2008

Information Uncertainty and the Momentum Effect

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SUBMITTED IN PARTIAL FULFILLMENT

OF THE REQUIREMENTS FOR

THE DEGREE OF MASTER OF SCIENCE IN FINANCE

SINGAPORE MANAGEMENT UNIVERSITY

2008

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Abstract

I identify simple proxies for uncertainty and attempt to determine if the returns to a momentum strategy vary with these proxies. The proxies identified include the stock's daily 6-month historical return volatility, the magnitude of alpha in a 6-month historical regression of the stock's daily returns on the Fama-French factors and the (1-R^2) value of the regression. The exposures to each of the risk factors were also tested as possible proxies for uncertainty related to the factors.

Using daily stock return data from CRSP from 1926 to 2006, stocks are first sorted into quintiles based on these proxies. A momentum strategy is pursued in each uncertainty quintile by taking long and short positions in the deciles with the highest and lowest past returns respectively over a 6 month ranking period, and holding these positions for a further 6 months. It was found that with greater volatility, momentum returns are higher. Similarly, as the magnitude of alphas rises, momentum returns increase. These results support the hypothesis that greater uncertainty contributes to momentum. Finally, momentum returns are higher with larger exposures to the market factor, but show no statistically significant trends with the size and book-to-market factors. When (1-R^2) values increase however, momentum returns decline, in contradiction with the hypothesis that greater uncertainty contributes to momentum.

Stocks were also sorted into industry groups according to Kenneth French's twelve industry portfolio classification. The industries were ranked according to the volatility of their daily returns and the returns to a momentum strategy within the industry. There was no clear relationship between the volatility of daily returns and momentum returns of the twelve industry portfolios.

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Acknowledgements

I would like to thank my fellow batch mates in the Finance and Economics programmes at SMU for the various discussions and study sessions we have held in the course of our studies. I have benefited from their deep thought and insight and I appreciate the opportunity to have learnt from them.

I would also like to record my thanks to my thesis supervisor, Dr Chua Choong Tze, for his advice and directions in shaping this thesis. Having enrolled in the programme part-time, other commitments had often taken priority over my research and I am grateful for his patience.

To my family

Chapter 1

Introduction - Review and Motivation

Momentum strategies

The profitability of momentum strategies, although first documented by Jegadeesh and Titman (1993), has long been exploited by practitioners. Jegadeesh and Titman (1993) show that a strategy of buying winners and selling losers, identified by their performance over the past three to twelve months, and then holding them for a further three to twelve months, yielded significant positive returns. Many studies have since corroborated those findings. For instance, Rouwenhorst (1998) extends the observation of momentum profits to twelve European markets, Rouwenhorst (1999) notes the same in twenty emerging markets, and Jegadeesh and Titman (2001) extend their earlier results by demonstrating the persistence of the momentum phenomenon using more recent data.

Other studies have discovered "reversals" – the opposite phenomenon in which past losers outperform past winners – over different time horizons. DeBondt and Thaler (1985) note that such overreaction allowed for positive returns to a contrarian strategy in which long and short positions are taken with losers and winners respectively over a time horizon of three to five years, while Jegadeesh (1990) and Lehmann (1990) observe similar profits over months and weeks respectively. This thesis, however, will be limited to the intermediate horizon when momentum dominates.

Related observations

Several studies have documented momentum effects when "winners" and "losers" are defined based on criteria other than past returns. For example, Chan, Jegadeesh and Lakonishok (1996), aside from noting price momentum, document "earnings momentum", in which winners and losers, defined as stocks with high and low earnings surprises respectively, extended their superior and inferior performances for up to three years after portfolio formation. Moskowitz and Grinblatt (1999) argue that winner and loser industry returns, rather than firm-specific returns, are responsible for momentum profits, while Lee and Swaminathan (2000) find that stocks with high and low trading volumes tend to be future winners and losers respectively. Grundy and Martin (2001) show that defining winners and losers by ranking based on the idiosyncratic components of stock returns (unexplained by Fama French 3 factor regressions) yield momentum returns that are higher than by ranking on raw returns.

Studies have also examined conditions under which momentum profits would vary. Rouwenhorst (1998) notes that within his sample of 12 European markets, momentum returns are stronger for small firms than large ones. Similarly, Hong, Lim and Stein (2000) show that for their sample of NYSE, AMEX and Nasdaq stocks, aside from the two deciles with the smallest market capitalization, momentum returns decrease as firm size rises. They attribute this to slower information diffusion in small stocks, leading to price continuation. Jegadeesh and Titman (2001) also show that between 1965 and 1998, NYSE, AMEX and Nasdaq stocks with capitalization below the market median show larger momentum returns than those above the median. Their aim is to determine if momentum profits are present in large cap stocks, since more prevalent trading might have reduced the viability of a profit-making strategy. Daniel and Titman (2000) find that stocks with high book-to-market ratio tend to have lower momentum returns than those with low book-to-market ratios. They reason that high and low book-to-market stocks are mainly value and growth stocks respectively, and that the latter involve greater valuation uncertainty. The greater uncertainty accounts for the higher momentum returns they observe.

Explanations for momentum

Since Jegadeesh and Titman's (1993) documentation of momentum profits, many have studied the phenomenon to identify its cause. Explanations for momentum can generally be divided into two categories. The first category seeks to defend the notion of the efficiency of financial markets. Their approach is to explain momentum profits as compensation for various forms of risk, or due to autocorrelation in returns, cross-serial correlation in returns, or cross-sectional variation in mean returns. The second category focuses on behavioural reasons and information asymmetries to explain momentum profits.

Efficient market explanations for momentum

Fama and French (1996) are able to explain price reversals but unable to explain momentum with their 3 factor regressions. While it was not pointed out at the time of publication, this is likely to be due to the longer ranking and holding periods used. Moskowitz and Grinblatt (1999) attribute a large portion of momentum profits to industry momentum, suggesting cross-sectional differences in returns based on industry.

Conrad and Kaul (1998) find that momentum and contrarian strategies work more successfully over different historical periods and argued that cross sectional dispersion in mean returns of individual securities is more important than time series return autocorrelation in explaining abnormal returns. However, these findings are contested by Jegadeesh and Titman (2001) and Jegadeesh and Titman (2002).

Jegadeesh and Titman (2001) use new data since the publication of their earlier paper to confirm the momentum effect, and found evidence of reversals after the one-year momentum holding period. They argued that this reversal is consistent with behavioral models (discussed subsequently) but inconsistent with cross-sectional variation as a basis of momentum profits as advanced by Conrad and Kaul (1998), since momentum profits should remain in any post-ranking period under their hypothesis. Jegadeesh and Titman (2002) also show that the cross-sectional variation evidence presented by Conrad and Kaul (1998) is in fact due to improper treatment of sample biases.

Berk, Green and Naik (1999) formulate a theoretical model based on firms' investment choices, assets and growth options that influence their cross-sectional expected returns and risk. These result in short term and longer term contrarian and momentum profits respectively, although these effects appear to develop over longer time horizons than observed in reality. Johnson (2002) also devises a simple model in which momentum arises from a positive relation between firm growth rates and consecutive expected dividend growth shocks.

Grundy and Martin (2001) discount both cross-sectional variation and industry momentum as the main sources of momentum profits and instead show that exposure to the Fama-French risk factors explains a large portion of the variation in the performance of winners and losers. However, having applied the risk factors, they note that the unexplained firm-specific return component is a better determinant of “winner” and “loser” status than raw returns in adopting a momentum strategy.

Lewellen (2002) finds momentum profits not only in Grundy and Martin’s (2001) industry portfolios but in size and book-to-market portfolios as well, and also observes significant negative autocorrelation in and cross-serial correlation between the portfolios. He thus argues that momentum can primarily be explained by time-series relationships between stock returns rather than underreaction.

Other risk-based explanations for momentum returns are centred around macroeconomic variables and market states. Liu, Warner and Zhang (2005) suggest that one such variable, the growth rate of industrial production could partially explain momentum returns. Chordia and Shivakumar (2002) find momentum profits are only positive during expansionary periods, and that four lagged macroeconomic variables, dividend yield, default spread, risk-free rate and term structure spread, are able to account for momentum profits. They argue, in essence, that time-varying cross-sectional expected returns are responsible for momentum. However, their findings were not corroborated outside the US in a study by Griffin, Ji and Martin (2003). The latter find that momentum profits cannot be explained by the factors suggested by Chordia and Shivakumar (2002) and that momentum profits exist regardless of the economic state, indicating that business cycle risk does not contribute to momentum. Park and Daves (2006) also suggest that Chordia and Shivakumar's (2002) results are spurious and due to high persistence in the macroeconomic variables over the momentum portfolio formation periods.

Behavioural explanations for momentum

There have also been attempts to explain momentum from the behavioural perspective, most of which employ a gradual spread of or response to new information. Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999) construct behavioral models to explain how beliefs, psychological biases and dissemination of private information may lead to momentum and reversals. Hirshleifer (2001) suggests that greater uncertainty increases the tendency for psychological biases to affect investors' behaviour. Zhang (2006) reasons that if the slow market response is due to psychological biases such as overconfidence, these biases will be larger under greater uncertainty. He uses six proxies for uncertainty and shows that following good news or higher past returns, stocks with higher uncertainty perform better than stocks with lower uncertainty, while following bad news or lower past returns, stocks with higher uncertainty perform worse. These proxies include firms' capitalisation, firms' age, the number of analysts covering the firm, the dispersion in analysts' earnings forecasts, the standard deviation of weekly market excess returns over the preceding year and firms' cash flow volatility. In the same vein, Hou, Peng and Xiong (2006) reason that the R^2 obtained from a regression of a stock's weekly returns on the contemporaneous returns of the market portfolio and the French 48 industry portfolio to which the stock belongs can also be a proxy for uncertainty. They show that a lower R^2 is associated with higher momentum returns and stronger reversals subsequently.

Motivation

Information uncertainty has been proposed as an explanation for the abnormal returns earned via momentum strategies. Faced with greater uncertainty, investors are increasingly unable to accurately determine the true value of an asset and are more likely to misprice it. Momentum strategies essentially bet on trends of price continuation – that prior winners and losers will tend to continue their superior and inferior performances respectively. It is intuitive to make a connection between uncertainty and momentum – in the presence of greater uncertainty, investors have less of a basis on which to estimate the value of an asset aside from its prior performance and are hence more likely to project past trends into the future. Supporting the literature in making a connection between information uncertainty and the returns to momentum strategies would contribute to our understanding of why momentum strategies have been successful.

Prior literature has suggested information uncertainty as an underlying reason for the profitability of a momentum strategy based on past returns. This study aims to re-inforce that idea by

a) proposing simple proxies for the level of uncertainty and

b) observing momentum returns as such proxies vary.

If the proxies are deemed to be reasonable approximations for uncertainty, then any observed trends in momentum returns may be attributed to cross-sectional differences in uncertainty.

Proxies for uncertainty

Uncertainty exists because investors do not have sufficient or reliable information about an asset to predict its future returns. As such, proxies for uncertainty that have been used in the literature seek to reflect the amount and reliability of available information about an asset that an investor could use to direct his investment flows. Proxies that assess the amount of information include the firm's size, age, and number of analysts. Proxies that assess the quality of past information as a yardstick of future performance include dispersions in forecasts, excess return volatility, cash flow volatility and factor model-based regression R^2 values.

The proxies identified in this study fall into the category of assessing the quality of past information. The first proxy identified is the volatility of daily stock returns in the prior 6 months. Lower volatility gives greater certainty over prospective performance, which reduces the tendency to project trends forward. This proxy is applied in Test 1. There may be concerns over the choice of using daily data since it is subject to stronger microstructure effects. However, since volatility is used as a relative measure of comparison for sorting into quintiles, this should not present a problem.

The second proxy identified is the absolute intercept, or absolute alpha, of a regression of stock returns on a factor model of asset pricing, specifically, the Fama-French 3 factor model. The greater the alpha, the greater is the unexpected component of returns and hence the greater the uncertainty associated with the stock. This proxy is reasonable to the extent to which investors base expectations of future value on the factor model. This may occur consciously by considering factor loadings or paying attention to historical co-movements with factors, or sub-consciously, by virtue of their perceptions of stocks' factor exposures. This proxy is applied in Test 2.

The third proxy identified uses the R^2 of a regression of stock returns on a factor model of asset pricing. In contrast to Hou, Peng and Xiong (2006), who used the contemporaneous returns of the market portfolio and the French 48 industry portfolio to which the stock belonged as the explanatory variables, the present study uses the Fama-French factors in the regression. The R^2 value of a regression reflects the extent to which the variation in stock returns is explained by the factor model. $(1-R^2)$ hence reflects the extent to which the factor model is unable to account for stock returns. If investors use the factor model to form expectations of stock returns, a higher $(1-R^2)$ value would lead to greater uncertainty in the prediction of the factor model. This is examined in Test 3.

While Tests 1, 2 and 3 use measures that are more intuitively similar to ones proposed in studies by Zhang (2006) and Hou, Peng and Xiong (2006), Tests 4, 5 and 6 seek to understand if stocks with greater loadings on the market, SMB and HML risk factors respectively in the asset pricing model also enjoy higher momentum returns. Factor loadings measure the extent of exposure to priced risk, and insofar as such risk gives rise to uncertainty, higher factor loadings could lead to greater momentum returns.

If stocks that have greater exposures to each of the risk factors do not display higher momentum returns, it is possible that higher factor exposure may not in fact imply greater uncertainty. For example, it is conceivable that over certain periods, it may be clear to investors that stocks with selected characteristics, say small stocks, are likely to perform well. In this case, greater exposure to the SMB factor would then imply lower uncertainty. Nevertheless, if factor exposures do indeed act as good proxies for uncertainty, and if the hypothesis that uncertainty leads to stronger momentum holds true, then we would expect momentum returns to rise with factor exposures.

Industry Analysis

Stock returns for firms in different industries may also have inherently different levels of volatility. In order to further test the relationship between volatility and momentum returns, stocks are sorted into 12 groups using Kenneth French's 12 industry portfolio classification. Each industry group is ranked according to its volatility and its momentum returns. This is done in Test 7.

Main Findings

Tests 1 and 2 find that momentum returns increase with the proposed measures of uncertainty. Specifically, monotonic increases in momentum returns are observed with increasing stock return volatilities and absolute intercepts of factor model regressions. These results support the hypothesis that uncertainty contributes to momentum.

Test 3 shows that momentum returns decrease almost monotonically with an increase in (1-R^2) values, in contrast with the opposite trend documented by Hou, Peng and Xiong (2006), albeit using a different regression model. These findings suggest that if (1-R^2) were a proxy for uncertainty, momentum returns would counter-intuitively decrease with uncertainty.

The evidence based on Tests 4 to 6 is mixed. Momentum returns increase with greater loading on the market factor, but not with the SMB or HML factor loadings. Taken in the context of results in Tests 1 and 2 and prior findings in the literature (Hong, Lim and Stein (2000), Jegadeesh and Titman (2001) and Daniel and Titman (2000)), it is likely that the market factor exposure acts as a good proxy for uncertainty associated with market risk, while the SMB and HML factor exposures do not act as good proxies for size and book-to-market uncertainty. The literature has shown that momentum returns vary with actual firm size and book-to-market values, which presumably are more direct measures of such uncertainty.

Finally, the industry analysis does not uncover any notable relationship between the volatility of an industry and its momentum returns. The rankings based on volatility had little correlation to those based on momentum returns.

Chapter 2

Research Methodology

Data

Daily and monthly stock return data are obtained from the Centre for Research in Security Prices (CRSP). Fama-French portfolio returns are available from CRSP and from Kenneth French's website. The above are used to obtain proxies for the level of uncertainty, which include the historical daily volatility of stock returns, alphas and (1-R^2) values of Fama-French regressions based on historical returns, and factor loadings for such regressions.

Procedure

Test 1 first sorts stocks into quintiles based on their prior daily return volatility over the past 6 months. After the sort, the data is winsorized by dropping the highest and lowest 1% of observations of daily return volatility from the highest and lowest volatility quintiles respectively. Volatility is calculated as the standard deviation of daily returns over the past 6 months. Within each quintile, stocks are then sorted into deciles based on their past returns over the past 6 months, calculated as the product of monthly returns over 6 months. The deciles with the highest and lowest prior returns are the winner and loser deciles respectively. For each volatility quintile, the returns to the momentum strategy are that of going long the winners and short the losers. Accordingly, the subsequent returns of the winner and loser deciles are tracked over the next 6 months and the monthly momentum return is the difference between the monthly returns of the winner and loser deciles. Following the methodology adopted by Jegadeesh and Titman (1993), overlapping monthly portfolios are formed and held. Specifically, with a 6 month holding period, month i will see 6 portfolios, one formed in each month from month (i-6) till month (i-1), which are long winners and short losers and are equally weighted to determine month i's momentum returns.

Previous studies have used different universes of stocks to perform analyses of momentum returns. Jegadeesh and Titman (1993) use NYSE and AMEX stocks but exclude NASDAQ ones, while Jegadeesh and Titman (2001) include NASDAQ stocks, but exclude stocks priced below \$5 and all stocks with market capitalizations that would place them in the smallest NYSE decile. Hong, Lim and Stein (2000) and Zhang (2006) similarly include NASDAQ stocks, although the latter excludes stocks priced below \$5 at the portfolio formation date. Since the motivation behind excluding selected stocks in prior studies is to reduce volatility and noise, all tests here use only NYSE and AMEX stocks. Test 1 imposes the additional condition that stocks need to be priced above \$5. The data used in Test 1 covers the period from 1925 to 2007. A sub-period from 1965 to 2007 is also studied.

Test 2 first performs Fama-French regressions of each stock's daily returns over the past 6 months on the Fama-French factors:

$$r_i - r_f = \alpha + \beta_1 \text{market} + \beta_2 \text{SMB} + \beta_3 \text{HML} + \varepsilon$$

Daily data on Fama-French factor realizations is only available from 1964 onwards. Stocks are then sorted into quintiles based on the absolute intercept of the regression. Following this first sort, each quintile is treated in a manner entirely identical to the procedure outlined for Test 1. Observations of the highest and lowest 1% absolute intercepts are winsorised from the extreme quintiles. Momentum returns for each quintile are calculated as described for Test 1 and reported.

Test 3 involves the same regression as in Test 2, also covering the period from 1964 to 2007. In this case, stocks are sorted into quintiles based on their ($1-R^2$) values from the Fama-French regression. 1% of extreme observations from the extreme quintiles are winsorised and momentum returns are calculated as described for Test 1 and reported.

Tests 4, 5 and 6 also perform the same regression as in Test 2, but instead sort the stocks into quintiles based on their absolute factor loadings for the market (β_1), size (β_2) and book-to-market value (β_3) factors respectively. As with Test 2, data from 1964 to 2007 is used. Subsequent winsorisation and calculation of momentum returns in each quintile is as above.

In Test 7, Kenneth French's 12 industry portfolio classification is used to sort stocks into 12 industry groups based on their SIC codes. Descriptions of each industry group and their corresponding SIC codes are provided in Table 1. Within each industry group, volatility is calculated as the standard deviation of daily stock returns. Monthly stock returns are used to calculate momentum returns as described for Test 1 - stocks are sorted into deciles based on their returns over the past 6 months, and the returns of going long the winner decile and short the loser decile are calculated over the next 6 months.

Data used in Test 7 is from 1965 to 2007. The 12 industry groups are independently sorted based on volatility of daily returns as well as on momentum returns for comparison. No winsorisation is performed in Test 7. The Spearman rank coefficient is then calculated.

Descriptive Statistics

Table 2 shows simple descriptive statistics for the various proxies for uncertainty. The first two columns examine the standard deviation of daily stock returns, using data from 1925-2006 and the sub-period from 1965-2006. Results from both periods are qualitatively similar, with volatilities varying between 0.008 to 0.06 between the 5^{th} and 95^{th} percentiles. Mean volatility in both cases is around 0.026 while standard deviations are around 0.017.

The next five columns examine the other proxies – the absolute intercept, $(1-R^2)$ value and factor loadings in Fama-French regressions. Daily data from 1964 to 2006 is used in the regressions. With the 5^{th} percentile of $(1-R^2)$ values at 0.61, it is clear that the Fama-French factors in most regressions have relatively low explanatory power (below 40%). All three Fama-French factors show a small number of observations with extreme loadings, and positively skewed distributions that give rise to positive mean values.

Chapter 3

Test 1 – Daily Return Volatility

Observations

In this Chapter, stocks are sorted into quintiles based on the standard deviation of their daily stock returns over the past 6 months before monthly momentum returns are calculated within each quintile. Table 3(A) uses data from 1925-2007 while Table 3(B) covers the sub-period from 1965-2007. Only stocks priced above $5 are included in the analysis. When stocks are first sorted based on their past return volatility, it is observed that increasing momentum returns generally accompany rising volatility.

Table 3(A) shows that the mean volatility in the lowest volatility quintile is 0.012 and 0.042 in the highest. Monthly momentum returns rise monotonically with daily return volatility over the past 6 months, from 0.0052% in the lowest volatility quintile, to 0.0115% in the highest. As reference, Jegadeesh and Titman (1993) documented monthly momentum returns of 0.0095% using their strategy of using 6 month ranking and holding windows. Assuming unequal variances between the lowest and highest volatility quintiles, the hypothesis that their momentum returns are the same is rejected with a t-statistic of 2.10.

The results over the sub-period 1965-2006 in Table 3(B) show similar trends to those over the entire sample history in (A). Mean volatility was 0.012 in the lowest volatility quintile and 0.045 in the highest. The sub-period data, if anything, appear to show a greater spread of momentum returns between the volatility quintiles compared to the full sample. Monthly momentum returns rise from 0.0038% in the lowest volatility quintile to 0.0125% in the highest, compared to 0.0052% in the lowest quintile and 0.0115% in the highest for the full sample. Between the sub-period and full period, momentum returns observed are of comparable statistical significance. Assuming unequal variances between the lowest and highest volatility quintiles in the sub-period, the hypothesis that their momentum returns are the same is rejected with a t-statistic of 2.99.

Discussion

The results in this Chapter demonstrate that an increase in momentum returns accompany a rise in stock return volatility. A predictable steam of returns allows investors to reliably estimate the present value of an asset. On the other hand, greater return volatility leads to a less predictable stream of expected returns. This hampers a consistent consensus on the value of an asset, leading to greater uncertainty. The empirical observations from this Chapter are consistent with the argument that uncertainty contributes to momentum.

Chapter 4

Test 2 – Intercept of Factor Model

Observations

In this Chapter daily stock returns over the past 6 months are first regressed on the Fama-French factors over that period. The stocks are then sorted into quintiles by the absolute value of the intercept of the regression, before monthly momentum returns are calculated within each quintile. The data used comprises NYSE and AMEX stocks over the period from 1964 to 2007, and is limited to that period by the availability of daily Fama-French factor realizations. Results are shown in Table 4.

Table 4 shows that the average absolute intercept in the quintiles rises from 0.00019 to 0.00499, and monthly momentum returns increase monotonically with the rise in absolute value of the intercept, from a statistically insignificant 0.0024% in the lowest absolute intercept quintile to a strongly significant 0.0156% in the highest. Assuming unequal variances between the lowest and highest absolute intercept quintiles, the hypothesis that their momentum returns are the same is rejected with a t-statistic of 3.52.

Discussion

The intercept in a Fama-French regression is the component that cannot be explained by the model. The results in this Chapter show that as the magnitude of unexplained returns increases, momentum returns increase. If investors assess stock values based on their exposure to the factors, then the intercept of the regression directly corresponds to the component of returns unaccounted for in their analysis. This neglected component reflects the extent to which the factor model is unable to explain stock returns, which is the uncertainty faced by investors who use the Fama-French factor loadings to estimate value.

An intercept of larger magnitude is indicative of greater uncertainty faced by such investors, who are less able to use prior exposures to estimate future returns. The lower reliability of the factor model in generating expectations consistent with reality leads to greater over-estimation or under-estimation of subsequent returns and hence stronger momentum. Based on this reasoning, the observations in this Chapter are consistent with the argument that momentum returns increase with uncertainty.

One concern that may be raised with this line of reasoning is the validity of the Fama-French model in asset pricing, and hence the application of the Fama-French factors to determine the return components expected and unexpected by investors. Implicit in this choice is the assumption that investors favour the Fama-French factors over other information in determining expected returns. While Fama and French (1992) have shown that their model broadly embodies the risks perceived by investors in pricing assets cross-sectionally, it should also be recognized that a simple model that can explain most variation in cross-sectional returns would be attractive to investors, in terms of considering risk according to an asset's exposure to the model's factors.

Chapter 5

Test 3 – (1-R^2) Values

Observations

As in the previous Chapter, daily stock returns over the past 6 months are first regressed on the Fama-French factors over that period. The stocks are then sorted into quintiles by the (1-R^2) values of the regression, before monthly momentum returns are calculated within each quintile. As in Test 2, the data includes NYSE and AMEX stocks over the period from 1964 to 2007, and is limited by the availability of daily Fama-French factor realizations. Results are shown in Table 5.

Table 5 shows that the average (1-R^2) value rises from 0.70 in the lowest (1-R^2) quintile to 0.98 in the highest, and that monthly momentum returns are statistically significant in all quintiles. Momentum returns decrease almost monotonically with the rise in (1-R^2) values, from 0.0128% in the lowest (1-R^2) quintile to 0.0054% in the highest. The exception to this trend is in the momentum returns of the second and third (1-R^2) quintiles, which are close and strongly statistically significant at 0.0118% and 0.0119% respectively. Assuming unequal variances between the lowest and highest (1-R^2) quintiles, the hypothesis that their momentum returns are the same is rejected with a t-statistic of 2.05.

Discussion

In a regression, R^2 is calculated as the explained sum of squares (ESS) as a proportion of the total sum of squares (TSS)[1]. R^2 reflects the extent of the variation of the observed variable around its mean that can be explained by the variation predicted by the model. A value of 1 indicates that the model is able to predict all of the variation of the observed variable, while a value of 0 indicates that it is not able to do so at all. Assuming that the model chosen is reflective of how investors form expectations of stock returns, a higher R^2 value would suggest that the stock in the regression has less idiosyncratic unpredictability not captured by the model. The value of $(1-R^2)$ could thus be an indicator of the level of uncertainty associated with expectations of asset values based on the predictions of the factor model.

As with the absolute intercept proxy for uncertainty studied in Test 2, the $(1-R^2)$ proxy would be subject to the extent to which the factor model used (in this case the Fama-French model) truly reflects investors' asset pricing psychology. The arguments proffered in Test 2 regarding the choice of a model-specific proxy apply here as well.

Test 3 presents curious findings. Here, momentum returns appear to decrease rather than increase when uncertainty is greater. The choice of $(1-R^2)$ values as a proxy for uncertainty appears to be a reasonable one, and is directly aligned with the reasoning

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[1] $ESS = \Sigma (y_{pred} - \hat{y})^2$ and $TSS = \Sigma (y_i - \hat{y})^2$, where

y_{pred} gives the model predicted values of y given x;

y_i gives the observed values of y;

$\hat{y}$ gives the mean of observed values of y.

adopted by Hou, Peng and Xiong (2006). The fact that Hou, Peng and Xiong (2006) chose to use the contemporaneous returns of the market portfolio and the French 48 industry portfolio to which the stock belonged as the explanatory variables, rather than the Fama-French factors, is not sufficient to explain why the opposite trend is observed. It remains unclear why a trend of decreasing momentum returns is seen with a rise in (1-R^2) values in the present study.

Chapter 6

Tests 4, 5 and 6 – Exposure to Risk Factors

Observations

As in Chapters 4 and 5, daily stock returns over the past 6 months are first regressed on the Fama-French factors. The stocks are then sorted into quintiles by their loadings on the market factor (Test 4 in Table 6), size factor (Test 5 in Table 7) and book-to-market factor (Test 6 in Table 8). As in Tests 2 and 3, the data comprises NYSE and AMEX stocks over the period from 1964 to 2007.

Table 6 shows that the average market factor loading in the quintiles rises from -0.03 in the lowest loading quintile to 1.97 in the highest, while momentum returns increase monotonically with the rise in market factor loading, from 0.0056% in the lowest loading quintile to 0.0145% in the highest. Momentum returns in all quintiles are statistically significant. Assuming unequal variances between the lowest and highest market loading quintiles, the hypothesis that their momentum returns are the same may be rejected with a t-statistic of 2.48.

Table 7 shows that the average SMB factor loading in the quintiles rises from -0.49 in the lowest loading quintile to 2.01 in the highest. Monthly momentum returns generally increase with the rise in SMB factor loading, from 0.0082% in the lowest loading quintile to 0.0134% in the highest. The momentum returns in the second quintile, at 0.0078%, appear to deviate from this trend, being lower than the returns in both the first and third quintiles. For the size factor, momentum returns in all quintiles are statistically significant. However, assuming unequal variances between the lowest and highest SMB loading quintiles, the hypothesis that their momentum returns are the same cannot be rejected with a t-statistic of 1.37.

Table 8 shows that for the sort based on the book-to-market factor loading, no discernible trends in momentum returns are observed across the quintiles. Statically significant monthly momentum returns varying from approximately 0.009% to 0.012% are observed across the quintiles.

Discussion

The results in this Chapter show that more positive exposure to the market factor is associated with greater momentum returns, but the extent of exposure to the HML factor does not affect momentum returns. While greater momentum returns are generally seen with more positive exposure to the SMB factor, the differences are not large enough to be statistically significant.

The observations relating to the market factor support the findings in Chapters 3 and 4 that greater uncertainty leads to higher momentum returns. However, the observations relating to the SMB and HML factors do not provide further evidence for that hypothesis. Rather than refute the connection between uncertainty and momentum however, they more likely suggest that the SMB and HML factor loadings are poor proxies for the uncertainty associated with each.

Previous studies have documented momentum returns of firms based on their size and book-to-market ratios, as noted in Chapter 1. While intuition might suggest that sorting based on a firm's size and book-to-market factor exposures should yield momentum trends similar to those based on their size and book-to-market ratios, empirical results have demonstrated that this is not the case. The intuition behind a factor pricing model is that each of the factors, in a broad cross-sectional aggregate, embodies risk characteristics that are not easily observable or quantifiable, but that are nevertheless priced by the market. An assessment of the uncertainty associated with the extent to which a stock is subject to such risky properties should be better served by its exposure to the risk factor rather than the firm's actual corresponding characteristic.

The above line of reasoning contrasts empirical observations in this study with those of Daniel and Titman (2000). When sorted based on the book-to-market factor exposure, no momentum trends are observed, but the sort by Daniel and Titman (2000) based on actual book-to-market ratios reveal a rise in momentum returns as book-to-market values fall. Such findings are aligned with the view that growth stocks often involve greater uncertainty in valuation that value stocks. The discrepancy in findings likely signal that actual firm characteristics provide a more direct assessment of exposure to associated risks, implying that contrary to the line of reasoning above, the HML factor loading acts as a poor measure of uncertainty associated with the factor.

The observations with respect to the size effect lead to a similar argument. Hong, Lim and Stein (2000) find that momentum returns generally decrease with firm size, which is aligned with the view that smaller firms involve greater uncertainty in valuation than larger, well-established ones. While the sort based on SMB factor exposures bears out the trend of momentum returns falling with firm size, differences in returns were not large enough to be statistically significant. This is a signal that, like the HML factor exposure, SMB factor exposure may not be a strong measure of uncertainty associated with the factor.

In summary, the sort based on market factor loadings supports the hypothesis that momentum returns rise with greater uncertainty associated with market fluctuations. However, the SMB and HML factor loadings are inadequate as proxies for uncertainty relating to size and book-to-market value.

Chapter 7

Test 7 - Industry Analysis

Observations

Test 7 uses daily and monthly stock return data from 1965 to 2007. Stocks are sorted into 12 industry groups using their SIC codes, based on Kenneth French's 12 industry portfolio classification. Each portfolio's volatility and momentum returns are determined. Volatility is calculated as the standard deviation of daily stock returns. Momentum returns are calculated using monthly stock returns. The 12 industries are ranked based on their volatility and momentum returns, with the lowest rank corresponding to the lowest volatility or momentum returns, and the Spearman rank coefficient is calculated. The results are displayed in Table 9.

The least volatile industries include utilities, finance, and chemicals and allied products, while the most volatile industries include business equipment, healthcare, medical equipment and drugs, and consumer durables. The industries with the lowest momentum returns are telephone and television transmission, utilities and oil, gas and coal extraction and products, while the highest momentum returns were seen in the wholesale, retail and selected services, manufacturing, and finance industries (aside from the "others" category).

Industry volatility ranges from 0.0186 to 0.0371. It appears that sorting using the 12 industry groups does not clearly distinguish firms by their volatility. The industry that ranks third has a volatility of 0.0267 while the industry that ranks tenth has a volatility of 0.0307. The standard deviations of volatility in each industry also appear high relative to their volatility.

Monthly industry momentum returns of up to 0.0111% are observed. The momentum returns shown in all but four industries are strongly statistically significant. These four industries are the ones with the lowest momentum returns and include healthcare, medical equipment and drugs, in addition to the three mentioned above. It also appears that sorting using the 12 industry groups does not clearly distinguish firms by their momentum returns. The five industries with the lowest significant monthly momentum returns vary between 0.0062% and 0.0070%.

Table 9 shows that there is little correlation in the rankings based on volatility and momentum. The Spearman rank coefficient is calculated to be 0.098.

Discussion

Several industries display relatively low volatility, in line with expectations, such as utilities and manufacturing. Similarly, other industries display relatively high volatility, also in line with expectations, such as healthcare, medical equipment and drugs. However, not all industries conform to intuition when ranked by volatility. For instance, business equipment has the highest volatility of all industries and the finance industry shows relatively low volatility.

As noted above, sorting using the 12 industry groups does not clearly distinguish firms by their volatility. The small differences in volatilities between many consecutively ranked industries make their rankings less meaningful, especially when the relatively large standard deviations of volatility are taken into consideration. The large standard deviations suggest that within each of the 12 industry groups, firms vary substantially in their volatilities.

As with volatility, sorting using the 12 industry groups also does not clearly distinguish firms by their momentum returns. The small differences between momentum returns of the fifth to tenth ranked industries noted above makes their rankings less meaningful.

Since the 12 industry classification does not clearly separate firms based on their volatility, each industry is likely to contain firms with different levels of uncertainty. This conclusion is supported by the similarity in momentum returns of numerous industries. It is hence unsurprising that there is no clear trend of increasing momentum returns with a rise in return volatility.

Chapter 8

Conclusion

The present work demonstrates that momentum returns rise with three simple measures - historical daily return volatility, the absolute intercept in a Fama-French regression and the loading on the market factor. The three measures may be interpreted as proxies for uncertainty. Higher return volatility makes asset valuation more uncertain, greater absolute Fama-French intercepts indicate that a larger component of returns cannot be accounted for by simple analysis (based on the Fama-French model) and higher loading on the market factor implies greater market risk.

The empirical observation that momentum returns rise with each of the three measures suggests that uncertainty contributes to momentum. This is because investors are more likely to project past trends into the future when presented with less reliable information to perform valuations.

Three other measures are also studied. It was found that momentum returns generally rise with loadings on the SMB factor, but the difference between the quintiles with the lowest and highest exposure is not statistically significant. On the other hand, loadings on the HML factor have no effect on momentum returns. Taken in the light of prior findings by Lim and Stein (2000) and Daniel and Titman (2000), these findings are likely due to the factor loadings being poor proxies for uncertainty associated with the SMB and HML factors respectively.

Momentum returns are surprisingly observed to decrease with a rise in (1-R^2) values of Fama-French factor model regressions. Considering the findings of Hou, Peng and Xiong (2006), in which momentum returns were observed to rise with (1-R^2) values, the reasons for the present findings are unclear. If the hypothesis that uncertainty contributes to momentum holds true, it would be more intuitive for uncertainty to rise with (1-R^2) values, leading to a corresponding increase in momentum returns.

The industry analysis does not reveal a clear relationship between the volatility of returns in an industry and its momentum returns. This is likely due to the 12 industry classification system being a poor basis for differentiating firms on their volatility rather than a contradiction of the hypothesis that uncertainty contributes to momentum.

In conclusion, the present work provides some proof that uncertainty contributes to the magnitude of momentum returns. However, proxies for uncertainty need to be judiciously selected.

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Table 1 – Fama-French 12 industry portfolio classification

For Test 7, stocks were sorted into 12 industry groups based on their SIC codes. The system for industry classification used is shown below. It is taken from the industry definitions file from Kenneth French's website. (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html)

Industry	Description	SIC codes
1	Consumer Non-Durables -- Food, Tobacco, Textiles, Apparel, Leather, Toys	0100-0999 2000-2399 2700-2749 2770-2799 3100-3199 3940-3989
2	Consumer Durables -- Cars, TVs, Furniture, Household Appliances	2500-2519 2590-2599 3630-3659 3710-3711 3714-3714 3716-3716 3750-3751 3792-3792 3900-3939 3990-3999
3	Manufacturing -- Machinery, Trucks, Planes, Office Furniture, Paper, Com Printing	2520-2589 2600-2699 2750-2769 3000-3099 3200-3569 3580-3629 3700-3709 3712-3713 3715-3715 3717-3749 3752-3791 3793-3799

		3830-3839 3860-3899
4	Oil, Gas, and Coal Extraction and Products	1200-1399 2900-2999
5	Chemicals and Allied Products	2800-2829 2840-2899
6	Business Equipment -- Computers, Software, and Electronic Equipment	3570-3579 3660-3692 3694-3699 3810-3829 7370-7379
7	Telephone and Television Transmission	4800-4899
8	Utilities	4900-4949
9	Wholesale, Retail, and Some Services (Laundries, Repair Shops)	5000-5999 7200-7299 7600-7699
10	Healthcare, Medical Equipment, and Drugs	2830-2839 3693-3693 3840-3859 8000-8099
11	Finance	6000-6999
12	Other -- Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment	All other SIC codes

Table 2 – Descriptive statistics for uncertainty proxies

The first two columns addressing return volatility use NYSE and AMEX stocks priced above $5, while the remaining columns use all NYSE and AMEX stocks. For each uncertainty proxy, the number of observations used, mean, standard deviation and empirically observed values at various percentile levels are shown.

Proxy	6-month Daily Return Volatility (1925-2007)	6-month Daily Return Volatility (1965-2007)	Absolute Intercept of F-F Reg (1964-2007)	$(1-R^2)$ value (1964-2007)	Market Factor Loading (1964-2007)	SMB Factor Loading (1964-2007)	HML Factor Loading (1964-2007)
Number of observations	1978294	1559133	1592385	1592623	1592385	1592385	1592385
Mean	0.026	0.026	0.00146	0.87	0.90	0.62	0.28
Std Dev	0.018	0.016	0.00156	0.13	0.67	0.86	0.97
Percentile							
0	0.002	0.002	7.73E-06	0.04	-2.35	-5.32	-10.14
5	0.009	0.009	9.6E-05	0.61	-0.05	-0.55	-1.28
25	0.015	0.015	0.00044	0.81	0.42	0.05	-0.21
50	0.021	0.022	0.00098	0.91	0.84	0.49	0.26
75	0.031	0.032	0.00193	0.96	1.30	1.07	0.78
95	0.058	0.057	0.00446	0.99	2.10	2.21	1.90
100	0.344	0.222	0.02886	1.00	5.51	8.98	10.57

Table 3 –Momemtum returns for low (Q1) to high (Q5) volatility quintiles

for NYSE and AMEX stocks priced above $5

Stocks are sorted into quintiles based on their daily return volatility over the previous 6 months. Panel A uses data over the period 1925-2007 while Panel B covers 1965-2007. For each quintile, monthly momentum returns and their corresponding t-stats are calculated. The mean and standard deviation of return volatility are also computed within each quintile. The difference between the momentum returns between the highest and lowest volatility quintiles is tested for statistical significance.

(A) 1925-2007

	First Sort Based on Past Return Volatility				
	Low Q1	Q2	Q3	Q4	High Q5
Momentum Return	0.0052	0.0082	0.0086	0.0089	0.0115
t-stat	5.18	6.59	5.89	4.61	4.1
Average volatility	0.012	0.017	0.022	0.029	0.042
SE of volatility	0.004	0.005	0.006	0.007	0.014

T-stat on equality test between momentum returns in Q1 and Q5 = 2.10

(B) 1965-2007

	First Sort Based on Past Return Volatility				
	Low Q1	Q2	Q3	Q4	High Q5
Momentum Return	0.0038	0.0073	0.0089	0.0096	0.0125
t-stat	3.76	5.69	5.82	5.22	4.61
Average volatility	0.012	0.017	0.022	0.030	0.045
SE of volatility	0.003	0.004	0.005	0.006	0.012

T-stat on equality test between momentum returns in Q1 and Q5 = 2.99

Table 4 –Momemtum returns for low (Q1) to high (Q5) Fama-French absolute intercept quintiles for NYSE and AMEX stocks between 1964-2007

Stocks are sorted into quintiles based on their absolute Fama-French regression intercepts using daily data over the previous 6 months. Data used covers the period 1964-2007. For each quintile, monthly momentum returns and their corresponding t-stats are calculated. The mean and standard deviation of the absolute regression intercepts are also computed within each quintile. The difference between the momentum returns of the highest and lowest absolute intercept quintiles is tested for statistical significance.

	First Sort Based on Absolute Value of Intercept of Fama-French Regression (1964-2007)				
	Low Q1	Q2	Q3	Q4	High Q5
Momentum Return	0.0024	0.0034	0.0061	0.0089	0.0156
t-stat	1.48	2.05	3.40	4.21	4.59
Average absolute intercept	0.00019	0.00056	0.00104	0.00183	0.00499
SE of intercept	0.00011	0.00016	0.00024	0.00041	0.00212

T-stat on equality test between momentum returns in Q1 and Q5 = 3.52

Table 5 – Momemtum returns for low (Q1) to high (Q5) ($1-R^2$) quintiles for NYSE and AMEX stocks between 1964-2007

Stocks are sorted into quintiles based on their ($1-R^2$) values from Fama-French regressions using daily data over the previous 6 months. Data used covers the period 1964-2007. For each quintile, monthly momentum returns and their corresponding t-stats are calculated. The mean and standard deviation of the ($1-R^2$) values are also computed within each quintile. The difference between the momentum returns of the highest and lowest HML factor loading quintiles is tested for statistical significance.

	First Sort Based on ($1-R^2$) value of Fama-French Regression (1964-2007)				
	Low Q1	Q2	Q3	Q4	High Q5
Momentum Return	0.0128	0.0118	0.0119	0.0103	0.0054
t-stat	5.79	5.33	5.45	4.26	1.91
Average ($1-R^2$) value	0.70	0.83	0.90	0.94	0.98
SE of ($1-R^2$) value	0.12	0.08	0.06	0.04	0.02

T-stat on equality test between momentum returns in Q1 and Q5 = 2.05

Table 6 – Momemtum returns for low (Q1) to high (Q5) market factor loading quintiles for NYSE and AMEX stocks between 1964-2007

Stocks are sorted into quintiles based on their market factor loadings in Fama-French regressions using daily data over the previous 6 months. Data used covers the period 1964-2007. For each quintile, monthly momentum returns and their corresponding t-stats are calculated. The mean and standard deviation of the market factor loadings are also computed within each quintile. The difference between the momentum returns of the highest and lowest market factor loading quintiles is tested for statistical significance.

	First Sort Based on Market Factor Loading of Fama-French Regression (1964-2007)				
	Low Q1	Q2	Q3	Q4	High Q5
Momentum Return	0.0056	0.0085	0.0100	0.0116	0.0145
t-stat	2.49	5.14	5.39	5.8	5.12
Average load	-0.03	0.51	0.85	1.22	1.97
SE of load	0.37	0.16	0.15	0.18	0.47

T-stat on equality test between momentum returns in Q1 and Q5 = 2.48

Table 7 – Momemtum returns for low (Q1) to high (Q5) SMB factor loading quintiles for NYSE and AMEX stocks between 1964-2007

Stocks are sorted into quintiles based on their SMB factor loadings in Fama-French regressions using daily data over the previous 6 months. Data used covers the period 1964-2007. For each quintile, monthly momentum returns and their corresponding t-stats are calculated. The mean and standard deviation of the SMB factor loadings are also computed within each quintile. The difference between the momentum returns of the highest and lowest SMB factor loading quintiles is tested for statistical significance.

	First Sort Based on SMB Factor Loading of Fama-French Regression (1964-2007)				
	Low Q1	Q2	Q3	Q4	High Q5
Momentum Return	0.0082	0.0078	0.0100	0.0111	0.0134
t-stat	3.39	4.84	5.98	5.66	4.63
Average load	-0.49	0.16	0.52	0.97	2.01
SE of load	0.45	0.17	0.21	0.29	0.72

T-stat on equality test between momentum returns in Q1 and Q5 = 1.37

Table 8 – Momemtum returns for low (Q1) to high (Q5) HML factor loading quintiles for NYSE and AMEX stocks between 1964-2007

Stocks are sorted into quintiles based on their HML factor loadings in Fama-French regressions using daily data over the previous 6 months. Data used covers the period 1964-2007. For each quintile, monthly momentum returns and their corresponding t-stats are calculated. The mean and standard deviation of the HML factor loadings are also computed within each quintile. The difference between the momentum returns of the highest and lowest HML factor loading quintiles is tested for statistical significance.

	First Sort Based on HML Factor Loading of Fama-French Regression (1964-2007)				
	Low Q1	Q2	Q3	Q4	High Q5
Momentum Return	0.0105	0.0098	0.0092	0.0092	0.0119
t-stat	4.15	5.71	5.38	4.89	4.33
Average load	-1.16	-0.14	0.27	0.69	1.77
SE of load	0.73	0.20	0.16	0.21	0.76

T-stat on equality test between momentum returns in Q1 and Q5 = 0.35

Table 9 – Industry analysis: Comparison of industry rankings based on daily stock return volatility and momentum returns between 1965-2007

Stocks were sorted into 12 industry groups based on the 12 industry portfolio classification system shown in Table 1. Within each group, daily and monthly stock returns from 1965-2007 were used to calculate volatility and monthly momentum returns respectively. The mean and standard deviation of volatility in each industry is shown. The industries were ranked in ascending order of volatility and momentum returns.

Industry	Description	Mean Volatility	Volatility Std Dev	Volatility Rank	Momentum Returns (t-stat)	Momentum Rank
1	Consumer Non-Durables -- Food, Tobacco, Textiles, Apparel, Leather, Toys	0.0280	0.0099	5	0.0070 (3.66)	8
2	Consumer Durables -- Cars, TVs, Furniture, Household Appliances	0.0307	0.0116	10	0.0067 (2.56)	7
3	Manufacturing -- Machinery, Trucks, Planes, Office Furniture, Paper, Com Printing	0.0279	0.0098	4	0.0075 (4.59)	10
4	Oil, Gas, and Coal Extraction and Products	0.0292	0.0104	6	0.0034 (1.44)	3

5	Chemicals and Allied Products	0.0267	0.0095	3	0.0062 (2.66)	5
6	Business Equipment -- Computers, Software, and Electronic Equipment	0.0371	0.0176	12	0.0065 (2.52)	6
7	Telephone and Television Transmission	0.0300	0.0160	7	0.0001 (0.04)	1
8	Utilities	0.0186	0.0087	1	0.0031 (1.73)	2
9	Wholesale, Retail, and Some Services (Laundries, Repair Shops)	0.0304	0.0187	9	0.0087 (4.65)	11
10	Healthcare, Medical Equipment, and Drugs	0.0347	0.0209	11	0.0036 (1.34)	4
11	Finance	0.0194	0.0107	2	0.0070 (3.59)	9
12	Other -- Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment	0.0302	0.0142	8	0.0111 (5.09)	12

Spearman rank coefficient = 0.098