25 portfolios based on size and momentum, the slopes on SMB range from about 1.50 for smallest size and lowest momentum quintiles to values near -0.21 in the biggest size and smallest momentum quintiles. The slopes on HML range from about 0.63 for portfolios in the smallest size and lowest momentum quintiles to -0.17 in the biggest size and highest momentum quintiles.

The empirical evidence on SMB slope estimates suggests that, except for smallest size and highest momentum quintile, returns on lower momentum and smaller size stocks are more sensitive to the risk captured by SMB than the returns on higher momentum or bigger size stocks. At the same time, the pattern on HML slope estimates indicates that returns on bigger size or higher momentum stocks are less sensitive to the risk captured by the HML than the returns on smaller size or lower momentum stocks. Similar to Table 3 results, with the incorporation of conditional heteroskedasticity, the slope coefficient for excess market return is significant for all 25 portfolios in both economic and statistical terms. The measure of systematic risk, b, indicates that market risk of the excess return on 25 portfolios return decrease gradually as we move from smaller to bigger size quintiles. The same observation is true for momentum quintiles except for the highest momentum portfolios. The above observations are also confirmed by figure 1a and 1b, which depicts the conditional volatility for smallest size with lowest momentum portfolio, and for biggest size with highest momentum portfolio respectively. It is evident that for both types portfolios the series is extremely variable and almost all the major episodes of high volatility are associated with marked drops.

For almost all momentum quintiles, both the HML and SMB slope shows a declining trend as we move from smaller to bigger size quintiles, an observation similar to Table 3 results. Most importantly, the t-statistics for slope coefficients on SMB is significant in all but one portfolio. This is in sharp contrast to the previous case of simple OLS where for the biggest size quintiles three SMB coefficients were insignificant. This implies that, by incorporating GARCH process, we may have picked up some effect of omitted variables from the regression model and a portion nonnormality of the regression disturbance terms. This observation is also supported by Figure 2a and 2b, where we plot the distributions of standardized innovations for smallest size with lowest momentum portfolio and biggest size with highest momentum portfolio regression respectively. Clearly the standardized innovations distributions are closer to normal that the residuals from homoskedastic regressions. The estimated results of the conditional variance equation in Table 4 shows that d_2 coefficient is always significant and d_1 coefficient is significant in all but two size and momentum sorted portfolios. However, there is a lack of homogeneity across different size and momentum quintiles concerning their magnitudes. For example, estimated value of d_2 ranges from 0.56 to 0.88 and estimated value of d_1 ranges from 0.09 to 0.32. The sum of d_1 and d_2 is high for all quintiles but always less than 1. In particular, the sum of d_1 and d_2 is above 0.95 in 21 out of 25 portfolios, implying that shocks to the volatility of these portfolios are much more persistent than shocks to other quintiles.

In terms of model specification and risk loadings, association of the SMB and HML slope with size and momentum quintiles seems to follow similar pattern as in Table 3. With conditional heteroskedasticity, the slopes on SMB (the mimicking returns for the size), are inversely related to the size of the firm. For all momentum quintiles, the SMB slope declines its value as we move from small to big size firms. Similarly, for all size firms, the SMB slope increases its value as we move from high to low momentum quintiles. Moreover, the slopes on HML, the mimicking return for the book-to-market factor, are also inversely related to both momentum and size quintiles. For the biggest size quintiles, the slope coefficient on SMB is always negative and as we move to higher momentum quintiles SMB slopes increases gradually. The results strongly support the evidence in Fama and French (1992a, 1993) that book-to-market equity is negatively correlated with average stock returns. In other words, in order to hold stocks with high book-to-market equity investors require high expected returns. This trend is in sharp contrast to Jegadeesh and Titman (1993, 1995) results that when portfolios are formed on short-term past returns, past winners tend to be future winners and past losers tend to be future losers, which is supported by our evidence from Table 2. Therefore, even though the three factor model captures a strong variation in the average excess returns it fails to capture the continuation of returns for portfolios formed on 12 to 2 months past returns.

Variability in Stock Returns Based on Both Momentum and Price Reversal Strategy

For many years, a debate has captured tremendous interest of finance academics and professionals about the performance of two investment strategies: popularly known as value and growth. Even though there is no common consensus about the distinction between types of stocks, broadly we can identify some basic characteristics of value and growth stocks. Typically, the firms with high ratios of BE/ME, E/P, or C/P are known as value stocks. Alternatively, firms that have low BE/ME, E/P, and C/P tend be known as growth stocks. In section 1, we briefly mentioned about some of these firm characteristics role in average-return anomalies. Fama and French (1992, 1995, 1996) and Lakonishok, Shleifer, and Vishny (1994) show that for U.S. stocks there is a strong value premium in average returns but that value premium is associated with relative distress. For example, high B/M, E/P, or C/P stocks have higher average returns but persistently low earnings than low B/M, E/P, or C/P stocks.

TABLE 5: DESCRIPTIVE STATISTICS FOR 10 STOCK PORTFOLIOS FORMED ON SIZE AND MOMENTUM; JANUARY 1926 TO DECEMBER 2007

	Deciles									
Portfolio Formation Months	Low	2	3	4	5	6	7	8	9	High
Average of annual averages of firm size										
t-12 to t-2	151	413	594	682	774	783	800	784	717	444
t-20 to t-2	201	463	573	666	713	727	736	700	593	289
t-60 to t-13	181	512	635	765	845	924	974	1050	1121	1142
Average of annual number of firms in portfolio										
t-12 to t-2	471	288	246	230	221	214	216	225	246	364
t-20 to t-2	477	300	271	255	246	242	241	246	262	416
t-60 to t-13	309	215	186	174	167	165	166	174	185	218

Note: The excess-returns of 10 portfolios are based on three types of past returns of all NYSE firms on CRSP: short-run (t-12 to t-2), medium-term (t-20 to t-2), and long-term (t-60 to t-13). These are equal-weighted simple returns in excess of the one-month bill rate calculated for each month. At the beginning of each month firms with returns for month *t-x* and *t-y* for all NYSE firms are allocated to deciles based on their continually compounded returns between *t-x* and *t-y*.

DeBondt and Thaler (1985, 1987) argue that when portfolios are formed on long-term (3 to 5 year) past returns, extreme losers (low past returns) outperform the market with high future returns and extreme winners (high past returns) underperform the market with low future returns. This is essentially in sharp contrast to the findings of Jegadeesh and Titman (1993) and Asness (1994). According to them the portfolios formed on short-term (up to a year of) past returns, past losers tend to be past losers and past winners tend to be future winners.

Therefore it is crucial to test if the three-factor model captures the continuation of short-term returns and reversal of long-term returns when the underlying model assumptions are violated. In the previous section, we took a first step in that direction and showed that the three factor model fails to capture the continuation of returns for 25 size and momentum sorted portfolios returns. In this section we supplement our previous result by showing exactly what role three factor model plays for return continuations and return reversals together for all NYSE firms between January 1926 and December 2007. For this we use all 10-decile equal-weight portfolios formed on various past returns as described in section 2.

Table 5 report some of the summary statistics for 10-decile stock portfolios formed on continuously compounded past returns. For portfolios based on long-term past returns (t-60 to t-13), simple average of annual averages of firm size increases as we move to upper deciles and average of annual number of firms in portfolio shows a reverse trend, i.e., as we move to lower deciles the average figure increases. For portfolios formed on short-term (t-12 to t-2) and medium-term (t-20 to t-2) average returns we don't observe any such clear pattern. For both of them, average of annual averages of firm size goes up until seventh decile and average of annual number of firms in portfolios decreases only upto seventh decile.

Table 6a to 6c contains our main result on the three factor regression of monthly excess stock returns (in percent) of 10 portfolios formed on past returns with and without conditional heteroskedasticity. Panel A of Tables 6a to 6c shows the average, standard deviations and t-statistics of excess returns on sets of ten equal-weight portfolios formed on short-run (t-12 to t-2), medium-term (t-20 to t-2) and long-term (t-60 to t-13) past returns respectively. The result on simple average estimate clearly indicates that continuation of short-term returns but reversal of medium-term and long-term returns. For example, for the portfolios formed on short-run past returns, the average excess return in the month after portfolio formation ranges from 0.03 percent for lowest decile of stocks to 1.27 percent for highest decile stocks (Table 6a). Similarly, for the portfolios formed on long-run past returns, the average excess return in the month after portfolio formation ranges from 1.20 percent for the decile of stocks with the worst long-term past returns to 0.61 percent for stocks with the best past returns (Table 6c).

Panel B of Table 6a-6c presents the regression results of monthly excess returns of 10-decile portfolios formed on past returns. We see that for all deciles, the regression intercepts are consistently small or insignificant. For example, short-term return based portfolio has three insignificant intercepts, medium-term return based portfolio has only four significant intercepts and long-term return based portfolio has virtually no significant intercepts. The explanatory power of the model in terms of R^2 is consistently high and a joint F-test (not reported) always supports the hypothesis that three factor model jointly describes the average excess returns. In terms of regression slopes, lower decile portfolios produce higher slopes on both SMB and even more so HML for short-term, medium-term and long-term return based portfolios. The surprising part of the story is that for portfolios formed on short term past returns, the intercepts are strongly negative for bottom six deciles and strongly positive for top four deciles. Moreover, short-term losers load more on SMB and HML than short-term winners (Table 6a). But we know that lower deciles represents short-term loser with low past returns and higher deciles represents short-term winners with high past returns. Therefore, what we find is contradicting assertions and the three factor model definitely misses the continuation of post-formation return of short-term losers and winners. We observe similar conclusions from Table 6b and 6c in terms of the loading on SMB and HML for long-term returns based portfolios but not for medium-term return based portfolios. Thus it is only for the long-term return based portfolios that the three factor model predicts a strong reversal for the post formation returns of short-term losers and winners.

Panel C of Table 6a-6c reports the estimation results of the three factor model with GARCH(1,1) error process. Overall, we see significant improvement in the three factor models performance without altering the basic tenets of causality between different variables. For short-term return based portfolios we see that short-term looser continue to load more on both SMB and HML (Table 6a). For medium-term returns based portfolios (Table 6b), the intercepts are strongly positive for lower deciles and strongly negative for upper deciles. Interestingly, for the same group of portfolios, compare to short-term winner, the short-term loser load more on SMB than HML. For long-term return based portfolios (Table 6c), the pattern in the loadings of both SMB and HML strongly supports the beauty of the three factor model. After the incorporation of conditional heteroskedasticity, none of the intercepts are statistically significant for all 10-deciles

TABLE 6A: THREE FACTOR REGRESSION RESULTS OF MONTHLY EXCESS STOCK RETURNS (IN PERCENT) OF 10 PORTFOLIOS FORMED ON PAST RETURNS WITH AND WITHOUT CONDITIONAL HETEROSKEDASTICITY (PORTFOLIO FORMATION MONTHS ARE t-12 TO t-2); JANUARY 1926 TO DECEMBER 2007

	Deciles									
	Low	2	3	4	5	6	7	8	9	High
Panel A: Mean, standard deviations and t-statistics of excess returns										
Mean	0.03	0.42	0.42	0.56	0.56	0.63	0.72	0.86	0.95	1.27
Std Dev	9.59	8.12	7.00	6.46	6.00	5.86	5.62	5.42	5.70	6.53
t-statistics	0.10	1.62	1.88	2.72	2.92	3.36	4.00	4.93	5.21	6.06
Panel B: Estimation results of simple three factor model										
a	-1.11	-0.58	-0.45	-0.24	-0.19	-0.09	0.07	0.26	0.35	0.72
b	1.37	1.23	1.12	1.06	1.00	1.00	0.98	0.95	0.97	1.02
s	0.57	0.22	0.06	0.03	-0.01	0.01	-0.05	-0.05	-0.01	0.15
h	0.34	0.34	0.27	0.23	0.21	0.15	0.05	-0.01	-0.05	-0.25
t(a)	-8.14	0.12	-5.23	-3.23	-3.25	-1.75	1.27	4.55	5.02	6.97
t(b)	29.1	25.9	32.5	31.9	36.2	52.7	49.8	48.5	41.1	27.8
t(s)	7.59	3.06	0.82	0.55	-0.08	0.16	-1.38	-1.82	-0.15	1.93
t(h)	3.70	3.55	4.32	5.23	4.30	5.27	1.77	-0.50	-1.26	-3.78
R^2	0.80	0.81	0.84	0.86	0.88	0.91	0.89	0.88	0.85	0.74
Panel C: Estimation results of three factor model with GARCH(1,1) error process										
a	-0.83	-0.41	-0.21	-0.11	-0.08	-0.03	0.06	0.19	0.25	0.50
b	1.15	1.03	0.95	0.97	0.94	0.99	1.00	0.98	1.02	1.10
s	0.60	0.17	0.04	-0.01	-0.00	-0.01	-0.09	-0.08	-0.03	0.13
h	0.19	0.10	0.08	0.10	0.12	0.10	0.04	-0.01	-0.05	-0.18
d_1	0.19	0.25	0.30	0.21	0.15	0.16	0.13	0.12	0.08	0.24
d_2	0.77	0.72	0.66	0.76	0.83	0.77	0.80	0.84	0.89	0.67
t(a)	-7.24	-4.13	-3.03	-1.87	-1.52	-0.68	1.34	3.68	3.92	5.58
t(b)	29.6	25.7	31.0	48.8	54.7	67.4	49.7	53.1	46.84	35.5
t(s)	8.30	3.18	1.26	-0.27	-0.20	-0.82	-3.31	-2.83	-0.94	1.90
t(h)	2.86	1.58	2.18	3.38	4.71	4.59	1.82	-0.28	-1.32	-2.93
$t(d_1)$	2.80	2.33	5.36	3.62	3.62	3.93	1.75	4.15	3.51	3.64
$t(d_2)$	10.35	6.57	13.82	12.21	18.34	13.96	7.63	26.36	35.94	8.68
R^2	0.67	0.73	0.70	0.81	0.86	0.90	0.74	0.81	0.70	0.69

Note: For all 10 portfolios, the portfolio formation months are t-12 to t-2. The dependent variable is equal-weighted simple returns in excess of the one-month bill rate calculated for each month. At the beginning of each month firms with returns for month *t-x* and *t-y* for all NYSE firms are allocated to deciles based on their continually compounded returns between *t-x* and *t-y*. For panel B we use the model: $R_t - RF_t = a + b\,[RM_t - RF_t] + s\,SMB_t + h\,HML_t + e_t$, and for panel C we use the model: $R_t - RF_t = a + b\,[RM_t - RF_t] + s\,SMB_t + h\,HML_t + e_t,\ e_t|F_{t-1} \sim N(0, h_t),\ h_t = d_0 + d_1\,(e_{t-1})^2 + d_2\,h_{t-1}$

TABLE 6B: THREE FACTOR REGRESSION RESULTS OF MONTHLY EXCESS STOCK RETURNS (IN PERCENT) OF 10 PORTFOLIOS FORMED ON PAST RETURNS WITH AND WITHOUT CONDITIONAL HETEROSKEDASTICITY (PORTFOLIO FORMATION MONTHS ARE t-20 TO t-2); JANUARY 1926 TO DECEMBER 2007

	Deciles									
	Low	2	3	4	5	6	7	8	9	High
Panel A: Mean, standard deviations and t-statistics of excess returns										
Mean	1.21	0.93	0.87	0.73	0.68	0.71	0.65	0.64	0.52	0.19
Std Dev	8.47	6.78	6.10	5.67	5.55	5.46	5.65	5.92	6.34	7.07
t-statistics	4.48	4.27	4.45	4.01	3.86	4.06	3.63	3.37	2.59	0.85
Panel B: Estimation results of simple three factor model										
a	0.26	0.15	0.17	0.07	0.07	0.07	-0.03	-0.05	-0.21	-0.63
b	1.27	1.09	1.03	0.98	0.94	0.96	0.98	1.02	1.05	1.08
s	0.35	0.13	0.02	-0.01	0.02	-0.02	-0.04	-0.04	0.04	0.24
h	0.09	0.07	0.04	0.03	-0.02	0.02	0.14	0.10	0.11	0.13
t(a)	2.25	1.85	2.46	1.31	1.39	1.59	-0.68	-0.99	-3.18	-6.38
t(b)	30.86	25.22	35.28	41.52	22.48	53.67	44.12	35.39	29.45	28.74
t(s)	3.85	2.07	0.60	-0.11	0.35	-0.74	-1.80	-1.28	0.74	4.25
t(h)	1.03	1.16	0.77	0.99	-0.15	0.77	5.09	2.04	1.88	1.76
R^2	0.77	0.82	0.87	0.89	0.85	0.91	0.92	0.89	0.86	0.80
Panel C: Estimation results of three factor model with GARCH(1,1) error process										
a	0.05	0.10	0.22	0.05	0.10	0.11	-0.05	-0.01	-0.18	-0.51
b	1.21	1.10	1.04	1.00	0.94	0.97	0.97	0.97	0.99	1.06
s	0.53	0.20	0.06	-0.01	0.01	-0.05	-0.06	-0.05	0.02	0.29
h	-0.01	0.04	0.04	0.05	0.03	0.01	0.08	0.03	-0.02	0.04
d_1	0.14	0.09	0.11	0.090	0.08	0.11	0.06	0.18	0.15	0.18
d_2	0.83	0.88	0.85	0.87	0.91	0.85	0.92	0.76	0.83	0.81
t(a)	0.61	1.77	4.15	1.11	2.23	2.62	-1.35	-0.12	-3.39	-6.75
t(b)	75.2	92.8	124	120	88.5	143	119	103	106	70.9
t(s)	22.5	10.6	3.78	-1.09	0.61	-4.95	-4.34	-3.50	1.48	12.63
t(h)	-0.69	3.07	2.54	4.28	2.00	0.83	7.54	2.30	-1.51	1.81
t(d_1)	7.26	8.30	6.49	6.70	10.49	7.24	6.87	9.63	7.95	9.19
t(d_2)	37.04	63.7	39.7	49.3	299	44.4	76.2	29.9	40.8	39.25
R^2	0.91	0.93	0.94	0.94	0.90	0.96	0.94	0.92	0.93	0.86

Note: For all 10 portfolios, the portfolio formation months are t-20 to t-2. The dependent variable is equal-weighted simple returns in excess of the one-month bill rate calculated for each month. At the beginning of each month firms with returns for month *t-x* and *t-y* for all NYSE firms are allocated to deciles based on their continually compounded returns between *t-x* and *t-y*. For panel B we use the model: $R_t - RF_t = a + b\,[RM_t - RF_t] + s\,SMB_t + h\,HML_t + e_t$, and for panel C we use the model: $R_t - RF_t = a + b\,[RM_t - RF_t] + s\,SMB_t + h\,HML_t + e_t$, $e_t|F_{t-1} \sim N(0, h_t)$, $h_t = d_0 + d_1\,(e_{t-1})^2 + d_2\,h_{t-1}$

TABLE 6C: THREE FACTOR REGRESSION RESULTS OF MONTHLY EXCESS STOCK RETURNS (IN PERCENT) OF 10 PORTFOLIOS FORMED ON PAST RETURNS WITH AND WITHOUT CONDITIONAL HETEROSKEDASTICITY (PORTFOLIO FORMATION MONTHS ARE t-60 TO t-13); JANUARY 1926 TO DECEMBER 2007

	Deciles									
	Low	2	3	4	5	6	7	8	9	High
Panel A: Mean, standard deviations and t-statistics of excess returns										
Mean	1.20	1.01	0.98	0.79	0.84	0.73	0.76	0.75	0.61	0.61
Std Dev	8.84	7.86	6.93	6.13	6.20	5.71	5.91	5.71	5.78	6.33
t-statistics	4.12	3.88	4.30	3.91	4.12	3.90	3.92	3.98	3.24	2.90
Panel B: Estimation results of simple three factor model										
a	-0.07	-0.13	-0.01	-0.05	0.00	-0.10	0.02	0.05	-0.02	-0.02
b	1.04	1.10	1.03	0.97	1.02	0.97	1.03	1.02	1.05	1.15
s	0.95	0.39	0.22	0.10	-.025	-0.08	-0.10	-0.12	-0.12	0.01
h	0.62	0.60	0.50	0.33	0.34	0.25	0.16	0.09	-0.05	-0.32
t(a)	-0.64	-1.52	-0.13	-0.82	0.07	-0.19	0.47	1.01	-0.47	-0.26
t(b)	32.25	22.07	33.77	32.71	32.86	49.37	34.93	51.62	49.65	39.45
t(s)	9.87	5.38	4.71	2.16	-0.49	-2.93	-3.59	-4.00	-3.84	0.14
t(h)	12.34	11.98	12.23	7.99	8.15	9.50	4.49	3.49	-1.91	-9.13
R^2	0.85	0.86	0.88	0.89	0.90	0.90	0.90	0.91	0.90	0.89
Panel C: Estimation results of three factor model with GARCH(1,1) error process										
a	-0.15	-0.05	.001	0.01	-0.01	-0.01	0.04	0.03	-0.01	-.002
b	1.05	0.97	0.95	0.91	0.98	0.95	1.00	1.02	1.04	1.18
s	0.86	0.29	0.14	0.06	-0.06	-0.10	-0.15	-0.12	-0.09	0.06
h	0.56	0.38	0.33	0.18	0.17	0.12	0.06	0.02	-0.11	-0.28
d_1	0.04	0.10	0.12	0.11	0.13	0.14	0.15	0.14	0.12	0.14
d_2	0.94	0.87	0.84	0.86	0.83	0.82	0.83	0.81	0.82	0.80
t(a)	-1.64	-0.74	0.02	0.34	-0.16	-0.17	1.00	0.65	-0.20	-0.03
t(b)	58.5	69.7	84.0	110	125	111	92.0	128	140	110
t(s)	34.4	12.5	7.46	5.04	-4.87	-7.00	-10.6	-9.62	-6.58	3.58
t(h)	21.0	21.6	18.1	15.4	16.7	9.71	4.65	2.15	-8.13	-18.9
t(d_1)	6.85	6.91	5.61	5.46	7.75	5.72	7.40	5.75	6.77	6.72
t(d_2)	115	41.9	32.9	36.0	37.1	24.4	42.8	25.6	33.3	23.3
R^2	0.89	0.90	0.91	0.95	0.96	0.93	0.91	0.95	0.96	0.94

Note: For all 10 portfolios, the portfolio formation months are t-60 to t-13. The dependent variable is equal-weighted simple returns in excess of the one-month bill rate calculated for each month. At the beginning of each month firms with returns for month *t-x* and *t-y* for all NYSE firms are allocated to deciles based on their continually compounded returns between *t-x* and *t-y*. For panel B we use the model: $R_t - RF_t = a + b [RM_t – RF_t] + s\, SMB_t + h\, HML_t + e_t$, and for panel C we use the model: $R_t - RF_t = a + b [RM_t – RF_t] + s\, SMB_t + h\, HML_t + e_t$, $e_t|F_{t-1} \sim N(0, h_t)$, $h_t = d_0 + d_1 (e_{t-1})^2 + d_2 h_{t-1}$

and short-term losers loading on both SMB and HML are way higher than the corresponding loading figure for short-term winners. In a nutshell, the common risk factors basically transform the strong correlation between average excess returns and firm characteristics (in terms of size premium and book-to-market premium) into statistically insignificant intercepts. The explanatory power of the model also shows marked improvement (in terms of higher R^2) for both medium-term and long-term return based portfolios.

The conditional variance equation for all three different past return based portfolios shows that for almost all deciles both d_1 and d_2 coefficients are highly significant. Overall, the magnitude of d_2 is more homogeneous than the magnitude of d_1. Moreover, the d_2 coefficient, which captures the tendency for shocks to the current volatility to remain important for long periods into the future, seems to have greater impact on medium-term and long-term return based portfolios. The average estimates of the persistence parameter d_1+d_2 is high but always less than one for all three different types of past return based portfolios. In particular, on an average 8 out 10 deciles produces an estimated value of d_1+d_2 that is above 0.95, suggesting that shocks to the volatility of those portfolios are highly persistent. In other words, existence of strong persistence in volatility strengthen our previous assertion that common risk factors exhausts the explanatory power for the variability of stock returns for portfolios formed on 60 to 2 months past returns. Therefore, average-return anomalies largely disappear in a three factor model for portfolios based on long-term past returns.

CONCLUSIONS

The meaningful relationship between average return and firm characteristics as well as past return behavior is widely known. In this paper, we re-examine the role of common risk factors for momentum and price-reversal based portfolios using a simple conditionally heteroskedastic three factor model. The empirical findings indicate that allowing conditional heteroskedastic specification in the basic model slightly improves the explanatory power and makes the model parameters estimate more precise but do not affect significantly the nature of premiums related to excess market return and mimicking risk factors based on size and book-to-market equity. For all 25 size and momentum based portfolios we have considered, the three factor model predicts the reversal of post formation returns of both short-term losers and short-term winners. These results strongly support earlier findings by Fama and French (1993, 1996) but contradict Jegadeesh and Titman (1993) and Asness (1994). In addition, for a set of 10-decile portfolios, we illustrate that accounting for conditional heteroskedasticity increases the evidence that even though it misses continuation of returns for portfolios formed on short-term past returns, a three factor model captures the reversal for the post-formation returns of long-term losers (smaller distressed stocks) and winners (strong stocks). This capturing of the reversal of long-term returns is in line with the findings of DeBondt and Thaler (1985) and Fama and French (1996). Overall, our analysis not only reemphasizes the role conditional volatility in risk-return relationship illustrated by Jegannathan and Wang (1996), Durack, Durand and Maller (2004) and Guo, Savickas, Wang, and Yang (2007); it also provides a stronger endorsement of the volatility model for asset pricing anomalies involving common risk factors.

FIGURE 1A: CONDITIONAL VOLATILITY FOR SMALLEST SIZE AND LOWEST MOMENTUM PORTFOLIO REGRESSION

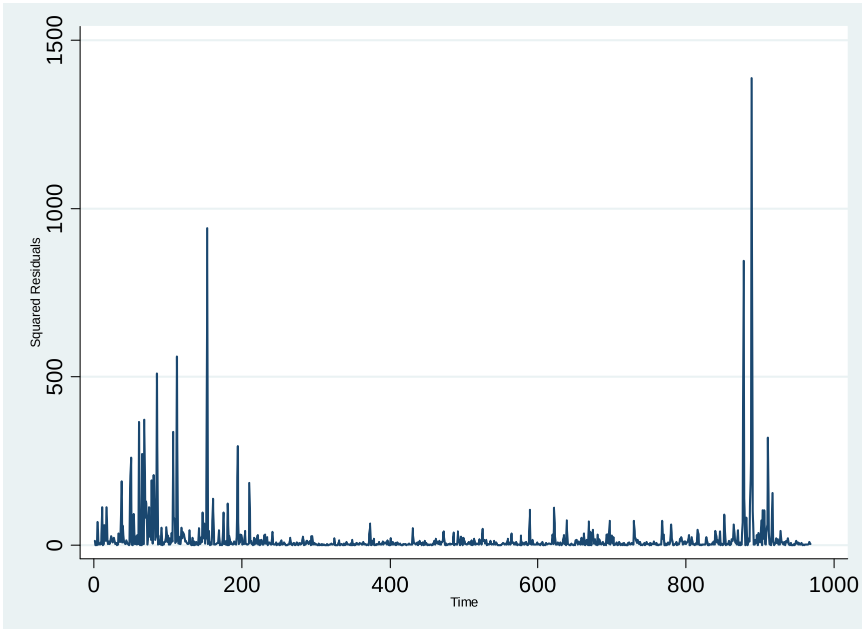


FIGURE 1B: CONDITIONAL VOLATILITY FOR BIGGEST SIZE AND HIGHEST MOMENTUM PORTFOLIO REGRESSION

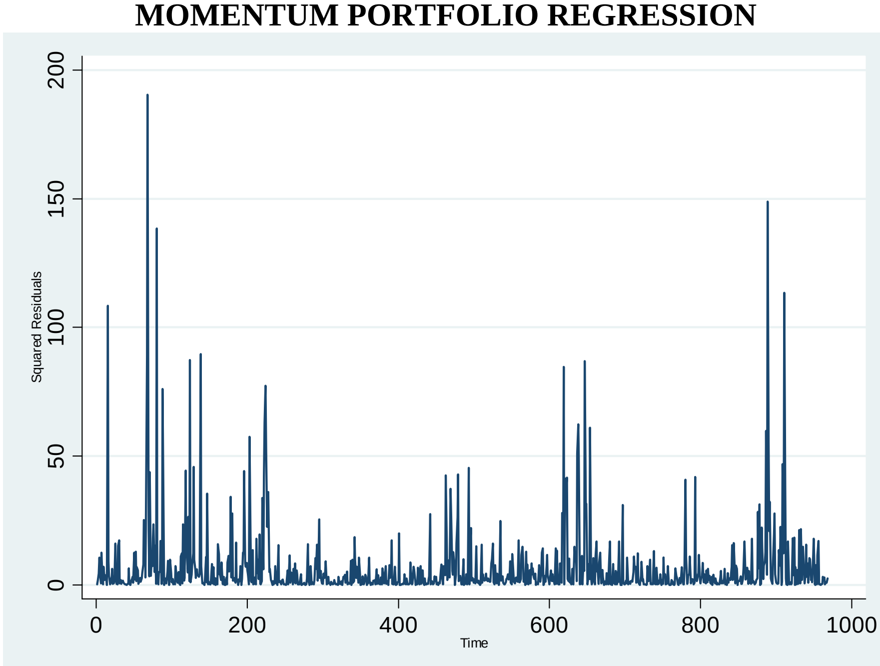


FIGURE 2A: DISTRIBUTION OF STANDARDIZED INNOVATIONS FOR SMALLEST SIZE AND LOWEST MOMENTUM PORTFOLIO REGRESSION

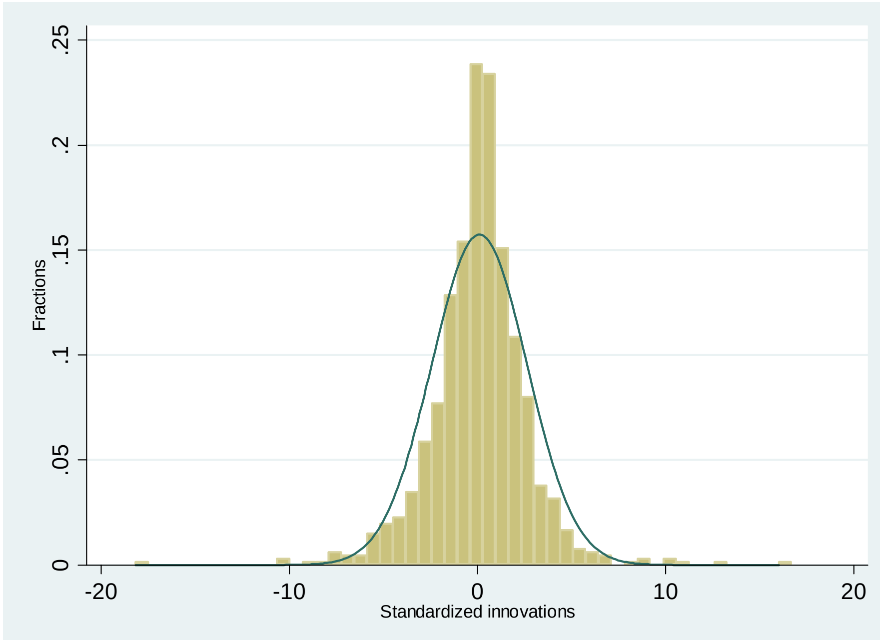
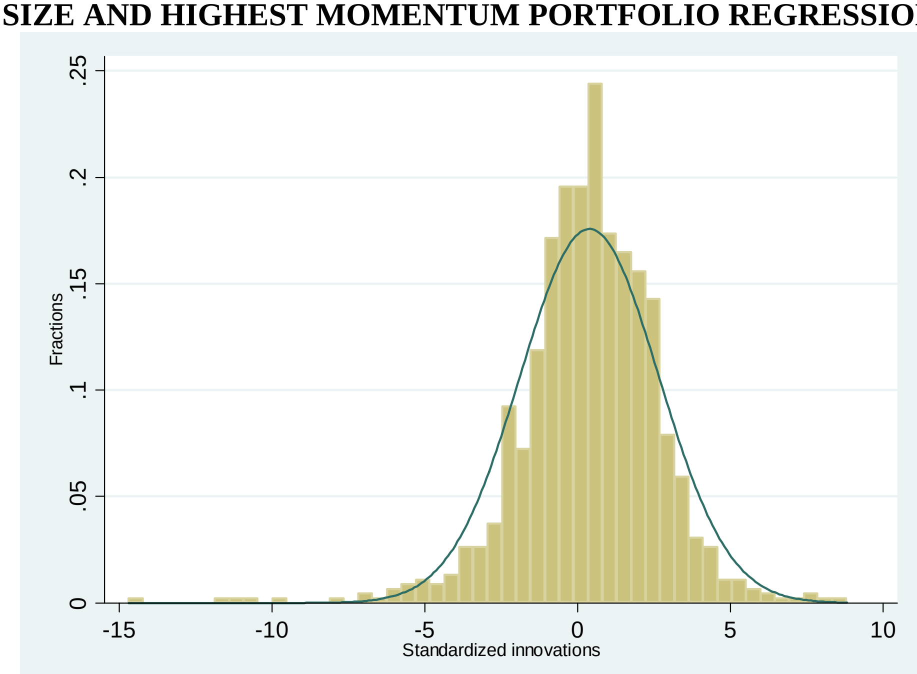


FIGURE 2B: DISTRIBUTION OF STANDARDIZED INNOVATIONS FOR BIGGEST SIZE AND HIGHEST MOMENTUM PORTFOLIO REGRESSION



REFERENCES

Asness, C. S. (1994). The power of past stock returns to explain future stock returns, *Working Paper*, Goldman Sachs Asset Management, June.

Banz, R. W. (1981). The relationship between return and market value of common stocks, Journal of Financial Economics, 9, 3–18.

Brooks, C. (1997). Linear and non-linear (non)-forecastability of high frequency exchange rates, Journal of Forecasting, 16, 125-145.

Bollerslev, T. P., Engle, R. F. and Wooldridge, J. M. (1986). A capital-asset pricing model with time-varying covariances, Journal of Political Economy, 96, 116-131.

DeBondt, W. F. M. and Thaler, R. H. (1985). Does the stock market overreact? Journal of Finance, 40, 793-805.

DeBondt, W. F. M. and Thaler, R. H. (1987). Further evidence on investor overreaction and stock market seasonality, Journal of Finance, 42, 557-581.

Durack, N., Durand, R. B. and Maller, R. A. (2004). A best choice among asset pricing models? The conditional capital asset pricing model in Australia, Accounting and Finance, 44, 139-162.

Engle, R. F. and Bollerslev, T. P. (1986). Modeling the persistence of conditional variances, *Econometric Review*, 5, 1-50.

Fama, E. F. (1965). The behavior of stock market prices, Journal of Business, 38, 34-105.

Fama, E. F. and French, K. R. (1992a). The cross-section of expected stock returns, Journal of Finance, 47, 427-465.

Fama, E. F. and French, K. R. (1992b). The economic fundamentals of size and book-to-market equity, *Working Paper* (Graduate School of Business, University of Chicago, IL).

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds, Journal of Financial Economics, 33, 3-56.

Fama, E. F. and French, K. R. (1995). Size and book-to-market factors in earnings and returns, Journal of Finance, 50, 131-155.

Fama, E. F. and French, K. R. (1996). Multifactor explanations of asset pricing anomalies, Journal of Finance, 51, 55-84.

French, K. R. and Schwert, G.W. and Stambaugh, R. (1987). 'Expected stock returns and volatility', Journal of Financial Economics, 19, 3-29.

Guo, H., Savickas, R., Wang, Z. and Yang, J. (2007). Is the value premium a proxy for time-varying investment opportunities: Some time series evidence, Forthcoming in Journal of Financial and Quantitative Analysis.

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

Jegadeesh, N. and Titman, S. (1995). Overreaction, delayed reaction, and contrarian profits. Review of Financial Studies, 8, 973-993.

Jegannathan, R. and Wang, Z. (1996). The conditional CAPM and the cross-section of expected returns, Journal of Finance, 23, 389-416.

Lakonishok, J., Shleifer, A. and Vishny, R. (1994). Contrarian investment, extrapolation, and risk, Journal of Finance, 49, 1541-1578.

Linter, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, Review of Economics and Statistics, 47, 13-37.

Mandelbrot, B. (1963). The variation of certain speculative prices, Journal of Business, 36, 394-419.

Newey, W. and West, K. (1987). A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, Econometrica, 55, 703-708.

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive evidence of market inefficiency, Journal of Portfolio Management, 11, 9–17.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk, Journal of Finance, 19, 425-442.

Stattman, D. (1980). Book values and stock returns, *Chicago* MBA: A Journal of Selected Papers, 4, 25–45.