

MOMENTUM: A RATIONAL INTERPRETATION

by

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Abstract

In this thesis, I examine existing theories that attempt to explain the asset pricing phenomenon known as momentum. I revisit the seminal work of Chordia and Shivakumar (2002); Cooper, Guitierrez and Hameed (2004); and Stivers and Sun (2010). Using an updated sample, I reexamine their findings, while also comparing the results by credit rating. It has been shown that, among rated firms, momentum appears to exist only among firms with a non-investment grade credit rating. By comparing the results of the investment grade firms with those of the non-investment grade firms, we can see which are being driven by firms that experience momentum. The results indicate that momentum is more closely related to the state of the market than the state of the economy. However, among market-state variables, it is the return dispersion within the market that is more important, as opposed to the returns of the market themselves. Return dispersion is negatively related to momentum returns. If return dispersion is considered to be a measure of market uncertainty, then this is inconsistent with many leading behavioural theories that include uncertainty as a driving factor of momentum. In response to this, I present an alternative risk-based explanation that is consistent with these findings, as well as reconcile them with much of the existing empirical evidence supporting these behavioural theories.

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Chapter 1: Introduction

Momentum is an asset return phenomenon in which it appears as though “winners” continue to “win” while “losers” continue to “lose”. It is the inexplicably profitable momentum *strategy* that gives rise to the phenomenon. A momentum strategy typically involves purchasing a portfolio of recent high return stocks while simultaneously selling a portfolio of recent low return stocks. Stocks are in the “winner” portfolio since they outperformed those in the “loser” portfolio, and positive strategy profits going forward indicate that they continue to outperform. Many interpret this as a continuation of returns – or in other words, that past returns can potentially predict future returns – in violation of the efficient market hypothesis.

The efficient market hypothesis states that markets efficiently price their assets, on average. At any given time, the price of an asset should be accurate given all known information – and quickly adjust to reflect any new information. One major implication is that future price movements cannot be predicted. Consistent momentum profits imply, however, that past returns can be used to predict future returns to some extent, in so much as that the portfolio of winners typically outperforms that of the losers.

In this thesis, I examine existing theories that attempt to explain this phenomenon and propose a new one which is able to withstand time and, I believe, reconciles much of the existing empirical evidence. Many of the leading behavioural theories of momentum – which are the theories with a great deal of empirical support – centre on, or include, uncertainty as a driving factor of momentum. Essentially the argument is that uncertainty leads to slower incorporation of new information and therefore price continuation as the information is slowly incorporated, i.e. uncertainty leads to greater momentum. Where these theories are lacking, however, is that they are

at odds with more current empirical evidence on market-level behaviour. While many studies demonstrate that momentum is positively related to uncertainty at the firm-level, more recent empirical work by Stivers and Sun (2010), Huang (2013) and Wang and Xu (2015) seem to indicate a negative relationship between momentum and uncertainty at the market-level. These empirical findings are inconsistent with leading behavioural theories. Therefore, I propose an explanation in which the level of “noise” contained in realized returns is able to account for these differences.

In Chapter 2, I review the existing literature on momentum. I provide a brief history on momentum research and examine some of its cross-sectional determinants, as well as discuss the competing behavioural- and risk-based theories.

In Chapter 3, I extend the review and delve deeper into one particular stream of research. I revisit the related series of seminal work on momentum by Chordia and Shivakumar (2002); Cooper, Guterrez and Hameed (2004); and Stivers and Sun (2010). Beginning with Chordia and Shivakumar, each subsequent paper builds off the previous and challenges its findings. Chordia and Shivakumar present a macroeconomic model that they claim potentially explains momentum. They also find that momentum depends on the state of the economy and is only profitable during expansionary periods (and is nonexistent during recessionary periods). This work is important because it establishes the possibility that momentum could be a rational result of exposure to a common set of macroeconomic factors. However, Cooper, Guterrez and Hameed argue that Chordia and Shivakumar’s main findings are driven by penny stocks that should be excluded from the analysis and that the state of the market is far more important than macroeconomic factors. They claim that inclusion of a market state variable subsumes the explanatory power of those

macro factors and that it is not necessarily the state of economy that momentum is conditioned on, but rather the state of the market; momentum is only profitable following bull markets (and non-existent following bear markets). Stivers and Sun claim that the dispersion of market returns explains momentum, implying that the previous results were proxying for this dispersion.

I re-examine this series of findings, updating the results using a more recent sample period; but I also use the findings of another study by Avramov et al (2007) to establish a momentum and “control group” to confirm whether the previous results are in fact driven by momentum. As Avramov et al find that profitable momentum only exists among firms with a non-investment grade credit rating, I compare the results of momentum strategies drawn from investment grade and non-investment grade firms separately. If the results hold among the non-investment grade group and not the investment grade group, I can conclude that they are in fact being driven by momentum.

I find that Chordia and Shivakumar’s macroeconomic model does not stand the test of time. Momentum is still profitable only during economic expansions, but the macroeconomic variables employed by Chordia and Shivakumar no longer adequately explain momentum. Momentum also continues to appear dependent on the market state (bull vs bear); however, the performance among the investment grade firms does not appear to be so black-and-white. When conditioned on the state of the market, momentum earns significant positive returns following bull markets, but not bear markets. But, overall, market return dispersion still appears to be the best indicator of momentum profits, consistent with Stivers and Sun. Momentum strategy returns are negatively related to the return dispersion of the market.

The prominence of this negative relationship between return dispersion and momentum returns presents a potential challenge for leading behavioural theories explaining momentum. In

these theories, momentum is the result of uncertainty (see Barberis, Schliefer and Vishny (1998), Hong and Stein (1999), Hong, Lim and Stein (2000), Grinblatt and Han (2005)). In the face of uncertainty, investors underreact to new information during the formation period. During the holding period, prices continue to move towards their true intrinsic value and so “winners” continue to “win” and “losers” continue to “lose”. Momentum profits are thus the market correcting this underreaction (or an overreaction to this original underreaction, depending on the theory, e.g. Hong and Stein (1999)). If return dispersion (or market volatility) is a measure of overall market uncertainty, then we should see greater momentum returns following periods of greater dispersion and thus greater uncertainty – which should lead to greater underreaction during the formation period. This, however, is contrary to the findings of Stivers and Sun (2010) that momentum is actually lower following periods of greater dispersion. Other work by Huang (2013) and Wang and Xu (2015) also find that momentum is negatively related to other measures of market dispersion and market volatility, respectively.

In Chapter 4, I propose a simple explanation for momentum that reconciles these empirical findings relating to momentum and market dispersion or volatility – that are at odds with these behavioural theories – and other empirical results that are consistent with these same theories. In my explanation, momentum profits are a rational result from the cross-sectional differences in the expected returns of the winner and loser portfolios. Over the holding period, the winner portfolio has a greater expected return (which is compensation for bearing greater risk) than the loser portfolio. This can be detected through controlling for the life expectancies of firms within the sample as well as through momentum’s relationship to measures of market dispersion/volatility.

Firms are sorted by their past realized returns in a momentum strategy. If those realized returns proxy well for expected returns, then we will see that firms are also sorted by their expected returns. The expected returns of the winners will be greater than those of the losers resulting in positive momentum returns, on average. Realized returns proxy well for expected returns if the idiosyncratic portion of those returns is relatively small. If the expected returns are relatively stable over the short to medium horizon, then increases in market dispersion and volatility are more likely the result of increases in the dispersion/volatility of idiosyncratic returns. This, in turn, decreases the degree to which realized returns proxy for expected returns and we see lower momentum returns as the sorting of the portfolios is more random, with respect to the expected returns of those firms. This is also detected through the life expectancies of firms. I show how all else being equal firms with lower life expectancies should be less sensitive to idiosyncratic shocks to their growth and, therefore, their realized returns depend on their expected returns to a greater degree. Momentum would therefore be stronger in these firms.

My empirical findings support these claims. Momentum is indeed stronger among firms with a lower life expectancy as predicted. In addition, the market return dispersion measures of Stivers and Sun (2010) continue to negatively predict momentum.

This is not to say that my findings *prove* that momentum is rational. They do, however, support the notion that rational momentum is plausible, and may in fact be more consistent with empirical evidence than even behavioural theories.

My main contributions are: 1) I provide a plausible explanation for the existence of positive momentum returns, which is consistent with the majority of empirical evidence related to momentum; 2) I document a previously unknown empirical relationship between momentum and

a measure of firms' life expectancies¹; and 3) through this relationship, I provide an explanation for the empirical findings of Avramov et al (2007) with respect to momentum among non-investment grade (credit rating) firms², and I believe I am able to extend their empirical findings to non-rated firms as well.

Other contributions include: 1) I review and update empirical findings from a series of highly cited research on momentum, and in part, present evidence that the previously popular macroeconomic model of Chordia and Shivakumar (2002) no longer adequately explains momentum; 2) I extend the work of Avramov et al (2007) in that I take a deeper look into the difference in behaviour between investment grade momentum portfolios and non-investment grade momentum portfolios; and 3) I find evidence that the original findings of Avramov et al (2007) are not so absolute and that there are conditions under which statistically significant momentum can be found among investment-grade firms.

¹ This is the logistic measure of the probability of delisting developed by Chen (2011).

² Avramov et al (2007) examine momentum among different credit ratings. They find that among rated firms, momentum exists only among non-investment grade firms (or firms with the lowest credit rating). They also note, however, that momentum also exists within non-rated firms as well.

Chapter 2: Literature Review

2.1 Discovery/Introduction

Momentum was first documented academically by Jegadeesh and Titman (1993). They examine the performance of the U.S. stock market, finding that a strategy based on past returns can earn abnormal profits, which would appear to imply that past returns may have some predictive power with regards to future returns and may be at odds with the concept of efficient markets. More specifically, Jegadeesh and Titman (1993) find that a portfolio that is long past extreme winners and equally short past extreme losers is profitable. In an efficient market – barring any systematic difference in risk – the winner portfolio should earn, on average, the same as the loser portfolio. The resulting zero-cost portfolio of the two should, therefore, earn a zero-return, on average.

The definition of momentum portfolios, as originally defined by Jegadeesh and Titman (1993), remains largely unchanged today. Typically, there are various sub-strategies based on differing lengths of the formation and holding periods. These sub-strategies are generally labelled as J/K strategies, where each month a portfolio is formed based on individual stock returns over the past J -months (where J is equal to 3, 6, 9 or 12 months), which is then subsequently held for the following K -months (where K is equal to 3, 6, 9 or 12). Each monthly portfolio consists of the top performing portfolio minus the bottom portfolio, where the top and bottom portfolios are the top decile and bottom decile, respectively, of stocks ranked on their J -month formation period. JT find that the profits from each iteration of the strategy are significantly positive over the period of 1965-1989.

In Jegadeesh and Titman (2001), the authors update the original study and find that momentum profits persisted even after its initial “discovery” in 1993. This puts the momentum in somewhat of a unique category given that not all asset pricing anomalies tend to disappear after their discovery, presumably as investors try to exploit them.

Further attesting to the robustness of momentum as an “anomaly”, Fama and French (1996) examine a set of anomalies (labelled as such due to their abnormal returns with respect to the CAPM) within the context of the Fama and French (1993) three-factor model. They conclude that momentum is the only such anomaly (of those examined) that remains largely unexplained by the 3-factor model. After controlling for the three factors (market return, big-minus-small (size) and high-minus-low (book-to-market ratios)), the monthly alphas of the momentum strategy remain statistically and economically significant, which *may* indicate misspecification of the model (under the assumption of efficient markets). This led to the addition of a fourth factor to the Fama-French three-factor model – the up-minus-down (UMD) momentum factor – in Carhart (1997).

Chan, Jegadeesh and Lakonishok (1996) examine the evidence and determine that traditional risk factors do not explain momentum. Instead, they argue that the results indicate that momentum is the market’s underreaction to new information. However, they also find no evidence of longer-term reversals among stocks with high momentum.

While the bulk of momentum research centres around U.S. equity markets, there is also substantial evidence that the pervasiveness of momentum does appear to be international and not limited to just U.S. markets or even to equities for that matter.

2.2 The Prevalence of Momentum

Momentum in Europe has been well documented. Schiereck and Weber (1995) find evidence of momentum in the German market; while Bacmann and Dubois (2000) find it present

in Switzerland. Rouwenhorst (1998) looks at stock returns across developed markets in Europe and documents evidence of momentum.

Chui, Titman and Wei (2000) and Hameed and Kusunadi (2002) look at momentum in Asia. Both find evidence of momentum; however, Chui, Titman and Wei find no evidence of momentum in Japan. In general, Chui, Titman and Wei find that momentum is weaker across Asia. Naughton, Troung and Veeraraghayan (2008) look at China specifically and document momentum there, however, they find no link between trading volume and momentum returns as found in Lee and Swaminathan (2000).

Alsubaie and Najand (2008) document evidence of momentum in the Saudi Arabian stock market. Bacmann, Dubois and Isakov (2001) do not restrict their study to any one particular geographical location, but rather, they examine the markets of the G-7 countries, finding evidence of momentum in all seven.

Griffin, Ji and Martin (2003) examine momentum in 40 countries across the globe and find that momentum returns are significant internationally. They also find that these momentum returns are not significantly related to the economic factors of Chen, Roll and Ross (1986), nor those of Chordia and Shivakumar (2002), concluding that momentum does not appear to be compensation for macroeconomic risk. In addition, these momentum returns are positive throughout the business cycle (contrary to the findings of Chordia and Shivakumar 2002).

The evidence of momentum within emerging markets is more mixed. Bekaert, Erb, Harvey and Viskanta (1997) report their momentum findings are inconsistent, where the results appear to depend on the weighting method used to form portfolios. However, Rouwenhorst (1999) finds more consistent momentum returns in a sample of 20 emerging markets. Bhojraj and Swaminathan (2001) also find strong momentum returns among emerging markets.

Asness, Liew and Stevens (1997) finds positive momentum profits in a modified take on the momentum strategy. Rather than ranking individual stocks, the authors rank country indices. The momentum portfolios are formed by buying the top performing indices and selling the worst performing indices. Chan, Hameed and Tong (2000) also look at momentum within the indices of international equity markets. They find that momentum appears to be stronger under shorter holding periods for the indices and they also document a link between the momentum returns and trading volume from the previous period.

The profitability of momentum strategies does not appear to be confined to just equity markets. Okunev and White (2003) document momentum in currency markets and Erb and Harvey (2006) find momentum in commodity markets. Moskowitz, Ooi and Pedersen (2012) find momentum in futures contracts (equity index, currency, commodity and bond futures), as well as a partial reversal in the long-run. They argue that these abnormal returns persist even after adjusting for standard asset pricing factors. Asness, Moskowitz and Pedersen (2013) and Jostova, Nikolova, Philipov and Stahel (2013) introduce evidence of momentum in bonds (as well as country equity index futures, currencies, and commodity futures).

2.3 Cross-sectional Determinants

Given that momentum was originally empirical evidence in search of a theory as opposed to a theory in search of empirical evidence, much of the research concentrated on describing the behaviour of the anomaly. This research has uncovered many cross-sectional determinants that would appear to be related to the momentum phenomenon.

Daniel and Titman (1999) report a negative relationship between momentum returns and book-to-market ratios. They interpret this as evidence that momentum is stronger among growth

firms. Hong, Lim and Stein (2000) find that momentum strategy returns are negatively related to firm size. They also find that momentum is stronger in firms with lower analyst coverage. Lee and Swaminathan (2000) establish a link between momentum and the relative trading volume of firms. Momentum returns appear to be stronger among firms experiencing higher relative trading volume: the level of trading volume relative to their average trading volume.

There also appears to be a link between momentum and information uncertainty. Both Jian, Lee and Zhang (2005) and Zhang (2006) claim that momentum returns are positively related to information uncertainty as evidenced by their empirical relationship to proxies of information uncertainty. These proxies include firm size, analyst coverage, dispersion in analysts' forecasts, return volatility, cash flow volatility, firm age, trading volume and cash flow duration.

Sagi and Seasholes (2007) identify a negative relationship with firms' cost of goods sold and a positive relationship with firms' revenue volatility. Avramov, Chordia, Jostova and Philipov (2007) examine momentum and credit rating. Their findings indicate that, among rated firms, momentum appears to exist only among low-grade firms. Once non-investment grade (NIG) firms are removed from the sample, momentum returns are insignificant. Avramov et al also note that NIG firms only account for 4% of the total market cap of rated firms, yet still drive momentum returns within this overall group.

There appears to be an ambiguous relationship between momentum and idiosyncratic volatility. Arena, Haggard and Yan (2008) find that momentum returns are positively related to idiosyncratic volatility. They also note that reversals of previous momentum returns are also positively related to idiosyncratic volatility, in that the reversals are larger and faster among firms with greater idiosyncratic volatility. However, McLean (2010) finds that momentum returns are not related to idiosyncratic volatility.

Stivers and Sun (2010) find that momentum returns are negatively related to the return dispersion of the market, while Wang and Xu (2011) argue that lagged market volatility can predict future momentum returns (negatively related). Antoniou, Doukas and Subrahmanyam (2010) find that investor sentiment is positively related to momentum. Chui, Titman and Wei (2010) claim there is a positive link between “individualism” (measure from Hofstede 2001) and the magnitude of momentum returns. Finally, Avramov, Cheng and Hameed (2013) claim that market illiquidity negatively predicts momentum returns.

2.4 Sources of Momentum

Moskowitz and Grinblatt (1999) propose that momentum is actually industry momentum. Traditional momentum profits are largely explained by industry momentum in U.S. markets: buying and selling stocks from past winning and losing industries, respectively. However, Grundy and Martin (2001) find that industry momentum profits disappear once a gap is introduced between the formation and holding periods (currently standard among momentum strategy methodology), while traditional momentum profits remain. Also, Chordia and Shivakumar (2002) find that traditional momentum is separate from industry momentum within their macroeconomic factor model.

Korajczyk and Sadka (2004) investigate the theoretical impact of trading and transaction costs on the returns of a momentum strategy and calculate a maximum capital investment that momentum investing can sustain. Overall, their models indicate that while transactions costs would have a significant impact on overall profits, momentum investing can still remain profitable after transaction costs. In other words, transaction costs, as a limiting effect on arbitrage, are not sufficient to fully explain the persistence of the momentum anomaly. Korajczyk and Sadka predict

that positive momentum returns would lose their statistical significance after \$1.1-\$2.0 billion dollars are invested and disappear entirely after the \$4.5-\$5.0 billion dollars level.

According to Kothari and Shanken (1992), portfolios formed on the basis of their past returns would have differing loadings on time-varying systematic factors. As an example, in momentum's case, buying and selling the extreme portfolios would also yield the more extreme factor loadings. In the case of positive (negative) factors during the formation period, it would be expected that the winner portfolio would tend to have higher (lower) loadings relative to the loser portfolio. Therefore, the resulting winner minus loser portfolio would be expected to have a positive (negative) loading on factors, and therefore, positive (negative) returns over the subsequent holding period.

Grundy and Martin (2001) examine this line of reasoning in more detail. While they claim that a momentum strategy “guarantees time-varying factor exposure”, they also claim that this factor exposure is not enough to fully explain momentum returns. Their findings indicate that factor models (e.g., Fama-French three-factor model) can only explain the variation in momentum returns; not their magnitude. Momentum strategies, adjusted for factor returns (therefore, based only on firm-specific return components as defined by the three-factor model), continue to be profitable.

Chordia and Shivakumar (2002), in a seminal momentum paper, present evidence in favour of a risk-based explanation, suggesting that time-varying factor exposure may be driving momentum returns. They examine momentum returns relative to common lagged macroeconomic factors. They find that it can be explained by their macroeconomic factor model and that a momentum investing is no longer profitable once the returns are adjusted for these lagged factors. Griffin, Ji and Martin (2003), on the other hand, do not find that the macroeconomic explanation

holds internationally (in non-U.S. markets). Chordia and Shivakumar (2002) also examine momentum returns over historic business cycles and find that momentum is only profitable during times of economic expansion (returns are negative and insignificant during recessions). Based on their findings, momentum investing would appear to be procyclical in nature.

Cooper, Gutierrez and Hameed (2004) re-examine Chordia and Shivakumar's (2002) work, rejecting their main findings. According to Cooper et al., once a gap month (between formation and holding periods) and a price screen (stocks less than \$1) are included, Chordia and Shivakumar's macroeconomic variables no longer explain momentum returns. They reject a risk-based explanation in favour of a behavioural explanation based on overconfidence. Rather than being dependent on the business cycle, they propose that the momentum strategy is dependent on market states.

Similar to the business cycle work, Cooper, Gutierrez and Hameed (2004) also examine momentum returns over lagged market returns, differentiating between UP and DOWN states, depending on whether or not the lagged 3-year market return was positive or negative, respectively. Similar to Chordia and Shivakumar's business cycle findings, Cooper et al find that momentum is only positive following UP market states and negative but insignificant following DOWN market states. They also find that momentum strategies implemented following UP market states eventually reverse in the long-run. They interpret this as support for overreaction theories, arguing that investors suffering from overconfidence would be more overconfident during bull markets leading to greater overreaction (and greater momentum returns) and then the eventual corrective reversal.

Stivers and Sun (2010) take both Chordia and Shivakumar's (2002) and Cooper, Gutierrez and Hameed's (2004) work one step further, and introduce return dispersion to the analysis. They

find that lagged market return dispersion is negatively related to subsequent momentum returns: momentum is greatest when return dispersion is low. They argue that this return dispersion explains the Chordia and Shivakumar's procyclical and Cooper et al.'s UP-state dependence findings, relating return dispersion to both the business cycle and market state. They do indeed find that their measure subsumes the predictive power of both Chordia and Shivakumar (2002) and Cooper, Gutierrez and Hammeed (2004).

2.5 Behavioural-based Theories

Barberis, Shleifer and Vishny (1998) present a model of investor behaviour which contains both the underreaction and overreaction of investors to new information. They incorporate two psychological concepts: conservatism and the representativeness heuristic. Conservatism causes investors to underreact over the short- to medium-term, while it is the representativeness heuristic which causes investors to overreact over the longer-term. Momentum is a consequence of this underreaction.

Within the Barberis, Shleifer and Vishny (1998) model, investors are subject to a conservatism bias as it relates to new information. Edwards (1968) first identifies conservatism, which is where individuals are reluctant to use new information while discarding old information when updating their beliefs. As new information arises, investors will still partly cling to older, less relevant news, and as a consequence, it will take longer for this new information to be fully incorporated into market prices. This underreaction leads to a continuation of price movement over the first 1-12 months, and thus, momentum.

Another interesting result of Barberis, Shleifer and Vishny (1998), as it relates to momentum, is the overreaction of investors over the longer-term due to their use of the

representativeness heuristic. As investors observe a series of price increases (price decreases), they will incorrectly conclude that this past price movement is representative of a trend and will thus bid the price up (down) further, beyond their fundamental value. This overreaction is eventually corrected in the long-term which leads to a long-term reversal. This is consistent, not only with the long-term reversal of DeBontd and Thaler (1985), but also with the findings of momentum portfolio long-term reversals in Lee and Swaminathan (2000) and Jegadeesh and Titman (2001).

Daniel, Hirshleifer and Subramanyam (1998) also propose a model that results in overreaction; however, they employ a different psychological basis than BSV. In Daniel, Hirshleifer and Subramanyam (1998), investors possess a self-attribution bias which results in overconfidence. Individuals with self-attribution tend to attribute positive outcomes to their own abilities and negative outcomes to their environment, or luck. In this model, informed traders experience the self-attribution bias and as a result, become overconfident in their own stock selection abilities. When they interpret news about a stock as positive, their overconfidence in themselves translates into overconfidence in these “winners” bid up the prices of these stocks, overreacting to this news. This overreaction is what causes momentum and then the subsequent correction to this overreaction is what causes the long-term reversals.

Grinblatt and Han (2005) argue that momentum is the result of prospect theory and mental accounting, combining to create the disposition effect. Investors tend to hold onto past losers and sell past winners, leading to an underreaction to new information. This reluctance to sell past losers causes a delay in the incorporation of new information into prices, leading to underreaction. As the information is slowly incorporated, the prices continue to move, resulting in momentum, but not long-term reversal.

The psychological concept of anchoring is used as an explanation for momentum in George and Hwang (2004). Looking at 52-week highs, the authors find that momentum is stronger as firms approach their 52-week high. They also argue that “nearness” to the 52-week high is an even better predictor of future returns than past returns (the traditional momentum strategy) which they interpret as evidence of anchoring. They propose that the closer the current price is to the 52-week high, the more reluctant investors are to pushing it to beyond that high (anchoring), leading to underreaction, and thus, momentum. Interestingly, they find that long-term reversal is not present when nearness to the 52-week is used to form portfolios, which the authors interpret as an indication that momentum and long-term reversal are separate phenomena. They investigate this further in George and Hwang (2007) where they find that long-term reversals are a result of a rational reaction to locked-in capital gains. Of note, is that unrealized capital gains are one of the measures used by Grinblatt and Han (2005).

There are also some behavioural theories that do not depend on any particular psychological concept. In one such study, Hong and Stein (1999), investors are divided into two groups: informed and uninformed traders. Informed traders trade on fundamentals, but not price history; while uninformed traders trade on the history of prices, but not fundamentals. Similar to BSV, Hong and Stein (1999)’s model predicts both underreaction and overreaction. As new fundamentals information is revealed, informed traders trade on it. This trading sends price signals to the uninformed traders who trade exclusively on price history. Trading by the informed group is not enough to fully incorporate the new information into prices and so the market underreacts to this new information as the uninformed group slowly pushes up (down) the prices to their fundamental values. At this point, underreaction becomes overreaction as the uninformed traders continue to trade based on past price movements and push the prices above (below) their

fundamental value. This price continuation results in momentum. Prices then begin to revert to their fundamentals as the informed group begins trading on fundamentals again, leading to an eventual reversal of the overreaction.

In Vayanos and Woolley (2013), the authors argue that flows of capital from investment funds can explain momentum (and its reversal). In their model, investors attribute a manager's efficiency to his or her performance. As a result, funds that hold more assets which experience greater negative shocks will also realize lower returns. Investors, attributing this performance to the manager, will begin to withdraw their investments from the fund. The withdrawals force the fund to sell assets to cover the outflows, which puts greater downward pressure on the price of their assets. The prices of the assets that originally experienced negative shocks will continue their downward movement, resulting in momentum and prices below their fundamental values. Eventually, the prices will revert to their fundamental values and reversal occurs.

Similar to Vayanos and Woolley, Barberis and Shleifer (2003) propose that momentum is the result of investors "switching"; but rather than switching funds, in this model they are switching "styles". Barberis and Shleifer break down investors into switchers and fundamental investors. Switchers group stocks by style and assume that performance of a style will continue into the future. As one style underperforms, they will switch, gradually, into other style by trading with the fundamental investors who ignore this concept of "style". It is the gradual movement out of certain styles that drives momentum returns.

2.6 Risk-based Theories

Conrad and Kaul (1998) propose that momentum profits are simply the product of buying “high mean” stocks and selling “low mean” stocks, resulting in positive profits on average. They decompose momentum returns into what they refer to as the “time-series predictability” component and the “cross-sectional variation” component and argue that momentum returns may be due entirely to the cross-sectional variation in unconditional mean returns of stocks. The idea is that if stock returns follow a random walk with drift, and even the time-varying changes in that drift is unpredictable, then there would be no time-series predictability; however, a momentum strategy could still earn positive returns due to cross-sectional dispersion. Past winners would tend to include more stocks with higher unconditional mean returns, on average, then compared to past losers. Therefore, momentum strategy would result in the long position having a higher unconditional mean relative to the short position, which would, in turn, result in positive returns of the combined portfolio. Conrad and Kaul’s empirical work indicates that only the cross-sectional variation component contributes positively to momentum returns.

The work of Conrad and Kaul (1998) was meant only to present the possibility of cross-sectional variation driving momentum, not to prove it conclusively. They also make no argument for or against any specific asset pricing model. Berk, Green and Naik (1999) base their model on a similar premise to Conrad and Kaul (1998) (if one interprets unconditional mean to represent expected return): momentum is ultimately the result of the winner portfolio having a greater expected return than the loser portfolio, *ex ante*. Their model concerns a firm’s optimal investment choices, its effects on the systematic risk of the firm, and how changes in this risk are predictable.

Berk, Green and Naik (1999) look at the firm as a portfolio of existing assets and growth options, where the systematic risk of the firm is the systematic risk of that portfolio. Existing assets

are considered less risky than the growth options. As a firm exercises their options (transforming those options into existing assets), their “existing assets” increase and their remaining options decrease, leading to a reduction in the overall weight of the riskier growth options (relative to existing assets), which leads to a reduction in the overall systematic risk of the firm. The reduction in systematic risk (and potentially increased future cash flows from exercising growth options) leads to an immediate stock price increase, as equity investors now require lower future returns corresponding to the drop in risk. The immediate increase in stock prices is followed by lower future expected returns, which results in contrarian effects followed by momentum effects as the lower expected returns persist. The simulation results of their model are consistent with previous empirical work, however, the order of contrarian and then momentum is the opposite of what we traditionally observe.

Another important contribution of Berk, Green and Naik (1999) is that their model provides a theoretical link between book-to-market and market value and the observed patterns of returns, through their investment decisions. Book-to-market captures the firm’s asset mix relative to its overall asset base, while market value captures the weighting of the assets in its asset mix. As both book-to-market (value) and market value (size) are factors in the popular Fama-French three-factor model, their model provides a theoretical foundation for the three-factor model’s *partial* success in explaining momentum.

Johnson (2002) presents a model in which time-varying growth rates and growth rate risk lead to positive momentum returns (or any other underreaction anomaly). In his model, growth rate risk is positively related to expected growth rate (firms with higher expected growth rates are more sensitive to changes in those rates) and a firm’s expected growth rate can vary over time. As a firm experiences a positive shock to their expected growth rate, the increase in the expected

future cash flows would lead to an immediate rise in the stock price and thus a positive return for that period. The increase in the growth rate would also lead to an increase in the firm's growth rate risk and, if growth rate risk is a compensated risk, its expected returns. Thus, the firm experiences the initial positive return followed by greater subsequent returns as its risk and expected return increases as well, resulting in price continuation. A momentum sort in such a model would tend to sort firms by their changes in their expected growth rates, and, therefore, also by their future expected return levels. The resulting portfolio is long in the higher expected return winner portfolio and short in the lower expected return loser portfolio and should result in positive subsequent returns, on average. Johnson does not claim, however, that his model is the explanation for momentum. As he puts it, the purpose of the paper is "just to call attention to a direct, plausible and rational mechanism."

Sagi and Seasholes (2007) identify what they consider to be two important cross-sectional determinants: costs of goods sold and revenue volatility. Momentum returns appear to be strongest among firms with a low cost of goods sold and high revenue volatility and the authors argue that they can create "enhanced" momentum returns by conditioning their strategy based on these attributes. Similar to Berk, Green and Naik (1999), a firm's growth options play an important role in Sagi and Seashole's model. According to their model, momentum is the result of firms exercising their valuable growth options and a firm's ability to capture those valuable growth options is dependent on their recent past performance. Winners, by definition, outperformed losers during the formation period and are, therefore, in a better position to exploit those options over the holding period and continue to outperform their loser counterpart, resulting in momentum profits, on average.

Sagi and Seasholes (2007) also claim that momentum returns can be enhanced by conditioning on cost of goods sold. A lower cost of goods sold, should translate into a lower cost to exercise these growth options and, therefore, a greater payoff value. The more value that can be captured from these options, the greater the return autocorrelation and the greater the momentum returns. These returns can also be enhanced by conditioning on revenue volatility. There is greater dispersion in the expected returns of high revenue volatility firms and, therefore, a greater probability that high expected return firms are placed in the winner portfolio. Their results are consistent with both of these claims.

In the following chapter, Chapter 3, I continue this review, but focus on one particular important stream of momentum research in greater detail. This stream begins with testing the idea that momentum can be rationally explained by a set of macroeconomic factors and then expands this to include various measures of market states. I replicate these studies and update the sample period to include the most recent data while also using the result of Avramov et al (2007) in an attempt to re-examine these results from a momentum vs non-momentum perspective.

Chapter 3: Economic/Market State Dependency of Momentum by Credit Rating

3.1 Introduction

What is momentum? What is its true nature and what is driving it? Does it fit into our concept of efficient markets or is it an aberration? Is it compensation for some as of yet unexplained risk or the result of psychological biases of investors? The primary obstacle to answering these important questions is that momentum is still just a result. And it is the result of a somewhat arbitrary strategy, at that. There is no compelling theoretical justification for this strategy; none beyond “that it works”. Why are we purchasing winners while simultaneously selling losers? Because by casting this wide of a net, we are able to capture these momentum profits.

Quite often, momentum is colloquially described as the tendency for winners to win and losers to lose over the intermediate horizon. This may be misleading as it implies that all winners/losers have this tendency. The portfolio, as a whole, has this tendency, but individual stocks in the winner or loser portfolios may not have this tendency at all. If some of the stocks within the portfolio are not contributing to momentum returns, then they are just noise – potentially masking the behaviour and determinants of actual momentum firms.

A great deal of research identifies various cross-sectional characteristics that strengthen the result of momentum. Zhang (2006), for example, finds that momentum is stronger among firms with higher cash-volatility. Up to this point, much of what we knew of the cross-section of momentum involved identifying where it was stronger. But as with all similar studies, the question remains: are the results stronger because momentum, itself, is stronger in these types of firms, or

are the results stronger because sorting on these dimensions filter out more non-performers (thereby increasing the average)?

Avramov et al (2007) identify credit rating as a cross-sectional determinant that appears to have a slightly different - but crucial - effect on momentum. Rather than strengthening the results, the authors find that credit rating appears to determine whether momentum even exists or not. Avramov et al (2007) find that (among rated firms) momentum exists only in non-investment grade firms and that it is non-existent in investment grade firms. However, the authors also find that momentum is still present among non-rated firms as well, and so credit ratings are not the whole story.

This finding is important for two reasons: one, it provides evidence for the first time that momentum is not a market-wide phenomenon – there is still a large group of firms that do not experience momentum; and two, it provides us with two groups of firms (momentum vs non-momentum) to compare the results. It allows us to re-examine past studies and to break down the results to see which group is driving these results – the momentum group or the non-momentum group – and rule out any determinants that were erroneously applied to momentum.

In the case of rated firms, the group as a whole still experiences momentum profits; yet we now know that it is comprised of both momentum and non-momentum firms. This is to be expected, since “momentum” portfolios consisting of momentum firms earn positive returns, while “momentum” portfolios consisting of non-momentum firms earn returns of zero. Anytime these two groups are combined, their returns will be greater than zero, on average. But by increasing the number of non-momentum firms in the portfolio, the portfolio’s average return decreases, and conversely, decreasing the number of non-momentum firms in the portfolio will cause the average return to increase. Therefore, any sorting procedure that results in “stronger” momentum returns

may either be the result of a greater concentration of momentum firms all earning approximately the same magnitude of momentum returns, a similar concentration earning greater momentum returns, or a combination of both.

Again, take as an example Zhang's (2006) finding that cash-flow volatility is positively related to momentum. By sorting firms by cash-flow volatility, Zhang finds that firms with greater cash-flow volatility also earn greater momentum returns. However, the result is more accurately described as portfolios consisting of firms with greater cash-flow volatility earn greater momentum returns. This could be the result of the relationship between cash-flow volatility and momentum, or merely the consequence of portfolio composition. If cash-flow volatility is related to credit rating (and it is, in part), then we would also expect that sorting on cash-flow volatility would systematically assign more and more IG firms (non-momentum) to the momentum portfolios as we move to each lower cash-flow volatility quantile. Therefore, the decreasing momentum returns with decreasing CF volatility may merely be the result of portfolio composition, and not evidence of a relationship (beyond the one with credit rating).

I re-examine some of the seminal research on momentum in an Investment Grade (IG) versus Non-Investment Grade (NIG) context. These studies examined momentum portfolios drawn from the entire sample of firms, which included both NIG and IG firms. Confirming the results of these previous studies among the NIG subsample would strengthen the evidence that they are indeed the result of momentum. Finding insignificant results among NIG firms, on the other hand, may indicate no relationship to momentum, which would be strengthened further by simultaneously finding significant results among IG firms.

The first group of studies that I re-visit is a series of related research examining momentum's dependence on the state of the economy and/or the market. They test various lagged

macroeconomic and market state variables to determine whether or not they are able to predict momentum returns. Chordia and Shivakumar (2002) (hereafter CS (2002)) find that momentum is dependent on macroeconomic variables and that momentum is only profitable during times of economic expansion. Cooper, Guitierrez and Hameed (2004) (hereafter CGH (2004)) re-examine CS's (2002) findings, but with the addition of standard pricing screens and including a gap-month between the formation and holding periods. They find that CS's (2002) findings do not hold with these additions, but that momentum is dependent on the lagged market return and is only significant during bull markets. Stivers and Sun (2010) then re-examine CGH's (2004) findings with the addition of market return dispersion (RD) variables. They find that momentum returns are negatively related to RD, as well as that the inclusion of their RD variable subsumes the predictive power of both CGH (2004) and CS (2002). The significance of any of these variables indicates a relationship to the state of the economy and/or market, which would in turn indicate the presence of a systematic factor driving these returns and a risk-based explanation for momentum.

My results suggest that momentum does continue to be dependent, both on the economic state, as well as the market state. Momentum is statistically and economically significant during times of economic expansion. This is true for momentum strategies drawn from all-firms, as well as from only non-investment grade firms where momentum appears to be more concentrated. The investment-grade sub-sample, which does not experience statistically significant returns unconditional on economic period, still does not exhibit significant returns even during expansionary periods exclusively. Momentum is negative (but not statistically significantly different from zero) during times of economic contraction across all sub-groups. Finally, the non-

investment grade group has the greatest positive returns and the lowest negative returns in the expansionary and contractionary periods, respectively.

Consistent with CGH (2004), momentum also appears to be dependent on the state of the market in that momentum is only significantly positive following bull markets, and negative (although not significant) following bear markets. This is true, however, for all sub-samples, including the investment grade group.

The economic model of CS (2002), however, appears to breakdown over this more recent sample period (1987-2013). It fails to adequately explain the momentum strategy returns, where the bulk of the returns appear to be due to the unexplained portion of the model. In terms of the significance of the coefficient estimates, however, the model does perform better among the non-investment grade sub-sample. Its partial success does seem to be driven by more concentrated momentum. Overall, though, my findings combined would suggest that the findings of CS (2002) are not robust in this more recent time period.

The market state and market state variables continue to significantly explain momentum returns and are more robust to the time period sampled. The results are even more striking among the non-investment grade firms, again, indicating that this result is in fact driven by the same firms driving momentum.

The return dispersion (RD) measures employed by Stivers and Sun (2010) (hereafter SS (2010)) appear to have the most power to explain momentum strategy returns. The measures continue to be statistically significant explanatory variables in this updated time period – although the sample period used by SS (2010) is also the most recent compared to CS (2002) and CGH (2004) and so has the most overlap with my sample period. More importantly, the inclusion of the RD variables also continue to subsume the explanatory power of the lagged market return (from

CGH (2004))³. The results are more mixed among the various sub-samples. The statistical significance of the RD measures does not appear to be dependent on the sub-sample – there does not appear to be any notable difference between the investment grade firms which are not thought to exhibit significant momentum and the non-investment grade firms among which momentum tends to be strongest. And while the inclusion of the RD variable in the regression modelling momentum returns on economic and market variables results in the loss of explanatory power among most variables, it also results in the loss of explanatory power of the RD variable as well, among non-investment grade firms. While the RD measures do appear to be significantly related to the returns of momentum portfolios, it is less clear whether that relationship is being driven by momentum firms themselves, or all firms within the portfolios.

This link between return dispersion and momentum is important in that it presents a challenge to current leading behavioural theories. In these theories it is primarily uncertainly that is driving momentum in some capacity. Therefore, increased return dispersion should lead to greater momentum; however, the relationship is negative. And given that this result continues to be the dominate force among macroeconomic factors and other market state variable, any updated momentum theory should account for such an important result – or at least be consistent with it.

³ Its inclusion also renders the economic variables' coefficients statistically insignificant; however, in most cases, these variables had no significant explanatory power in the first place.

3.2 Methodology

Data

The data used in the empirical analysis is obtained from a variety of sources. All stock and index return data is from the CRSP Monthly Stock File. All interest rate and yield data (corporate bonds and T-bills) are from the Federal Reserve Economic Data (FRED) database, with the exception of the Long-term Composite Rate (Treasury bonds) data, which is obtained from the U.S. Treasury's website's Resource Center. Economic business cycle dates are from the National Bureau of Economic Research (NBER). The Fama-French three-factor model monthly factors (high-minus-low and small-minus-big) and book-to-market/size portfolios are from Kenneth French's website. And lastly, all credit rating data is obtained from Compustat.

The period under observation is 1985 – 2013; S&P credit ratings on Compustat are unavailable prior to 1985. The main sample includes all common stocks listed on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) with a share code of 10 or 11 in CRSP, excluding any foreign firms, trusts, closed-end funds, REITS and ADRs/units. In some cases, the sample is expanded to include common stocks listed on the NASDAQ. Some work employs a price-screen of \$1 or \$5 on stock prices at the formation date (previous month's closing price). Stock return data includes delisting returns reported by CRSP; however, a significant number of delisting returns are missing from CRSP (Shumway (1997)), therefore I employ the adjustment of -30% proposed by Shumway (1997) for missing NYSE/AMEX delisting returns (and -55% proposed by Shumway and Warther (1999) in the case of missing NASDAQ delisting returns). I also use the CRSP Value-Weighted Index to proxy for the market return whenever applicable.

Five subsets of data will be created from the main sample: All (all firms in the entire sample); Rated (all firms that have an S&P rating in this sample); Non-rated (all firms that do not have an S&P rating in this sample); Investment Grade (all rated firms rated BBB or higher); and Non-Investment Grade (all rated firms rated BB or lower). Much of the analysis will be repeated for each subset and compared across subsets.

The four macroeconomic variables that comprise the macroeconomic model are defined as follows: DIV is the market dividend yield, measured as the difference between the CRSP Value-Weighted Index return with distributions and the CRSP Value-Weighted Index return excluding dividends; DEF is the default spread measured as the difference in the average yields of corporate bonds rated BAA and AAA (Moody's ratings); TERM is the term spread measured as the difference between the Long-Term Composite Rate (average of all non-callable U.S. Treasury bonds that mature in over 10-years); and YLD is the yield on three-month T-bills.

Momentum Portfolios

Consistent with Jegadeesh and Titman (1993), each month t , all stocks in our sample are sorted according to their buy-and-hold return over the previous 6-months ($t-6$ through $t-1$). This constitutes the *formation period*. In the event that a gap-month is included, the formation period would instead be months $t-7$ through $t-2$, where $t-1$ would be the gap-month. The stocks are then divided up into deciles according to their formation period return, with the “winners” being the top-performing decile (P10) and the “losers” being the bottom-performing decile (P1). Each decile can be considered a separate equally weighted portfolio (P1 through P10). Momentum portfolios are then formed by taking a long position in the winner portfolio and a short position in the loser portfolio (P10 – P1), resulting in a zero-cost portfolio. A new momentum portfolio is formed in

each month t and held for the next six months (t through $t+6$), which is known as the *holding period*.

The result is that the momentum *strategy* return in any given month is an equally-weighted average of the returns of the six most recent momentum portfolios (the portfolios formed at the beginning of months t through $t-5$). Unless specified otherwise, this 6/6 strategy is the method of forming and holding momentum portfolios used throughout the paper.

Macroeconomic Model

CS (2002) conclude that macroeconomic factors can explain momentum returns. They also find that momentum is only positive during expansions (and negative, yet statistically insignificant during recessions). The point here is to determine whether these findings are driven by momentum (NIG credit firms), non-momentum (IG credit firms), or both.

Following CS (2002), the purpose of this section is to examine whether momentum strategy returns can be explained by a set of common macroeconomic variables, as opposed to testing whether or not momentum returns are indeed compensation for its exposure to set of risk factors; and in particular, to compare the ability of this macroeconomic model to explain among various subsets of the momentum strategy based on credit rating.

The relationship between momentum returns and the macroeconomic variables is examined in two ways: first, each time-series of momentum returns is regressed on the macroeconomic model to determine which, if any, of the variables have any explanative power (through the significance of the estimated model parameters); and then, the adjusted monthly returns (adjusted for the predicted returns of the macroeconomic model) of each individual stock is estimated and the momentum strategy returns are then recalculated using the adjusted returns (rather than the raw returns) to examine whether or not the strategy returns retain any significance.

A time-series of momentum strategy returns will be generated in the manner described above from each sub-sample of the main sample: whole sample; rated firms; non-rated firms; investment grade (IG) firms; and non-investment grade (NIG) firms. Each time-series is regressed on the set of lagged macroeconomic variables to estimate the parameters:

$$R_t = c_0 + c_2DIV_{t-1} + c_3DEF_{t-1} + c_4TERM_{t-1} + c_5YLD_{t-1} + \theta JANDUM + e_{it} \quad (1)$$

where *JANDUM* is a dummy variable equal to 1 if month *t* is January and 0 for all other months. The parameters, c_{ij} and θ , are estimated each month *t* using the previous 60-months (*t* through *t*-59, and *t*-1 through *t*-60 for the macro variables), with a minimum of 12-months required. All the monthly coefficients are collected and the average reported. Newey-West standard errors are used to calculate the *t*-statistics to correct for the autocorrelation introduced by the overlapping estimation periods (Newey and West (1987)).

Next, the monthly returns of individual stocks are adjusted (for the predicted returns of the macroeconomic model) by regressing the raw monthly returns on the set of lagged macroeconomic variables:

$$R_{it} = c_{i0} + c_{i2}DIV_{t-1} + c_{i3}DEF_{t-1} + c_{i4}TERM_{t-1} + c_{i5}YLD_{t-1} + \theta JANDUM + e_{it}, \quad (2)$$

for each stock *i*. The adjusted return is defined as the residual plus constant from the regression, as this is the portion that is not explained by the macroeconomic variables (as opposed to the model). The regression model is estimated by regressing the *t* through *t*-59 returns on the *t*-1 through *t*-60 macroeconomic variables independent variables. The adjusted return from month *t* is not excluded because I am examining the variables' explanatory power as opposed to their predictive power. The residual and constant are then estimated for month *t* using the model parameters and the *t*-1 macroeconomic variables. This process is repeated for each stock in each month.

The momentum strategy (as previously described) is then rerun for each sub-sample; however, the holding period returns are calculated using the adjusted returns rather than the raw returns. Each new time-series of momentum returns is tested for statistical significance and compared to the others. Comparing the results of the tests of raw returns with those of the adjusted returns allows us to determine whether the macroeconomic model (equation 2) can explain momentum return. Statistically significant positive returns using raw returns, followed by statistically insignificant returns using adjusted returns, would indicate that the macroeconomic variables can fully explain the momentum strategy returns and imply that momentum may be compensation for exposure to certain macroeconomic factors.

Market States

The momentum strategy returns are then tested on differing market states: up and down. The findings of CGH (2004) indicate that momentum is procyclical and dependent on the market state. These tests will determine whether this holds across all five sub-samples. Returns are calculated similarly to CGH (2004). The strategy returns are calculated and presented in a different method from the above section. Rather than calculating the average return of each active portfolio (e.g., six portfolios for a strategy with a six-month holding period), the returns are calculated as the sum for each individual portfolio.

Momentum portfolios are created as *described* above in each month t , with a \$1 price screen and a gap month, from a formation period of $t-7$ through $t-2$ ($t-1$ being the gap month). While not as common in earlier work, it is now quite common to include a gap-month in-between the formation and holding periods in order to lessen the impact of potential bid-ask bounce effects. It is included in this section, rather than the prior section, in order to examine whether CGH's (2004) claim that CS's (2002) macroeconomic model loses its explanatory power after the

inclusion of a gap-month still holds. The holding period return of each momentum portfolio is calculated for each holding period month over t through $t+60$. In other words, each portfolio has its own time-series of 60 monthly returns (over months t through $t+60$). The cumulative abnormal return (CAR) is calculated for any given portfolio for any given holding period is calculated as the sum of the monthly portfolio returns over the holding period (the CAR allows for average monthly returns to be calculated by simple arithmetic average).

Each momentum portfolio formed in month t is designated as an UP month or DOWN portfolio depending on the lagged market return and all subsequent holding period returns for that portfolio are share the same designation. The lagged market return (at time t) is defined as the CRSP Value-Weighted Index return over $t-36$ through $t-1$ (same definition as CGH (2004)). A non-negative (positive or zero) lagged market return is designated UP and a negative lagged market return is designated DOWN. Each CAR over each holding period $t+K$ is divided by K to determine the average monthly return over that holding period. The average monthly returns are then separated by their market state designation (UP or DOWN) and the average for each designation is calculated and the null hypothesis that each mean is equal to zero is tested by simple one-sample t -test ($H_0: \mu=0$). The two means are then tested for equality by two-sample t -test ($H_0: \mu_{up}=\mu_{down}$). Heteroskedasticity-and-autocorrelation-consistent estimates of variance are used to calculate the standard errors to compensate for the overlapping returns (unique through construction in this section).

Adjusted returns (adjusted for various models: CAPM; Fama-French 3-factor; and macroeconomic), where applicable, are also calculated in a slightly different manner in this section. The returns of each momentum portfolio's time-series of holding period returns are adjusted separately (from the other time-series). For each momentum portfolio time-series, the raw

returns are regressed on the applicable factors over months t through $t+60$. This is repeated for each momentum portfolio.

Return Dispersion

SS (2010) find that their measure of return dispersion is a better explanation than either that of CS (2002) or CGH (2004).

Here, momentum strategy returns are defined in the alternate manner described in the previous section (Market States). The momentum return for any given month t is considered the cumulative six-month return (t to $t+5$) of only the momentum portfolio formed in month t , divided by six to provide the average monthly return. This differs from the more conventional definition of the equally-weighted average return of all open momentum portfolios for that month alone.

I then construct two measures of return dispersion – RD (return dispersion) and RRD (residual return dispersion) – using the primary return dispersion measures from SS (2010).

Stivers and Sun define RD as the cross-sectional standard deviation of the monthly returns across 100 portfolios formed on size and book-to-market (BM) ratios. This is calculated each month t :

$$RD_t = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (R_{i,t} - R_{\mu,t})^2}, \quad (3)$$

where n is the number of size/BM portfolios (100), $R_{i,t}$ is the monthly return of size/BM portfolio i in month t , and $R_{\mu,t}$ is the equally-weighted return of all size/BM portfolios in month t .

Stivers and Sun point out that their RD measure should be positively related to the absolute market return (Stivers (2003)). In order to capture the dispersion that is independent of the current

market return, they also construct the residual return dispersion (RRD) measure, which is a market-adjusted dispersion measure. The RRD measure is defined as the residual of the previous RD measure controlled for the market return. RD is regressed on the following model:

$$RD_t = \lambda_0 + \lambda_1 |R_{M,t}| + \lambda_2 D_t |R_{M,t}| + \varepsilon_t, \quad (4)$$

where $|R_{M,t}|$ is the absolute market return in month t and D_t is a dummy variable equal to 1 when the market return is negative (and 0 otherwise). The RRD_t , for each month t , is defined as the residual term ε_t estimated in each month t .

Again, following SS (2010), the momentum returns are regressed on the newly constructed return dispersion measures (RD and RRD) and lagged market return:

$$MOM_t = \beta_0 + \beta_1 RD + \beta_2 R_{M,1-36} + \varepsilon_t, \quad (5)$$

where MOM_t is the momentum return in month t , RD is the return dispersion measure (RD or RRD) and $R_{M,1-36}$ is the lagged 3-year market return. As with the previous section, due to the overlapping returns of the momentum returns by construction, standard errors are estimated as heteroskedasticity-and-autocorrelation-consistent standard errors.

The above model is expanded to include the macroeconomic variables from the Macroeconomic Model section to test whether the inclusion of the return dispersion measure still subsumes the explanatory power of the macro variables. The regression model is as follows:

$$MOM_t = \gamma_0 + \gamma_1 RD + \gamma_2 R_{M,1-36} + \gamma_3 DIV_{t-1} + \gamma_4 DEF_{t-1} + \gamma_5 TERM_{t-1} + \gamma_6 YLD_{1-1} \varepsilon_t, \quad (6)$$

where DIV_{t-1} , DEF_{t-1} , $TERM_{t-1}$ and YLD_{t-1} are the lagged dividend yield, default spread, term spread and three-month T-bill yield, respectively.

3.3 Results

Momentum Returns by Economic Cycle

In their original paper, CS (2002) find that momentum returns are only statistically significantly positive over expansionary periods. Overall, the mean monthly returns tend to be positive during economic expansions and negative during economic contractions⁴. Their sample period covers 1926-1994.

From the end of 1985 until April, 2013, there were seven separate economic periods as defined by the NBER: four expansionary periods and three contractionary periods. Table 1 presents the average monthly returns to the momentum strategy over that period for the various credit-rating subsets. Panel A presents the average monthly returns and t-statistics over each of the expansionary periods, as well as the overall mean over all the expansionary periods. Panel B presents the results over the contractionary periods.

While there are far fewer periods, overall, in this shorter sample period, the results for the all firms sample are in line with the original CS (2002) results; positive returns during expansions and mainly negative returns during contractions. The returns are positive in all expansionary periods and statistically significant in three out of four periods. The mean monthly return over all expansionary periods is obviously also positive, as well as both economically and significantly positive at 1.11% per month.

In Panel B, the reported monthly mean return over all contractionary periods is -2.76%, and although quite large, it is not statistically significant. The results over individual periods are

⁴ The mean monthly returns are not strictly positive and negative over expansions and contractions, respectively. However, the mean monthly returns over all periods is positive for expansionary periods and negative for contractionary periods.

negative, but statistically insignificant for two of the three contractionary periods. In the other period, however, the mean return is both positive and statistically significant. While not as clear or consistent as the results over the expansionary periods, they are similar to CS's findings in contractionary periods, which also show a mix of positive and negative returns. These results are also more difficult to interpret relative to those of the expansions given that the contractionary periods are both fewer and shorter than the expansions. There are only a total of 34 contractionary months over this sample period.

Panel C presents the difference (and t-statistics) in means between the expansionary and contractionary periods. While the overall negative mean monthly return of the all-firm sample during contractions is not statistically significant, the difference in means is. On average, momentum returns earn 3.87% per month more during expansionary periods than they do during contractionary periods.

Overall, the original findings continue to hold for the traditional momentum strategy. It appears to only be statistically profitable during times of economic expansion, which is the basis of the argument for the inclusion of common economic variables as explanatory variables in a regression of momentum returns.

Table 1 also presents the results of the various credit-rating subsamples. Looking at credit-rated firms versus firms with no credit-rating, we see that the results are more-or-less consistent with those of the all-firm sample during both expansionary and contractionary periods. Both these sub-samples exhibit statistically significant positive returns during expansions, for the most part. The main exception being the June 2009 – April 2013 expansionary period, when no mean return

of any sub-sample is statistically significant⁵. The mean return of the rated sub-sample during the previous expansionary period is also statistically insignificant (while the all-firm and non-rated sub-samples are significant); however, the magnitudes are quite similar (1.03%, 1.16% and 1.00% for the all-firm, credit-rated, non-credit-rated sub-samples, respectively). All three groups experienced statistically significant mean monthly returns of roughly 1% over all expansionary months.

The results over the contractionary periods are also very similar. The mean returns of all sub-samples over all periods share the same signs. And most are not statistically significant⁶. The overall mean returns over all contractionary months are negative for all three sub-samples and all are also statistically insignificant; while the difference in means for expansionary versus contractionary months are positive and significant for all three.

Overall, there does not appear to be a difference in the way the rated and non-rated sub-samples experience momentum over both economic expansions and contractions (in terms of a mean monthly return).

Table 1 further breaks down the credit-rated sub-sample into two more sub-samples: investment grade (IG) and non-investment grade (NIG) firms. NIG firms behave much like the all-firm, credit-rated, and non-credit-rated sub-samples: positive statistically significant returns during economic expansions and negative statistically insignificant returns during contractions⁷. Given that momentum, overall, appears to only exist in NIG firms (within the credit-rated sub-sample),

⁵ The monthly return of the rated sub-sample is also negative during this period, but small (-0.19%).

⁶ The exceptions being the Mar 2001 – Oct 2001 period all-firm and non-rated sub-sample returns.

⁷ Again, this is with the exception of a positive mean return during the Mar 2001 to Oct 2001 contractionary period (similar to all-firms, credit-rated and non-credit rated firms).

it is not surprising that momentum does not appear to exist (statistically) in either expansions or contractions.

Raw and Adjusted Momentum Returns

In CS (2002), the authors adjust the momentum strategy returns for their business cycle model (dividend yield, default yield, term spread and the three-month T-bill yield). They find that positive statistically significant raw returns from their momentum strategy become negative but statistically insignificant once the strategy returns predicted by the business cycle model are deducted. This leads them to conclude that the unexplained portion of momentum returns from their macroeconomic model are not predicted by past returns.

In updating the data using my more recent sample, I find that the results are dramatically different. Following CS (2002), I calculate the monthly raw returns of the momentum strategy⁸. Each month, these returns are then regressed on the lagged values of the economic model's explanatory variables over the months, $t-60$ through $t-1$. The raw monthly return is then adjusted for the predicted return from that month's model (excluding the constant). The adjusted returns are therefore, the model's estimated constant and residual. In Table 2, I report the raw (or unadjusted) and the macroeconomic model adjusted returns for the momentum strategies in each of the sample's sub-sample (based on credit-rating). The adjusted returns are reported for the macroeconomic model, with and without a dummy variable that controls for the January effect⁹. The table includes the raw and adjusted monthly returns for the winner portfolio (P10) and loser portfolio (P1) as well as the momentum strategy portfolio (P10 – P1).

⁸ A strategy that is based on a 6-month formation period and a 6-month holding period.

⁹ The dummy variable equals 1 if the month is January and 0 for all other months.

Panel A reports the results of the total sample, the credit-rated firms sample, and the non-credit-rated firms sample. The pattern of results is mainly consistent for each sub-sample. The raw returns are statistically significant or nearly significant and just below 1% a month; however, the adjusted monthly returns positive, very large and statistically significant. This is the case for both models, with and without January dummies. The monthly returns range from approximately 15-27%. Based on the original CS (2002) interpretation, the past returns of momentum stocks seem to predict an unreasonably large unexplained portions of the business cycle model's returns.

In examining the winner and loser portfolios separately, these dramatic results appear to be driven by the loser portfolio. The returns and adjusted returns of the winner portfolio (P10) appear much more reasonable. The monthly raw momentum strategy returns are all positive and economically significant around 1.3%, while the adjusted returns vary from positive to negative, but all are not statistically significantly different from zero. The mean monthly adjusted returns are positive for the non-credit-rated sample and negative for the credit-rated sample. From this test, the macroeconomic model would appear to explain the holding period returns of the winner portfolio. The loser portfolio, on the other hand, exhibit the opposite result; insignificant raw returns and statistically significant adjusted returns. The returns are large and negative, which drive the positive returns of the momentum portfolio strategy since the loser portfolio is shorted in the strategy.

Table 2 also presents the above results for January and non-January months separately. Momentum strategies tend to lose in January, as can be seen from the January strategy return of -7.25%, presumably because of the January effect, and so separating the months can give a clearer picture of behaviour of momentum returns when momentum is present. While the

magnitudes of the means vary slightly, the results are essentially the same with the exception of the raw strategy returns which are larger and statistically significant across all three sub-samples.

Panel B presents the results of the credit-rated sub-sample as well as the two sub-samples of that sub-sample: investment grade (IG) and non-investment grade (NIG). With the exception of magnitude, the results of the momentum strategy portfolio returns are not noticeably different between the two sub-samples. Both groups experience very large statistically significant positive unexplained returns in the macroeconomic model of returns, as is the case with the other sub-samples as well (all, rated and non-rated). The magnitudes of the mean returns, however, are very different. While both groups' means are very large, mean of the IG group is approximately 19% compared to the mean of the NIG group which is closer to 33%¹⁰. Of note is that the means of the unexplained returns for the IG group are much closer to those of the non-credit-rated group, which were approximately 15-17%. And it would seem that the NIG firms within the rated sub-sample are responsible for the differences between the rate and non-rated groups overall.

Again, the very large unexplained returns appear to be driven by the loser portfolios of both the IG and NIG sub-samples. The risk-adjusted losses of the NIG group are almost double that of the IG group. The risk-adjusted returns of the winner portfolio are not significantly different from zero within the IG sub-sample, while the returns of the winners in the NIG sub-sample are statistically significant losses of approximate 4% per month. The NIG sub-sample is the only group to experience statistically significant losses by its winner portfolio¹¹.

¹⁰ The results of the macroeconomic model with a January dummy are 19.51% for the IG group versus 31.9% for the NIG group.

¹¹ Other sub-samples' winner portfolios exhibit negative mean risk-adjusted returns, however, none are statistically significant.

The pattern of risk-adjusted returns for the two sub-samples remain essentially unchanged between January and non-January months. The magnitudes of the mean unexplained strategy returns are lower during January months, however, still very large in either case.

Overall, the macroeconomic model employed by CS 2002 appears to do a much poorer job of explaining momentum returns over this more recent time period as measured by the unexplained portion of returns. While extremely economically significant, the mean monthly unexplained returns of the momentum strategy portfolios are far too large to have any meaningful interpretation. Based on the sub-group results, this failure of the employed macroeconomic model appears to apply to both “momentum” returns of both the so-called momentum firms and non-momentum firms (NIG and IG sub-groups). The IG sub-group exhibits no significant raw momentum returns and yet still experiences very large positive monthly returns unexplained by the macroeconomic model. While these mean returns are substantially lower than the means of the of NIG sub-group, they are still quite large and statistically significant themselves. This failure on behalf of the model renders conclusions regarding the differences between groups that experience momentum and groups that do not with respect to this macroeconomic model not very insightful.

Macro Model Regression Estimates

Table 3 presents the average coefficients and their t-statistics from the macroeconomic model of momentum strategy returns for each of the five sub-samples. Following CS (2002), each month t , the monthly return from the momentum strategy portfolio is regressed on the set of lagged macroeconomic variables (dividend yield, default spread, term spread and the T-bill yield, as defined earlier) over the period of $t-1$ through $t-60$, and the coefficients are collected. The result is separate coefficient estimates for each month over the sample period. These monthly coefficient

estimates are then averaged and reported with their t-statistics that are based on Newey-West autocorrelation consistent standard errors. Panel A presents the results with a separate set of average coefficients for each sub-sample.

Within the all-firm sub-group, the intercept is both positive (and quite large) and statistically significant, while the average coefficient of the market dividend yield is negative and statistically significant. The coefficients are negative on the default spread and positive on the term spreads and the T-bill yield, however, none of the average coefficients on these predictors are statistically significant. Within this macroeconomic model, it appears that only the market dividend yield has any predictability power. And similar to the results in Table 3, the magnitude on the intercept is far too large to be interpreted with much meaningful insight. The model implies that the momentum strategy earns a risk-adjusted return of over 18% per month. The results presented in Table 3 are consistent with the poor performance of the model shown in Table 3. The unexplained portion of the model dwarfs the original raw momentum strategy returns.

These model results are also in stark contrast to the original results of CS 2002. While the signs on the coefficients are consistent, the significance of the coefficients have completely flipped. In CS 2002, they found that the average coefficients on the default spread, term spread and T-bill yield were statistically significant and that of the dividend yield was not; while the results in this paper indicate that only the coefficient on the dividend yield is statistically significant. Both this paper and CS 2002 find that the intercept is statistically significant, the signs have changed, as CS originally found that the intercept was negative (and much lower). A non-positive intercept was a main criterion for the success of the model as explicitly stated by CS. By CS's own criteria, the model fails to explain momentum strategy returns in this more recent sample

period. These newer results would appear to cast doubt on the robustness of the original findings of CS.

While these results are in stark contrast to the overall findings of CS, the authors repeat the test over five-year sub-periods and these more recent results are much more consistent with the results from their last reported sub-period (1991-94). All of the signs of the coefficients and intercept are the same and even the magnitudes are very similar with the exception of the larger default spread and T-bill yield coefficients in CS.

Average Monthly Returns of Double-Sorted Momentum Strategy

Table 4 shows the results of two different dependent double-sort momentum strategies. Each month, individual stocks are sorted by either their raw past return or their predicted return over the formation period into quintiles, and then each quintile is then sorted by the other return measure. Each strategy results in 25 separate portfolios and various momentum strategy portfolios are created from combinations of those 25 portfolios. The results are presented as the mean monthly returns over the holding period for each portfolio. The table also reports the mean monthly returns of the high-minus-low portfolio. In the top portion of each panel firms are first sorted by raw returns and then by predicted returns. In the bottom portion firms are first sorted by predicted returns and then by raw returns.

Panel A of Table 4 presents the results of the all-firm sample. Overall, the evidence is mixed with respect to the original findings of CS (2002). The top-half reports the average monthly returns of various portfolios formed by the raw past return sort followed by the macroeconomic model predicted returns sort. The momentum strategy returns (high-minus-low) are also reported on the right-hand side (along with their t -statistics). None of the mean momentum strategy returns

are statistically significant (p -value < 0.05) for any of the 5 predicted return quintiles – although the mean return for the highest predicted return quintile is very close to statistical significance (p -value = 0.051). The implication being that momentum returns do not appear to be due to any firm-specific component beyond common macroeconomic factors, which is consistent with the original findings of CS (2002). The results here are even stronger given that CS originally found that significant momentum returns remained for the top two highest predicted return quintiles. The pattern of individual portfolio returns, however, does differ quite significantly from CS (2002). The returns across the raw returns portfolios along each predicted return quintile do not increase monotonically. While this differs from the pattern of returns in CS (2002), the lack of a pattern presented here actually strengthens the credibility of the argument that past returns do not predict future returns beyond what is contained in the common factor component; once the cross-sectional differences in predicted returns are presumably controlled for there is no discernible pattern based on past returns, consistent with the efficient market hypothesis.

The results from the bottom-half of Panel A, on the other hand, are at odds with CS (2002). When the firms are originally sorted by their predicted returns over the formation period, then sorted by their past returns (thereby controlling for past returns) there are no statistically significant positive returns among the high-minus-low predicted return portfolios, reported along the bottom as the difference between portfolios (5) and (1). There is also the lack of a distinguishable pattern of holding period returns along each raw past return quintile that one would expect if past predicted returns were to predict future predicted returns, and thus, future total returns. Compounding this, is the statistical significance of several of the momentum strategy portfolios among some of the predicted return quintiles. We see positive significant momentum among the bottom two and top

predicted return quintiles. Past raw returns appear to retain some predictive power even when sorted by past predicted returns.

In Panels B & C, the results for the rated firms and non-rated firms sub-samples are presented. For the most part the results of both sub-samples are consistent with the results from the all-firm sub-sample in Panel A. The momentum strategy mean monthly returns are statistically insignificant, for the most part, and there is a lack of a monotonically increasing pattern of mean monthly returns by past returns (for each predicted return quintile) seen in the top-halves of the panel, which is consistent with CS (2002); and there are no statistically significant mean returns among the high-minus-low predicted return strategies and no monotonically increasing pattern of returns by predicted returns seen in the bottom-halves, which is inconsistent with CS (2002). The overall interpretation of the results does not differ between rated firms and non-rated firms; however, there are some slight differences in the results between the two groups. The momentum strategy returns of the rated firms sub-sample, once controlled for predicted returns, are almost entirely negative; although the magnitudes are too small to be either economically or statistically significant. The momentum strategy returns of the non-rated sub-sample are all positive, with much greater magnitudes and the mean monthly return of the strategy among the highest predicted return quintile is even statistically significant.

The returns of the Investment Grade and Non-Investment Grade sub-samples, shown in Panels D & E, exhibit much of the same behaviour as the previous three sub-samples – the all-firm and non-rated firm sub-samples in particular. And the interpretation is the same as well; the raw past return followed by the predicted return sort supports CS (2002), while the predicted return followed by the raw past return sort appears to contradict CS (2002). With the exception of the high predicted return quintile – which is increasing monotonically by past raw return and has a

statistically significant momentum strategy return – there are no discernable patterns to the returns across portfolios. The momentum strategy is largely not statistically profitable within these subsamples after controlling for predicted returns. However, there is also no evidence to support the notion that past predicted returns predict future total returns among the results presented here. Interestingly, however, there are more statistically significant momentum portfolios among the various predicted return quintiles within the IG sample, when momentum is typically insignificant, than within the NIG sample. Three of the five predicted return quintile momentum strategy portfolios have significant returns (bottom half of the panel) versus one of five for the IG and NIG sample, respectively.

Average Monthly Returns

Table 5 presents the various momentum sub-samples' average monthly returns over differing holding periods. In Table 6, the results are separated by market state, but Table 5 presents results from each market state combined to provide a reference point for comparison. Each month, t , the momentum portfolios are formed based their past 6-month return as previously described. Momentum strategy portfolios are formed by combining the winner and losers portfolios as winner-minus-loser. The returns reported here, however, are defined in a different manner from the previous non-overlapping returns. After the portfolios are formed in month t , returns for each portfolio are cumulated over the holding period and the mean monthly return is reported.

In other words, each month t 's return is the mean monthly return over the t to $t+K$ holding period of only the strategy portfolio formed at t . Defining returns in this manner allows us to examine the relationship to the market state and the subsequent returns of a portfolio formed following that state. In the case of non-overlapping returns, the return from any given month is

average return from K separate portfolios, some of which may have been formed following a different market state.

The returns are presented over three periods: months 1-6, months 1-12, and months 13-60. The first two periods are common medium return holding periods in momentum literature. The long-term average (months 13-60) is included to test for any significant long-term reversal. The returns presented include the raw returns, as well as CAPM- and Fama-French-3-factor-risk-adjusted returns.

Panel A reports the mean monthly returns of the all-firm subsample, as well as the rated and non-rated subsamples. Momentum from within the all-firm subsample exhibits economically and statistically significant raw returns over both the 6-month holding period and the longer 12-month holding period at 0.95% and 0.56% per month, respectively; however, the mean return over the 6-month period is greater than that of the 12-month period which suggest that the momentum phenomenon is stronger over the first 6-months (within the all-firm subsample). The momentum strategy also appears to exhibit long-term return reversal indicated by the statistically significant -0.18% mean monthly return over months $t+13$ to $t+60$. Momentum strategy portfolios are not actually held over this longer period – strategies typically entail liquidating the portfolio 6-12 months after it is formed – but these returns are included as a “what if” analysis to examine their long-term behaviour. CGH (2004) interpreted this negative long-term return as evidence that the momentum is due to market overreaction, which is corrected in the long-term. The raw return results from this more recent sample period presented here are consistent with the findings of CGH (2004). Table 5 also reports the risk-adjusted (CAPM and Fama-French 3-factor) mean returns of the momentum strategy. The results from both models are also positive and statistically significant over the 6-month and 12-month holding periods. The long-term returns, however, are not

statistically different from zero (at the 5% level). Consequently, there is no long-term risk-adjusted¹² return reversal reported for the all-firm subsample.

The mean monthly returns for the rated and non-rated subsamples, presented in Panel B, are essentially the same as those of the all-firm subsample. The one exception is the 12-month raw return for the momentum strategy from the rated firms, which, while similar in sign and magnitude to the other subsamples' returns, is not statistically significant. Both subsamples report statistically significant raw and risk-adjusted mean returns and raw long-term reversals, but neither report significant long-term reversals on a risk-adjusted basis. In this context, there appears to be little difference in the behaviour of these returns between these subsamples.

Panel C of Table 5 breaks down the rated subsample into the Investment Grade firms and the Non-Investment Grade firms (the rated subsample returns are presented again as well for comparison). The momentum strategy raw returns of the IG group are not statistically different from zero over the typical holding periods (although the mean returns are positive). This is not a surprising result given that profitable momentum is not thought to exist among IG rated firms. They do, however, appear to exhibit the same significant long-term reversal experienced by the all-firm subsample. The overreaction explanation for the long-term reversal within this group should be viewed with more skepticism in this case given that the reversal is much larger relative to the initial positive returns as compared to the previous subsamples. The “correction” is of a similar magnitude, but the initial profits that are to be “corrected” are much lower and far lower than the subsequent “correction.” With initial mean raw returns that are not even statistically different from zero, there may not even be any overreaction to be corrected. There are statistically

¹² Adjusted for the CAPM and Fama-French 3-factor models.

significant Fama-French-adjusted returns over the 6- and 12-month periods, however; but no subsequent reversal.

The NIG group, on the other hand, experiences statistically significant raw returns over the first 6-months, but then no significant raw return reversal over the long-term (although the long-term mean raw return is negative). The 12-month raw return, while quite large and positive at 0.91%, is not statistically significant due to the large variation in the returns of the momentum strategy among the NIG subsample. The economical and statistical significance of the mean returns of the NIG momentum strategy remains even after controlling for risk (CAPM and Fama-French 3-factor), and neither risk-adjusted returns exhibit significant long-term reversal.

It would appear that the statistically significant long-term reversal found by CGH (2004) – and confirmed over my more recent sample-period here in Table 5 – is not driven by the NIG group which is thought to drive momentum returns among credit-rated firms. Statistically significant reversal is present in all subsamples, except the NIG group, and this includes the IG subsample which does not even experience significant positive momentum prior to the long-term. At the very least, it does not appear that this reversal is driven exclusively by positive profits earned by momentum portfolios over the shorter-term.

Average Monthly Returns by Market State

Similar to Table 5, Table 6 reports the average monthly momentum strategy returns over different holding periods, however, the results are differentiated by market state: UP versus DOWN states. The sorting procedure and definition of the momentum returns are the same as with Table 5. The only difference is that the returns are separated depending on whether the portfolio was formed following 36-month non-negative market return – defined as a market UP state – or

36-month negative market return – defined as a market DOWN state. Table 6 also includes the results of a test for equality of mean returns between the UP and DOWN states.

Panel A presents the results of the all-firms subsample. The mean returns for all measures and across all holding periods following UP markets are the similar to the results from the combined state results of Table 5, in terms of sign and statistical significance. The magnitude of the mean positive returns following the UP state, however, are much greater than those of the combined state. For example, the mean monthly raw return over the 6-month holding period following UP markets is 1.42% versus 0.95% of the same holding period following both UP and DOWN markets. The long-term returns are much closer in magnitude regardless of whether the portfolios are only formed following UP states or formed following either state. The mean returns of portfolios formed following DOWN states are dramatically different. While the mean returns over the 6-month and 12-month periods are not statistically significant, they are quite large and negative. The mean monthly raw return over the 6-month period following DOWN markets is -1.36%. The negative raw return over months $t+13$ to $t+60$ cannot be interpreted as a correction of a previous overreaction given that there are no positive profits to correct – neither raw nor abnormal. In testing the equality of the long-term raw returns following UP and DOWN states, the idea that these returns are in fact equal cannot be rejected. On the other hand, the shorter-term returns are statistically different from one another. The profitability of these momentum strategy portfolios formed following DOWN markets are at best, economically insignificant, and at worst, very negative.

If these long-run returns are in fact the same, and given that the long-term returns following DOWN markets do not appear to be a response to overreaction in the previous short-term, then it

also casts doubt on the interpretation that the UP state long-term return is a response to overreaction.

Panel B presents the results of the rated and non-rated subsamples. The results of these two subsamples are, again, very similar to those of the all-firm sample; a statistical difference between the shorter-term raw and risk-adjusted mean returns following UP and DOWN markets, and the long-term returns are not statistically different from each other. The shorter-term returns (raw and risk-adjusted) following UP states are, again, large, positive, and significant, while the returns following DOWN states are large, negative, but not statistically significant. The long-term returns of the rated subsample is – while similar in magnitude to the other subsamples – not statistically significant. That would be the most striking difference between the two groups, but with the exception of this, both groups appear to be fairly representative to the all-firms subsample, as a whole.

The rated firms are broken down into IG and NIG in Panel C. The behaviour of these groups is a little more interesting, especially in comparison to their “baseline” presented in Table 5. The behaviour of the NIG sample is very similar to that of the rated sample as a whole, but with magnified returns – both raw and risk-adjusted. The returns following UP states are significant and the returns following DOWN states are not; however, the magnitudes of both are quite large. The mean raw return following UP states is 2.25% per month and the mean raw return following DOWN states is -2.20% per month. The long-term returns remain statistically insignificant even after separating by market state, with no statistical difference between them.

The IG sample’s momentum strategy exhibits statistically and economically significant, positive returns over the shorter-terms (6-month and 12-month). This is quite an interesting result

given that previous work has found that profitable momentum was not found among exclusively IG firms (Avarmov et al. (2007)). Even the results of the IG subsample in Table 5 indicate that the positive raw returns were not statistically different from zero. So it would appear that unconditional momentum is not present within the IG sample, but that momentum strategy returns conditioned on market state can be statistically profitable following market UP states. It would also appear that the losses sustained following DOWN markets effectively wipe out the positive profits following UP markets; this is the only subsample where this is the case. The absolute value of the negative returns (following DOWN markets) are almost double those of the positive returns (following UP markets). The momentum strategy portfolios earn -1.24% per month over the first 6-months for portfolios formed following a 36-month DOWN market, while they earn 0.62% per month over the same holding period for those portfolios formed following a 36-month UP market. Like many of the subsamples, the IG sample exhibits negative long-term returns; however, unlike the all-firm sample as a whole, the IG sample's negative long-term returns are not statistically significant following the strategies positive returns in the UP state. The IG group is peculiar among the subsamples as it is the only one to earn statistically significant returns in the shorter-term, followed by insignificant returns over the long-term (in UP states), and statistically insignificant returns in the short-term, followed by significant returns over the long-term (in DOWN states).

Two-Way Dependent Sorts in UP vs DOWN Markets

Recall that CS (2002) suggest that the macroeconomic environment can explain momentum strategy returns; however, CGH (2004) argue that momentum returns are better explained by market states rather than the economic model of CS (2002). They cite the fact that when they sort by the macroeconomic model predicted returns, momentum strategy returns remain positive and significant across all predicted return groups following market UP states and not

statistically significant across most predicted return groups following DOWN markets. The presence of statistically significant momentum returns within groups of similar predicted returns indicates that the momentum returns are driven by factors beyond the macroeconomic model.

Table 7 presents the results of a two-way dependent sort, similar to Table 4, separated by market state. Portfolios are formed in month t by first sorting by macroeconomic model predicted returns into quintiles and then sorting by past returns over the 6-month formation period into further quintiles. Momentum strategy portfolios are then formed by combining winner and loser portfolios as winner-minus-losers within each predicted return quintile. The average monthly cumulative returns (overlapping returns) are reported for the 25 individual portfolios formed following market UP states and DOWN states separately. Momentum strategy returns are presented as the difference between the “high” and “low” past return quintiles (winner-minus-loser) along with their t -statistics.

The results of these double-sorts are very similar across most subsamples. Both the rated and non-rated subsamples (Panel B) display essentially the same pattern of momentum returns as the all-firm sample (Panel A). With the single exception of the third predicted return quintile within the rated firm subsample, the momentum strategy returns (high-minus-low) in the UP state are all positive and statistically significant across all predicted return quintiles. The presence of momentum within groups of firms with similar macroeconomic predicted returns indicate that momentum is more than just the cross-sectional differences in predicted returns between the winner and loser quintiles. These strategy returns contain information beyond which the macroeconomic model can explain.

The results of the portfolios formed in DOWN states, on the other hand, are, without exception, negative but not statistically significant across all predicted return quintiles. The separation of portfolio returns by market state seems to demonstrate the explanatory power of the market state – even in cases where the macroeconomic model appears to have none. The lack of statistical significance in the momentum returns of the portfolios in the DOWN state could indicate that the macroeconomic model is sufficient to explain DOWN state momentum; however, this is unlikely. As seen in Table 6, these same subsamples lack significant profitable momentum in DOWN states. The lack of statistical significance here is more likely reflecting that than the result of the explanatory power of the macroeconomic model. The similarity across subsamples also indicates that both the rated and non-rated subsamples are representative of each other and of the market as a whole (as represented by the all-firm sample).

The results of the NIG sample is in line with those of the previous subsamples, but with stronger returns (as is often the case with the NIG sample); and the interpretation is much the same. The results of the IG sample are more ambiguous. The IG group exhibits statistically significant positive returns for the highest and lowest predicted return quintiles, but not for the middle three. The existence of significant UP state momentum returns among the IG sample presented in Table 5 means that the lack of statistical significance here cannot be easily attributed to a lack of significant momentum overall. The market state appears to still have power to explain some of the momentum strategy returns among IG firms, but the macroeconomic model may or may not have some explanatory power within this same group.

Overall, the results here seem to be consistent with CGH (2004), both their reported results and their interpretation. The market state still seems to be a better predictor of subsequent momentum returns than the macroeconomic factor model, regardless of subsample.

Two-Way Dependent Sorts: Screen vs No Screen

One of CGH's (2004) criticisms of the findings of CS (2002) was that their methodology failed to include a gap-month between the formation and holding periods, as well as a price screen to screen out the smallest stocks, which are two common practices in more recent momentum studies. The gap-month and price screens are included in order to minimize the impact of market microstructure biases. CGH (2004) claim that CS's (2002) findings are not robust to the inclusion of these practices.

Table 8 revisits the two-way dependent sort, comparing the results by two screening methods. Just as in Table 7, portfolios are formed in month t by first sorting by macroeconomic model predicted returns into quintiles and then sorting by past returns over the 6-month formation period into further quintiles. The top portion of each panel presents the average monthly cumulative holding period returns of each portfolio, where the holding period begins immediately after the formation period – no gap-month – and the sample includes all firms in that particular sub-sample – no price screen. The bottom portion of each panel presents the average monthly cumulative holding period returns of each portfolio, where the holding period begins 1-month after the formation period ends – 1-month gap – and the sample includes all firms in that sub-sample whose stock prices is greater than one dollar at the time of portfolio formation – \$1 price screen. The table also reports the momentum strategy average monthly cumulative return for each predicted return quintile, as the difference between the high (winner) portfolio and the low (loser) portfolio (as (5) – (1)), and the t -statistic of each average return.

The results in Table 8 are not as striking as those of CGH (2004); however, they do appear to be consistent with their findings. The results of the all-firm sample in Panel A are improved

slightly with the inclusion of gap-month and price screen within the lowest predicted return quintile; and the magnitudes of all the momentum strategy returns increase. Their inclusion appears to have a minimal effect within the rated firms subsample – only increasing the magnitudes of the strategy returns. However, the improvement within the non-rated sample is much more dramatic. With the exception of middle predicted return quintile, all the momentum strategy returns are statistically significant with the inclusion of the gap-month and price screen. The discrepancies between the rated and non-rated subsamples, however, do not allow us to make inferences regarding the non-rated subsample from the results of the IG or NIG subsamples (in this context).

Panel C reports the results of the rated firms separated into the IG subsample and the NIG subsample. The inclusion of the gap-month and price screen does not appear to necessarily have much of an impact on the results of the IG subsample; but keeping in mind the fact that the IG subsample does not exhibit statistically significant unconditional momentum returns in the first place, the lack of apparent improvement may just be reflecting this. The improvement of the NIG subsample results, on the other hand, is more apparent. While the predicted returns fail to explain the momentum returns fully in the first place without the gap-month or price screen, their inclusion does increase the statistical significance of momentum strategy returns within more predicted return quintiles. The minimization of market microstructure biases still appears to be very important with respect to the interpretation of momentum strategy returns, especially among the more momentum concentrated NIG sample.

Monthly Returns Regressed on Lagged-Market Return

Table 9 presents the results of monthly momentum strategy profits regressed on lagged market return measures. These regressions will indicate how well the lagged market measure explains momentum profits as a continuous variable, as opposed to the discrete state variable from Tables 7 & 8. Each month t , momentum portfolios are formed based on their 6-month formation period return. The momentum strategy portfolio is defined as the winner portfolio minus the loser portfolio and its 6-month cumulative return (t to $t+5$) is then regressed on the lagged 36-month market return ($t-36$ to $t-1$) and the lagged 36-month market return squared. The momentum strategy's raw return, CAPM-adjusted return and the Fama-French 3-factor-adjusted return are all regressed in this manner. The regression coefficients are reported along with their t -statistics and the regression's adjusted- R^2 .

The results in Panel A indicate that the lagged-market return or market-state variable has explanatory power as a continuous variable as well, among the all-firms sample. This is consistent with CGH (2004). The lagged-market coefficient is positive and statistically significant across all three regression models for each dependent return variable (raw, CAPM-adjusted and Fama-French-adjusted), which is consistent with the results of the lagged-market variable as a discrete variable.

Also, similar to CGH (2004), the squared lagged-market variable's coefficient is negative indicating that the momentum strategy may not fare as well following more extreme market conditions (bull or bear); however, it does not continue to be statistically significant (at the 5% level) for over this more recent sample period. The model also appears to be a better fit according

to the r-squared measures, which are almost double those of CGH (2004), at roughly 17% compared to 3-10% from CGH (2004).

The results of the rated and non-rated firms are also included in Panel A. While the magnitudes and signs of the various regression model coefficients are comparable to the results of the all-firm sample, the statistical significance of the coefficients vary by these sub-samples. The rated firms show no statistical significance (at the 5% level) for any coefficient¹³, while all of the coefficients on the lagged-market and squared lagged-market variables are statistically significant among the non-rated firms.

Panel B breaks down the rated firms into IG and NIG firms and presents the results separately. The lagged market variable appears to lack significant power to explain the momentum returns within the IG sub-sample, similar the results of the rated firm sample, and the model's fit is about half that of either the NIG sub-sample or the rated firms as a whole (as indicated from the R^2 values). The lagged-market coefficients within the NIG sample, on the other hand, are statistically significant across all three dependent variables. The squared lagged-market return coefficients are not significant in either sub-sample.

The differing results across the rated and non-rated sub-samples makes comparisons perilous, but within the rated firms at least, it appears that it is the NIG firms that are driving statistical significance of the market variables. The relationship is strongest among firms that have significant momentum returns and so it is likely that this relationship is in fact a momentum result.

¹³ Although the *t*-statistics on the lagged-market coefficients are very close to significance at the the 5% level.

The significance would seem to be drowned out by the firms that do not contribute as much to actual momentum profits – at least among the rated firms.

Momentum Returns and Return Dispersion

In SS (2010), the authors examine the hypothesis that momentum returns are procyclical. They argue that market return dispersion is a countercyclical state variable, and therefore, if momentum is procyclical, then the relationship between momentum returns and return dispersion should be negative. They also examine this relationship between return dispersion and the change-in-momentum returns, defining this as the change in momentum returns from the period subsequent the return dispersion period and the momentum returns in the period just prior to the return dispersion (RD) period. They hypothesize that this relationship should also be negative, but also more negative than that of the raw momentum returns. They claim that if a higher RD indicates a change to a weaker state, then momentum from prior to this change should be greater than momentum following this change, if momentum is indeed procyclical. Their findings support their hypothesis and they conclude that momentum is both dependent on the market state as well as procyclical, similar to the conclusions of CGH (2004).

Table 10 presents the results of momentum strategy monthly returns regressed onto measures of market cross-sectional return dispersion. Each month t firms are ranked by their past 6-month return and sorted into deciles. Momentum strategy portfolios are formed as winner-minus-loser (high decile minus low decile). Each momentum strategy portfolio's 6-month cumulative return over t to $t+5$ (skipping month $t-1$) is calculated, which results in a monthly time-series of cumulative momentum returns. These returns are then regressed on two models. In the first, the cumulative momentum returns are regressed onto the lagged residual return dispersion

(RRD) measure (over months $t-3$ to $t-1$). In the second, the cumulative momentum returns are regressed onto lagged return dispersion (RD) measure (over months $t-3$ to $t-1$) and the lagged market return (over months $t-36$ to $t-1$). The two return dispersion measures, RD and RRD, are defined as in SS (2010). The RD measure is the cross-sectional standard deviation of the monthly returns of 100 book-to-market and size portfolios in month t . The RRD measure is defined as the RD measure that is unexplained by the market return. It is the residual of the RD measure regressed on the absolute value of the market return in month t and the absolute value of the market return in month t multiplied by a dummy variable that equals 1 when the market return is negative in month t . Table 10 also presents the results of the same two regression models but with the change-in-momentum – the momentum strategy return in month t minus the momentum strategy return in month $t-9$ – as the dependent variable. The raw momentum return dependent variable regression will capture the relationship between the levels of momentum return and RD, whereas the change-in-momentum dependent variable regression will capture the relationship between the level of RD and the relative change in momentum.

Looking at the all-firm sample's results in Panel A, the overall relationships are very similar to those of the original return dispersion results in SS (2010). The coefficients on all the return dispersion measures (both RD and RRD) in both models (raw momentum and change in momentum) are negative as well as statistically significant. In addition, the coefficients on the change-in-momentum models are more negative than their raw momentum model counterparts. All this supports SS (2010) original conclusions that momentum is procyclical and dependent on the market state. If a higher return dispersion does in fact indicate a weaker market state, then it appears that momentum strategy returns perform worse during these economic periods. If a higher return dispersion indicates a *change* to a weaker market state, then the significant relationship

within the change-in-momentum model – along with the greater coefficient magnitude – it would also appear that momentum strategy returns perform better prior to these changes. Both of these findings and interpretations certainly point to the procyclical nature of momentum returns.

However, the results among the various sub-samples is more mixed. Overall, the coefficients on both return dispersion measure for both models are negative; however, not all are statistically different from zero. Again, looking at Panel results, we can compare the result of the rated and non-rated firm sub-samples. The statistically significant relationship with raw momentum returns appears to be driven by the non-rated sample, while the statistically significant relationship with the change-in-momentum returns appears to be driven by the rated firm sample. In this context, the two groups do not appear to be representative of the other.

In Panel B, the results of the rated firm sample is broken down into investment grade and non-investment grade sub-samples. Among the NIG firms, the reported mean is negative, yet the relationship between raw momentum returns and lagged market return dispersion is not statistically significant. The results for this model appear to be stronger among the IG firms, where the RRD measure is significantly related to raw momentum. The relationships between the return dispersion measures and the change-in-momentum, on the other hand, are significant (and negative) among both groups. The magnitudes are also greater than those of their raw momentum model counterparts for both sub-samples as well. These results still lend credibility to the idea that momentum could be procyclical and, therefore, dependent on the state of the market, even without the significant results among raw momentum. Within these groups, it just appears that the relationship is more relative than absolute; RD measures predict the movement and direction of momentum returns even if they do not predict the magnitude of them very well. A negative relationship with the RD measures imply the procyclicality of momentum, to the degree that the

RD measures are countercyclical state variables. Of note, however, is that the magnitudes of the coefficients are greater within the NIG firms, compared to the IG firms. While the relationship appears slightly more stable among the IG firms (as indicated by the t -statistics) the greater magnitude indicates a potentially greater impact among the NIG firms. If this is indeed the case than the impact of this potentially countercyclical state variable is greater among the more “pure” momentum group (the NIG firms), in that it is greater among a group with greater momentum returns.

Combined Economic and Market State Model

In addition to claiming that momentum is state dependent and procyclical just as CGH (2004) do, SS (2010) also claim that their return dispersion measures subsume the findings of both CGH (2004) as well as CS (2002). They regress all of the market state and economic state variables used by CGH and CS and include their own return dispersion measures. They find that their return dispersion measures retain their significance, while those of CGH and CS do not. SS (2010) claim that their measures are better indicators of the cyclical nature of momentum.

Table 11 reports the results of the regression model that combines the macroeconomic model from Table 4 with the residual return dispersion measure (RRD). The time-series of momentum strategy returns is calculated for each month. The portfolios are determined by their past 6-month formation cumulative return and the strategy portfolio is formed as the winner-minus-loser portfolios (high-minus-low). The return for month t is defined as the 6-month cumulative return over months $t+1$ to $t+6$ (month t is the gap-month) for the momentum strategy portfolio that was formed in month t . The momentum strategy returns are then regressed on the lagged macroeconomic model – the default spread, market dividend yield, term spread and 3-

month T-bill yield – combined with market state variable (proxied by the lagged 36-month market return) and the lagged 3-month moving average of the residual return dispersion.¹⁴ As with Table 10, the regression is run with both the raw momentum cumulative return and the change in momentum cumulative return from month t and month $t-9$ as the dependent variables. The coefficients of the regression models and their t -statistics are reported for each credit-rating sub-sample.

The results reported in Table 11 are very similar to those reported by SS (2010) with a couple of notable exceptions. The coefficients on the macroeconomic variables and the market state variable are largely insignificant across all sub-sample groups, just as reported by SS (2010). In addition, the coefficient on the lagged residual return dispersion variable negative and statistically significant on the raw momentum return model across most sub-sample groups, again, in line with SS (2010). Notably, however, the coefficient on the default spread variable is negative (and quite large) and statistically significant across all sub-sample groups, in contrast to SS's (2010) findings. The other exception is that while SS (2010) also reported significant coefficients on the change in momentum returns model, none of the coefficients (in any sub-sample) are statistically significant in my results (although the coefficients are all negative).

In most of these sub-samples, the inclusion of the RRD measure results in significant coefficients on both those measures as well as the default spread variable. If we consider the RRD measure to be partially reflecting the level of uncertainty in the market, it could be that both RRD and the default spread are both capturing the negative impact uncertainty in the overall market has on momentum returns.

¹⁴ In month t the lagged RRD measure is the average RRD over months $t-3$ to $t-1$.

The results from the all-firms, rated firms and non-rated firms groups are very similar (in terms of coefficient signs, magnitudes and statistical significance), indicating that there are not likely any significant differences in the behaviour of the returns between the rated and non-rated firms, with respect to this model. The rated firms sub-sample appears to be representative of both non-rated firms as well as the all-firms group as a whole. The lack of statistical significance of the coefficients of the lagged economic variables (for the most part) across these sub-samples, when compared to the results from Table 4, are not surprising. The macroeconomic model from Table 4 does not sufficiently explain the momentum returns over the sample period used in this study. In other words, there is not much explanatory power for the residual return dispersion variable to subsume in the first place. The residual return dispersion variable does, however, appear to subsume the explanatory power of the market state variable, which was found to significantly explain momentum strategy returns in Table 4.

Breaking down the rated firms sub-sample into IG and NIG sub-samples, the results of the IG group are consistent with the previous groups (all-firms, rated, non-rated). The interpretation is much the same as well, given that the macroeconomic model largely failed to explain the results in the first place (as can be seen in Table 4). The NIG group, on the other hand, is slightly different. The NIG group model retains the statistical significance of the default spread coefficient from Table 4 and while the inclusion of the RRD measure does subsume the apparent explanatory power of the dividend yield, the coefficients on the RRD measures are not statistically significant themselves (although they are larger in magnitude than those of other subsamples).

Overall, the evidence regarding the RD measures appears to be largely consistent with the original findings of SS (2010), that the RD measure is a better predictor of momentum return behaviour than the market return variable. Both of these measures can be considered market state

variables, which would then imply the procyclical nature of momentum, but RD can have another interpretation as well. According to SS (2010), some Wall Street practitioners believe that RD can be a measure of market uncertainty. If RD is considered a measure of market uncertainty, then the conclusions would be that momentum is negatively related to market uncertainty as a whole. This relationship would appear to be at odds with current leading behavioural theories.

3.4 Comment on Uncertainty

The behavioural models of momentum typically involve an underreaction or overreaction (or both) to new information. These models differ on the mechanisms or psychological biases that drive these reactions. In Hong and Stein (1999) and Hong, Lim and Stein (2000) there is both under- and overreaction that stems from uninformed traders following informed traders. Barberis, Shleifer and Vishny (1998) also employ both, where the underreaction is driven by investors' conservatism leading to a reluctance to include new information. Whereas Daniel, Hirshleifer and Subramanyam (1998, 2001) and Hirshleifer (2001) rely on overreaction caused by investor overconfidence.

Empirical evidence from Hong, Lim and Stein (2000), Jiang, Lee and Zhang (2005) and Zhang (2006) suggest that information uncertainty is positively related to momentum. They all find links between various proxies for information uncertainty and momentum returns. The various authors argue that it is this information uncertainty that is driving momentum. The explanation from Jiang, Lee and Zhang (2005) and Zhang (2006) is that uncertainty exacerbates these psychological biases leading to greater under- or overreaction.

Jiang, Lee and Zhang (2005) use the Daniel, Hirshleifer and Subramanyam (1998) model and argue that momentum should be greater amongst greater information uncertainty. Investor overconfidence is increased in the face of uncertainty as they "trade more aggressively on private

signals.” Another consequence is that the pessimistic investors are reluctant to participate allowing the other side’s overconfidence to drive momentum returns even further.

Zhang (2006) claims that uncertainty also leads to greater underreaction. In the case of Barberis, Shleifer and Vishny (1998) and their investors’ conservatism, we would expect even greater conservatism with respect to new information – a greater reliance on their old beliefs – when that new information is more ambiguous. Even in the case of the informed versus the uninformed traders, we would expect fewer informed traders in the presence of greater uncertainty.

The problem, however, is that these explanations are not consistent with the aggregate findings of SS (2010) and Wang and Xu (2015). SS (2010) find that momentum is negatively related to the cross-sectional return dispersion of the market and Wang and Xu (2015) find that momentum is negatively related to market volatility. According to the interpretations above, increased uncertainty should be positively related to momentum. However, in times of greater uncertainty in the market as a whole momentum appears to decrease. Therefore, we lack a theoretical model which can explain empirical data at both the firm-level and the market-level.

Table 3-1 – Momentum Returns by Economic Cycle

Each month t , stocks from each of the five sub-samples (all, non-rated, rated, investment grade, non-investment grade firms) are sorted by their cumulative returns over months $t-7$ to $t-2$ (month $t-1$ is the gap month) and assigned into deciles. Momentum portfolios are formed by taking a long position in the top performing decile and a short position in the bottom performing decile. These portfolios are held over months t to $t+5$. In any given month, the monthly return is the average of all of the six outstanding momentum portfolios in that month. Panel A presents the mean monthly return for each sub-sample over each economic expansionary period as well as the mean over all expansionary months from December, 1985 to April, 2013. Panel B presents the mean monthly return for each sub-sample over each contractionary period as well as the mean over all expansionary months from December, 1985 to April, 2013. Panel C presents the results of the test of difference in means (expansionary minus contractionary) for each sub-sample. t -statistics are reported below in parentheses. Statistically significant results (at 5%) are bolded.

Panel A: Expansionary						
Period	All	Rate	Non-Rate	IG	NIG	
1985m12 - 1990m7	1.82 (3.60)	1.60 (3.12)	1.83 (3.22)	0.27 (0.55)	2.69 (3.14)	
1991m4 - 2001m2	1.16 (1.82)	1.17 (1.87)	1.13 (1.74)	0.31 (0.82)	2.17 (2.19)	
2001m11 - 2007m11	1.03 (1.94)	1.16 (1.61)	1.00 (2.00)	0.55 (1.12)	1.93 (1.86)	
2009m6 - 2013m4	0.23 (0.35)	-0.19 (-0.28)	0.41 (0.58)	-0.83 (-1.58)	0.52 (0.67)	
Mean	1.11 (3.43)	1.03 (3.03)	1.12 (3.40)	0.18 (0.78)	1.95 (3.77)	

Table 3-1 – Momentum Returns by Economic Cycle (cont'd)

Panel B: Contractionary						
Period	All	Rate	Non-Rate	IG	NIG	
1990m8 - 1991m3	-3.32 (-0.64)	-2.76 (-0.53)	-3.40 (-0.66)	-1.36 (-0.53)	-5.31 (-0.66)	
2001m3 - 2001m10	3.08 (2.40)	2.23 (1.62)	3.60 (2.89)	1.34 (1.14)	2.88 (1.26)	
2007m12 - 2009m5	-5.11 (-1.40)	-5.70 (-1.15)	-4.78 (-1.47)	-1.70 (-0.50)	-8.40 (-1.41)	
Mean	-2.76 (-1.19)	-3.14 (-1.08)	-2.48 (-1.15)	-0.90 (-0.48)	-5.02 (-1.35)	
Panel C: Difference (Expansionary - Contractionary)						
	All	Rate	Non-Rate	IG	NIG	
Mean	3.87 (3.14)	4.18 (2.98)	3.60 (2.98)	1.09 (1.16)	6.97 (3.54)	

Table 3-2 – Raw and Adjusted Momentum Returns

Each month t , momentum portfolios are formed as they were in Table 1. Risk-adjusted returns are calculated by regressing the monthly raw returns on the lagged values of the following economic model's explanatory variables:

$$R_t = c_0 + c_2DIV_{t-1} + c_3DEF_{t-1} + c_4TERM_{t-1} + c_5YLD_{t-1} + \theta JANDUM + e_{it}$$

where DIV is the market dividend yield; DEF is the default spread measured as the difference in the average yields of corporate bonds rated BAA and AAA; TERM is the term spread on U.S. Federal bonds; YLD is the yield on three-month T-bills; and JANDUM is a dummy variable equal to 1 if month t is January and 0 for all other months. Each month t , the model parameters are estimated over the months, $t-60$ through $t-1$. Risk-adjusted returns are defined as the unexplained portion of the returns and calculated as intercept plus the residual. This table reports the mean monthly returns of the loser portfolio (P1), the winner portfolio (P10), and the strategy portfolio (P10-P1), over the 6-month holding period, t to $t+5$, for each of the five sub-samples. Each panel presents the mean risk-adjusted return without the Jan dummy (“Ex Dum”), risk-adjusted return with the Jan dummy (“Dummy”), and raw return. It also presents the result for the non-January months, the January months, separately. t -statistics are reported in parentheses underneath. Panel A presents the result of the entire sample. Panel B presents the results of the rated and non-rated subsamples. Panel C presents the result of the investment grade and non-investment grade subsamples. Statistically significant strategy results (at 5%) are bolded.

Panel A: All firms

		Non-Jan						Jan						All Months					
		P1	% > 0	P10	% > 0	P10-P1	% > 0	P1	% > 0	P10	% > 0	P10-P1	% > 0	P1	% > 0	P10	% > 0	P10-P1	% > 0
All	Ex Dum	-20.88 (-9.38)	30.52 (1.00)	-0.38 (-0.23)	44.16 (0.98)	20.50 (12.30)	72.73 (0.00)	-13.99 (-1.73)	30.52 (1.00)	-3.13 (-0.67)	44.16 (0.98)	10.86 (1.82)	72.73 (0.00)	-20.32 (-9.46)	30.52 (1.00)	-0.60 (-0.38)	44.16 (0.98)	19.72 (12.24)	72.73 (0.00)
	Dummy	-17.64 (-6.63)	32.47 (1.00)	0.84 (0.43)	42.86 (0.99)	18.48 (10.96)	70.45 (0.00)	-20.07 (-2.37)	32.47 (1.00)	-3.45 (-0.71)	42.86 (0.99)	16.62 (2.77)	70.45 (0.00)	-17.84 (-7.03)	32.47 (1.00)	0.49 (0.27)	42.86 (0.99)	18.33 (11.30)	70.45 (0.00)
	Raw	-0.19 (-0.40)	52.85 (0.16)	1.24 (3.79)	66.67 (0.00)	1.43 (4.28)	68.17 (0.00)	9.97 (4.07)	52.85 (0.16)	2.72 (2.52)	66.67 (0.00)	-7.25 (-3.32)	68.17 (0.00)	0.63 (1.24)	52.85 (0.16)	1.36 (4.33)	66.67 (0.00)	0.73 (1.93)	68.17 (0.00)

Table 3-2 - Raw and Adjusted Momentum Returns (cont'd)

Panel B: Rated and Non-rated firms

		Non-Jan						Jan						All Months					
		P1	% > 0	P10	% > 0	P10-P1	% > 0	P1	% > 0	P10	% > 0	P10-P1	% > 0	P1	% > 0	P10	% > 0	P10-P1	% > 0
Rate	Ex Dum	-29.68 (-10.75)	26.95 (1.00)	-1.71 (-1.13)	36.36 (1.00)	27.97 (12.96)	76.30 (0.00)	-25.91 (-2.94)	26.95 (1.00)	-4.48 (-1.18)	36.36 (1.00)	21.43 (3.07)	76.30 (0.00)	-29.37 (-11.16)	26.95 (1.00)	-1.93 (-1.36)	36.36 (1.00)	27.44 (13.31)	76.30 (0.00)
	Dummy	-27.71 (-9.06)	25.65 (1.00)	-0.46 (-0.26)	36.04 (1.00)	27.25 (12.31)	77.60 (0.00)	-28.30 (-3.11)	25.65 (1.00)	-3.91 (-0.99)	36.04 (1.00)	24.39 (3.46)	77.60 (0.00)	-27.76 (-9.57)	25.65 (1.00)	-0.74 (-0.44)	36.04 (1.00)	27.02 (12.80)	77.60 (0.00)
	Raw	0.28 (0.50)	52.85 (0.16)	1.26 (3.69)	63.86 (0.00)	0.98 (2.35)	65.17 (0.00)	5.40 (2.41)	52.85 (0.16)	1.77 (1.60)	63.86 (0.00)	-3.63 (-1.75)	65.17 (0.00)	0.69 (1.27)	52.85 (0.16)	1.31 (3.99)	63.86 (0.00)	0.61 (1.43)	65.17 (0.00)
Not Rate	Ex Dum	-17.59 (-8.50)	34.74 (1.00)	0.37 (0.20)	47.73 (0.80)	17.95 (11.23)	64.61 (0.00)	-9.58 (-1.20)	34.74 (1.00)	-2.26 (-0.43)	47.73 (0.80)	7.32 (1.24)	64.61 (0.00)	-16.94 (-8.43)	34.74 (1.00)	0.15 (0.09)	47.73 (0.80)	17.09 (11.02)	64.61 (0.00)
	Dummy	-13.79 (-5.46)	36.36 (1.00)	1.55 (0.75)	46.10 (0.92)	15.34 (10.04)	63.31 (0.00)	-16.94 (-2.03)	36.36 (1.00)	-2.96 (-0.55)	46.10 (0.92)	13.98 (2.41)	63.31 (0.00)	-14.04 (-5.82)	36.36 (1.00)	1.19 (0.61)	46.10 (0.92)	15.23 (10.30)	63.31 (0.00)
	Raw	-0.37 (-0.79)	51.05 (0.37)	1.23 (3.74)	65.17 (0.00)	1.60 (5.10)	68.17 (0.00)	11.64 (4.56)	51.05 (0.37)	3.10 (2.84)	65.17 (0.00)	-8.54 (-3.89)	68.17 (0.00)	0.60 (1.18)	51.05 (0.37)	1.38 (4.38)	65.17 (0.00)	0.78 (2.10)	68.17 (0.00)

Table 3-2 - Raw and Adjusted Momentum Returns (cont'd)

Panel C: IG-rated and NIG-rated firms

				Non-Jan		P10-			Jan		P10-			All Months		P10-			
		P1	% > 0	P10	% > 0	P1	% > 0	P1	% > 0	P10	% > 0	P1	% > 0	P10	% > 0	P1	% > 0		
IG	Ex Dummy	-19.77 (-10.04)	24.03 (1.00)	-0.48 (-0.38)	39.29 (1.00)	19.29 (11.04)	71.75 (0.00)	-19.05 (-3.30)	24.03 (1.00)	-3.59 (-1.11)	39.29 (1.00)	15.46 (2.94)	71.75 (0.00)	-19.71 (-10.56)	24.03 (1.00)	-0.73 (-0.62)	39.29 (1.00)	18.98 (11.44)	71.75 (0.00)
	Dummy	-18.61 (-8.69)	26.95 (1.00)	1.11 (0.72)	39.29 (1.00)	19.72 (10.76)	73.70 (0.00)	-19.19 (-3.09)	26.95 (1.00)	-2.06 (-0.60)	39.29 (1.00)	17.13 (3.03)	73.70 (0.00)	-18.66 (-9.20)	26.95 (1.00)	0.85 (0.59)	39.29 (1.00)	19.51 (11.19)	73.70 (0.00)
	Raw	0.93 (2.35)	61.86 (0.00)	1.18 (4.24)	66.87 (0.00)	0.24 (0.83)	58.26 (0.00)	2.45 (1.95)	61.86 (0.00)	0.77 (0.74)	66.87 (0.00)	-1.68 (-1.49)	58.26 (0.00)	1.06 (2.79)	61.86 (0.00)	1.14 (4.26)	66.87 (0.00)	0.08 (0.29)	58.26 (0.00)
NIG	Ex Dummy	-38.59 (-12.03)	22.73 (1.00)	-4.59 (-2.52)	35.06 (1.00)	34.00 (14.13)	77.60 (0.00)	-33.04 (-2.95)	22.73 (1.00)	-6.72 (-1.46)	35.06 (1.00)	26.32 (3.24)	77.60 (0.00)	-38.14 (-12.38)	22.73 (1.00)	-4.76 (-2.78)	35.06 (1.00)	33.38 (14.47)	77.60 (0.00)
	Dummy	-35.80 (-9.91)	20.78 (1.00)	-3.78 (-1.82)	33.44 (1.00)	32.02 (13.24)	78.25 (0.00)	-37.86 (-3.38)	20.78 (1.00)	-7.28 (-1.51)	33.44 (1.00)	30.58 (4.02)	78.25 (0.00)	-35.96 (-10.47)	20.78 (1.00)	-4.06 (-2.09)	33.44 (1.00)	31.90 (13.86)	78.25 (0.00)
	Raw	-0.38 (-0.54)	45.95 (0.94)	1.46 (3.55)	64.16 (0.00)	1.84 (3.17)	66.37 (0.00)	8.70 (2.41)	45.95 (0.94)	3.13 (2.49)	64.16 (0.00)	-5.57 (-1.73)	66.37 (0.00)	0.36 (0.50)	45.95 (0.94)	1.60 (4.08)	64.16 (0.00)	1.24 (2.06)	66.37 (0.00)

Table 3-3 – Macro Model Regression Estimates

This table presents the coefficients of the macroeconomic model. Momentum portfolios are formed just as they were in Table 1. The model is then estimated for each monthly momentum strategy return at time t , over months $t-60$ to $t-1$, from the following model:

$$R_t = \alpha + \beta_1 DIV_{t-1} + \beta_2 DEF_{t-1} + \beta_3 TERM_{t-1} + \beta_4 YLD_{t-1} + \varepsilon_t$$

where DIV is the market dividend yield; DEF is the default spread TERM is the term spread; YLD is the yield on three-month T-bills; and JANDUM is a dummy variable equal to 1 if month t is January and otherwise. This is done for each of the five subsamples. The coefficients reported are the means of all of the monthly estimates over the sample period. INT is the mean intercept of the model. RES is the mean unexplained monthly returns, defined as the intercept plus the residual. t -statistics are reported in parentheses (calculated from Newey-West standard errors). Panel A reports the results of the macro model with no Jan dummy. Panel B reports the results of the model that includes the Jan dummy. Statistically significant results (at 5%) are bolded.

Panel A: Macro model (no January dummy)

Sub-group	RES	% > 0	INT	DIV	DEF	TERM	YLD
All	18.55 (2.20)	0.73 (0.00)	18.65 (2.25)	-10.96 (-3.17)	-4.14 (-1.29)	1.47 (1.71)	0.70 (0.73)
Rate	26.49 (2.40)	0.75 (0.00)	26.74 (2.40)	-12.21 (-2.62)	-5.13 (-1.43)	0.39 (0.33)	-0.50 (-0.37)
Non-Rate	15.58 (2.04)	0.65 (0.00)	15.65 (2.09)	-10.33 (-3.51)	-3.62 (-1.18)	1.79 (2.42)	1.14 (1.34)
IG	21.40 (2.16)	0.72 (0.00)	21.67 (2.17)	-7.75 (-2.32)	-2.69 (-0.81)	-0.07 (-0.07)	-0.69 (-0.64)
NIG	28.98 (2.41)	0.74 (0.00)	29.38 (2.46)	-13.32 (-3.09)	-8.54 (-2.01)	0.59 (0.39)	-0.58 (-0.32)

Table 3-3 – Macro Model Regression Estimates (cont'd)

Panel B: Macro including January dummy

Sub-group	RES	% > 0	INT	JANDUM	DIV	DEF	TERM	YLD
All	18.96 (2.07)	0.71 (0.00)	19.10 (2.10)	-8.82 (-5.69)	-10.25 (-2.62)	-1.93 (-0.68)	0.77 (0.92)	0.17 (0.18)
Rate	27.09 (2.38)	0.75 (0.00)	27.37 (2.37)	-4.77 (-4.10)	-11.73 (-2.39)	-4.18 (-1.25)	-0.01 (-0.01)	-0.82 (-0.62)
Non-Rate	15.91 (1.89)	0.64 (0.00)	16.01 (1.93)	-10.24 (-6.02)	-9.54 (-2.75)	-1.01 (-0.38)	0.99 (1.41)	0.54 (0.63)
IG	22.22 (2.13)	0.74 (0.00)	22.52 (2.13)	-1.95 (-4.17)	-7.68 (-2.18)	-2.57 (-0.73)	-0.28 (-0.25)	-0.86 (-0.77)
NIG	29.31 (2.47)	0.77 (0.00)	29.70 (2.51)	-7.99 (-2.83)	-12.27 (-2.62)	-6.41 (-2.01)	-0.07 (-0.05)	-1.11 (-0.68)

Table 3-4 – Average Monthly Returns of Double-Sorted Momentum Strategy

Presented are the results of two-way dependent sorts based on past returns and past predicted returns. Each month t , firms are first sorted into quintiles by their cumulative past return (past predicted return) over months $t-7$ to $t-2$, each quintile is then further sorted into quintiles by their cumulative past predicted return (past return). This yields 25 individual portfolios. The returns are reported as average monthly returns over months t to $t+5$. Momentum strategy returns are reported on the left hand side as the difference between high and low past return portfolios, within each past predicted return quintile. The predicted returns are determined from the macroeconomic model in the same method as from Table 3. Panel A presents the results of entire sample. Panel B presents the results of the rated firm sample and the non-rated firm sample. Panel C presents the results of the investment grade sample and the non-investment grade sample. t -statistics are reported in parentheses. Statistically significant results (at 5%) are bolded.

Panel A: All Firms (in sample)

Raw Returns							
Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5) - (1)	
All Firms, Sorted by Raw then Predicted Returns							
1 (low)	0.95	1.13	1.21	1.18	1.45	0.50	(1.48)
2	1.04	1.11	1.10	1.01	1.20	0.16	(0.67)
3	1.09	1.04	0.98	0.92	1.05	-0.04	(-0.17)
4	1.00	1.14	1.04	1.00	1.23	0.23	(0.98)
5 (high)	0.84	1.16	1.13	1.22	1.48	0.64	(1.96)
Difference (5) – (1)	-0.11 (-1.06)	0.03 (0.63)	-0.08 (-1.54)	0.04 (0.90)	0.03 (0.60)		
All Firms, Sorted by Predicted then Raw Returns							
1 (low)	0.48	0.93	1.27	1.33	1.60	1.12	(2.55)
2	0.79	1.12	1.25	1.23	1.29	0.50	(2.48)
3	0.94	1.06	0.97	0.94	0.99	0.05	(0.30)
4	0.90	1.16	1.13	1.24	1.30	0.40	(1.88)
5 (high)	0.28	1.00	1.14	1.37	1.62	1.34	(3.29)
Difference (5) – (1)	-0.20 (-1.37)	0.08 (1.03)	-0.13 (-1.81)	0.03 (0.55)	0.02 (0.22)		

Table 3-4 – Average Monthly Returns of Double-Sorted Momentum Strategy (Sorted on Raw and Predicted Returns) (cont'd)

Panel B: Rated vs Non-rated firms

Raw Returns								Raw Returns							
Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5) - (1)		Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5) - (1)	
Rated Firms, Sorted by Raw then Predicted Returns								Non-Rated Firms, Sorted by Raw then Predicted Returns							
1 (low)	1.04	1.17	1.07	1.09	1.16	0.09	(0.33)	1 (low)	0.82	0.93	1.15	1.00	1.74	0.94	(1.40)
2	1.16	1.14	1.09	0.98	0.97	-0.20	(-0.93)	2	0.72	0.96	1.00	1.20	1.34	0.62	(1.42)
3	1.14	1.13	1.05	0.92	0.99	-0.15	(-0.75)	3	0.75	1.17	1.04	1.19	1.28	0.53	(1.33)
4	1.12	1.20	1.03	1.00	0.95	-0.17	(-0.82)	4	0.63	0.84	1.26	1.42	1.44	0.80	(1.91)
5 (high)	1.13	1.09	1.09	1.10	1.13	-0.01	(-0.02)	5 (high)	-0.08	0.96	0.96	1.10	1.58	1.66	(3.05)
Difference (5) – (1)	0.06	-0.08	0.02	0.01	-0.04			Difference (5) – (1)	-0.87	0.03	-0.19	0.09	-0.16		
	(0.56)	(-1.30)	(0.31)	(0.24)	(-0.54)				(-2.23)	(0.18)	(-1.21)	(0.66)	(-0.97)		
Rated Firms, Sorted by Predicted then Raw Returns								Non-Rated Firms, Sorted by Predicted then Raw Returns							
1 (low)	1.05	1.34	1.31	1.29	1.45	0.34	(1.29)	1 (low)	-0.06	0.44	0.83	0.82	1.72	1.83	(1.67)
2	1.16	1.35	1.24	1.12	1.18	0.03	(0.12)	2	0.05	0.42	1.07	1.39	0.99	0.94	(2.22)
3	1.20	1.19	1.16	1.02	1.03	-0.17	(-0.82)	3	0.38	0.86	0.79	0.94	1.18	0.80	(1.89)
4	1.26	1.30	1.21	1.15	1.10	-0.16	(-0.71)	4	-0.31	0.56	0.86	1.53	1.25	1.56	(3.62)
5 (high)	1.24	1.22	1.28	1.31	1.42	0.18	(0.65)	5 (high)	-1.18	-0.06	0.61	0.85	1.36	2.54	(3.66)
Difference (5) – (1)	0.12	-0.13	-0.03	0.01	-0.04			Difference (5) – (1)	-1.07	-0.50	-0.22	0.03	-0.36		
	(1.18)	(-1.71)	(-0.38)	(0.16)	(-0.43)				(-1.50)	(-1.77)	(-1.00)	(0.11)	(-1.50)		

Table 3-4 – Average Monthly Returns of Double-Sorted Momentum Strategy (Sorted on Raw and Predicted Returns) (cont'd)

Panel C: IG vs NIG firms

Raw Returns								Raw Returns							
Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5) - (1)		Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5) - (1)	
IG Firms, Sorted by Raw then Predicted Returns								NIG Firms, Sorted by Raw then Predicted Returns							
1 (low)	0.98	1.10	1.23	1.16	1.45	0.47	(1.44)	1 (low)	0.86	1.14	1.12	1.11	1.40	0.54	(1.38)
2	1.06	0.99	1.04	0.97	1.32	0.26	(1.06)	2	1.00	1.21	1.12	1.03	1.03	0.03	(0.11)
3	1.01	0.95	0.91	0.92	1.02	0.01	(0.06)	3	1.14	1.14	1.07	0.98	1.04	-0.11	(-0.42)
4	0.98	1.03	0.97	0.99	1.30	0.33	(1.43)	4	1.05	1.22	1.10	1.07	1.06	0.02	(0.07)
5 (high)	0.99	1.13	1.09	1.24	1.54	0.55	(1.65)	5 (high)	0.65	1.07	1.09	1.11	1.38	0.74	(2.02)
Difference (5) – (1)	0.00	0.03	-0.14	0.08	0.09			Difference (5) – (1)	-0.22	-0.07	-0.02	0.00	-0.02		
	(0.02)	(0.48)	(-1.92)	(1.36)	(1.04)				(-1.52)	(-1.02)	(-0.38)	(-0.02)	(-0.27)		
IG Firms, Sorted by Predicted then Raw Returns								NIG Firms, Sorted by Predicted then Raw Returns							
1 (low)	0.47	0.88	1.14	1.35	1.63	1.16	(2.53)	1 (low)	0.46	0.94	1.27	1.21	1.42	0.95	(1.92)
2	0.75	1.04	1.20	1.22	1.37	0.62	(2.84)	2	0.84	1.26	1.23	1.19	1.16	0.32	(1.50)
3	0.89	0.94	0.94	0.85	0.97	0.09	(0.48)	3	0.93	1.18	1.16	1.00	1.01	0.09	(0.42)
4	0.93	1.11	1.10	1.19	1.32	0.39	(1.74)	4	0.92	1.24	1.17	1.26	1.19	0.27	(1.15)
5 (high)	0.41	0.92	1.03	1.44	1.67	1.26	(2.79)	5 (high)	0.02	0.93	1.22	1.16	1.41	1.39	(3.49)
Difference (5) – (1)	-0.06	0.04	-0.11	0.09	0.04			Difference (5) – (1)	-0.45	-0.02	-0.05	-0.05	-0.01		
	(-0.36)	(0.48)	(-1.19)	(0.93)	(0.40)				(-1.95)	(-0.15)	(-0.56)	(-0.62)	(-0.13)		

Table 3-5 – Average Monthly Returns

Each month t , momentum portfolios are formed as they were in Table 1. This table presents the results of these portfolios over three different holding periods: 6-month period (t to $t+5$); 12-month period (t to $t+11$); and lagged 4-year period ($t+12$ to $t+59$). These holding periods are calculated each month t , for the momentum portfolio formed in that month. The returns reported are the monthly mean returns of all the momentum portfolios formed. The table reports the raw return, the CAPM-adjusted and the Fama-French three factor-adjusted return. Panel A presents the results of entire sample. Panel B presents the results of the rated firm sample and the non-rated firm sample. Panel C presents the results of the investment grade sample and the non-investment grade sample. t -statistics are reported in parentheses. Statistically significant results (at 5%) are bolded.

Panel A: All firms, Rated vs Non-rated

All Firms	Months 1-6	Months 1-12	Months 13-60
Average Monthly Profits Across Both States (UP and DOWN)			
N	326	320	272
Raw return	0.95	0.56	-0.18
(t-statistic)	(3.06)	(2.11)	(-2.23)
CAPM alpha	1.11	0.71	-0.14
(t-statistic)	(3.62)	(2.60)	(-1.52)
Fama-French alpha	1.22	0.85	-0.03
(t-statistic)	(4.02)	(3.23)	(-0.46)

Table 3-5 – Average Monthly Return by Market State (cont'd)

Panel B: Rated vs Non-rated

Rated Firms	Months 1-6	Months 1-12	Months 13-60
Average Monthly Profits Across Both States (UP and DOWN)			
N	326	320	272
Raw return	0.80	0.54	-0.17
(t-statistic)	(2.06)	(1.63)	(-2.03)
CAPM alpha	0.98	0.68	-0.16
(t-statistic)	(2.56)	(2.06)	(-1.61)
Fama-French alpha	1.12	0.87	0.02
(t-statistic)	(3.02)	(2.80)	(0.21)
Average Monthly Profits Across Both States (UP and DOWN)			
Non-Rated Firms	Months 1-6	Months 1-12	Months 13-60
Average Monthly Profits Across Both States (UP and DOWN)			
N	326	320	272
Raw return	1.02	0.58	-0.19
(t-statistic)	(3.59)	(2.29)	(-2.25)
CAPM alpha	1.18	0.72	-0.15
(t-statistic)	(4.18)	(2.80)	(-1.52)
Fama-French alpha	1.26	0.84	-0.07
(t-statistic)	(4.53)	(3.32)	(-0.81)

Table 3-5 – Average Monthly Return by Market State (cont'd)

Panel C: IG vs NIG

IG Firms	Months 1-6	Months 1-12	Months 13-60
Average Monthly Profits Across Both States (UP and DOWN)			
N	326	320	272
Raw return	0.31	0.26	-0.14
(t-statistic)	(1.19)	(1.21)	(-2.18)
CAPM alpha	0.41	0.34	-0.13
(t-statistic)	(1.60)	(1.63)	(-1.83)
Fama-French alpha	0.54	0.52	0.02
(t-statistic)	(2.19)	(2.71)	(0.59)
NIG Firms	Months 1-6	Months 1-12	Months 13-60
Average Monthly Profits Across Both States (UP and DOWN)			
N	326	320	272
Raw return	1.51	0.91	-0.18
(t-statistic)	(2.90)	(1.92)	(-1.76)
CAPM alpha	1.69	1.03	-0.21
(t-statistic)	(3.23)	(2.15)	(-1.58)
Fama-French alpha	1.86	1.25	-0.02
(t-statistic)	(3.67)	(2.73)	(-0.16)

Table 3-6 – Average Monthly Returns by Market State

Momentum portfolios are formed and their holding period returns are calculated as they were in Table 5. In this table, however, the holding period are separated into UP states and DOWN states, depending on the market return of the previous 36-months prior to portfolio formation. If the lagged 36-month market return is non-negative (negative), it is considered to be UP (DOWN) state. Each panel also reports the results of t-tests for equality between the mean returns of the UP and DOWN states. The table reports the raw return, the CAPM-adjusted and the Fama-French three factor-adjusted return. Panel A presents the results of entire sample. Panel B presents the results of the rated firm sample and the non-rated firm sample. Panel C presents the results of the investment grade sample and the non-investment grade sample. *t*-statistics are reported in parentheses. Statistically significant results (at 5%) are bolded.

Panel A: All firms, UP and DOWN states

All Firms	Months 1-6	Months 1-12	Months 13-60
Average Monthly Profits Following 36-month UP Markets			
N	271	265	244
Raw return	1.42	0.88	-0.19
(t-statistic)	(8.33)	(6.09)	(-1.98)
CAPM alpha	1.55	1.00	-0.16
(t-statistic)	(8.77)	(6.22)	(-1.40)
Fama-French alpha	1.62	1.12	-0.05
(t-statistic)	(9.36)	(6.69)	(-0.54)
Average Monthly Profits Following 36-month DOWN Markets			
N	55	55	28
Raw return	-1.36	-1.00	-0.12
(t-statistic)	(-0.98)	(-0.99)	(-3.75)
CAPM alpha	-1.09	-0.79	-0.06
(t-statistic)	(-0.81)	(-0.80)	(-1.15)
Fama-French alpha	-0.82	-0.51	0.03
(t-statistic)	(-0.62)	(-0.55)	(0.47)
Test for Equality Between UP and DOWN Markets			
Raw return	(2.27)	(2.95)	(-0.73)
CAPM alpha	(2.38)	(3.11)	(-0.80)
Fama-French alpha	(2.29)	(3.02)	(-0.69)

Table 3-6 – Average Monthly Return by Market State (cont'd)

Panel B: Rated vs Non-rated firms, UP and DOWN states

Rated Firms	Months 1-6	Months 1-12	Months 13-60	Non-Rated Firms	Months 1-6	Months 1-12	Months 13-60
Average Monthly Profits Following 36-month UP Markets				Average Monthly Profits Following 36-month UP Markets			
N	271	265	244	N	271	265	244
Raw return	1.35	0.93	-0.19	Raw return	1.45	0.85	-0.21
(t-statistic)	(5.60)	(4.78)	(-1.77)	(t-statistic)	(9.17)	(5.63)	(-2.05)
CAPM alpha	1.49	1.06	-0.19	CAPM alpha	1.58	0.98	-0.17
(t-statistic)	(6.12)	(5.01)	(-1.46)	(t-statistic)	(9.61)	(5.83)	(-1.42)
Fama-French alpha	1.59	1.21	-0.01	Fama-French alpha	1.64	1.07	-0.08
(t-statistic)	(6.93)	(6.04)	(-0.11)	(t-statistic)	(9.94)	(6.04)	(-0.83)
Average Monthly Profits Following 36-month DOWN Markets				Average Monthly Profits Following 36-month DOWN Markets			
N	55	55	28	N	55	55	28
Raw return	-1.96	-1.46	-0.09	Raw return	-1.12	-0.77	-0.11
(t-statistic)	(-1.14)	(-1.29)	(-1.71)	(t-statistic)	(-0.89)	(-0.81)	(-2.44)
CAPM alpha	-1.63	-1.21	-0.01	CAPM alpha	-0.86	-0.56	-0.06
(t-statistic)	(-0.99)	(-1.09)	(-0.20)	(t-statistic)	(-0.71)	(-0.61)	(-1.03)
Fama-French alpha	-1.24	-0.81	0.16	Fama-French alpha	-0.63	-0.33	0.01
(t-statistic)	(-0.76)	(-0.78)	(3.36)	(t-statistic)	(-0.53)	(-0.38)	(0.07)
Test for Equality Between UP and DOWN Markets				Test for Equality Between UP and DOWN Markets			
Raw return	(2.15)	(3.05)	(-0.78)	Raw return	(2.41)	(2.82)	(-0.88)
CAPM alpha	(2.23)	(3.14)	(-1.10)	CAPM alpha	(2.55)	(2.98)	(-0.83)
Fama-French alpha	(2.10)	(2.97)	(-1.62)	Fama-French alpha	(2.46)	(2.92)	(-0.64)

Table 3-6 – Average Monthly Return by Market State (cont'd)

Panel C: IG vs NIG firms, UP and DOWN states

IG Firms	Months 1-6	Months 1-12	Months 13-60	NIG Firms	Months 1-6	Months 1-12	Months 13-60
Average Monthly Profits Following 36-month UP Markets				Average Monthly Profits Following 36-month UP Markets			
N	271	265	244	N	271	265	244
Raw return	0.62	0.47	-0.14	Raw return	2.25	1.44	-0.22
(t-statistic)	(2.92)	(2.90)	(-1.79)	(t-statistic)	(6.19)	(4.18)	(-1.65)
CAPM alpha	0.70	0.54	-0.14	CAPM alpha	2.40	1.55	-0.27
(t-statistic)	(3.33)	(3.23)	(-1.56)	(t-statistic)	(6.42)	(4.29)	(-1.51)
Fama-French alpha	0.81	0.69	0.02	Fama-French alpha	2.52	1.72	-0.07
(t-statistic)	(4.06)	(4.79)	(0.31)	(t-statistic)	(7.20)	(4.90)	(-0.42)
Average Monthly Profits Following 36-month DOWN Markets				Average Monthly Profits Following 36-month DOWN Markets			
N	55	55	28	N	55	55	28
Raw return	-1.24	-0.83	-0.14	Raw return	-2.20	-1.75	0.01
(t-statistic)	(-1.19)	(-1.13)	(-2.47)	(t-statistic)	(-1.04)	(-1.32)	(0.16)
CAPM alpha	-1.03	-0.63	-0.10	CAPM alpha	-1.89	-1.56	0.03
(t-statistic)	(-1.03)	(-0.90)	(-1.58)	(t-statistic)	(-0.92)	(-1.18)	(0.43)
Fama-French alpha	-0.79	-0.36	0.07	Fama-French alpha	-1.41	-1.09	0.20
(t-statistic)	(-0.82)	(-0.57)	(1.58)	(t-statistic)	(-0.69)	(-0.88)	(1.71)
Test for Equality Between UP and DOWN Markets				Test for Equality Between UP and DOWN Markets			
Raw return	(1.76)	(2.23)	(0.01)	Raw return	(2.47)	(3.70)	(-1.48)
CAPM alpha	(1.78)	(2.18)	(-0.32)	CAPM alpha	(2.55)	(3.77)	(-1.55)
Fama-French alpha	(1.77)	(2.16)	(-0.78)	Fama-French alpha	(2.41)	(3.60)	(-1.71)

Table 3-7 – Two-Way Dependent Sorts in UP vs DOWN Markets

Firms are sorted here in the same method here as in Table 4. This is a two-way dependent sort, where firms are first sorted by their predicted returns over the formation period and then sorted by their past returns over the formation period. Except, in this table the results are separated by the lagged-market state (market return over the previous 36 months) of each monthly portfolio when it was formed. Each month t , if a momentum portfolio is formed following a non-negative 36-month lagged market return, the holding period returns of that portfolio is placed into the UP state group, otherwise it is placed into the DOWN state group. Presented are the mean returns of each individual portfolio as well as the momentum strategy portfolio which is the difference between portfolios (5) and (1). Panel A presents the results of entire sample. Panel B presents the results of the rated firm sample and the non-rated firm sample. Panel C presents the results of the investment grade sample and the non-investment grade sample. t -statistics are reported in parentheses. Statistically significant results (at 5%) are bolded.

Panel A: All firms

Raw Returns							
Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5)-(1)	t-stat (5)-(1)
All Firms, UP State							
1 (low)	0.01	0.04	0.06	0.06	0.08	0.07	(6.72)
2	0.03	0.05	0.06	0.06	0.06	0.03	(3.72)
3	0.04	0.05	0.05	0.04	0.05	0.02	(2.22)
4	0.03	0.05	0.05	0.06	0.07	0.03	(4.02)
5 (high)	0.00	0.04	0.06	0.07	0.08	0.07	(7.25)
All Firms, DOWN State							
1 (low)	0.25	0.17	0.16	0.14	0.15	-0.10	(-1.38)
2	0.14	0.12	0.11	0.10	0.10	-0.04	(-1.22)
3	0.11	0.09	0.08	0.07	0.08	-0.03	(-1.22)
4	0.15	0.12	0.10	0.10	0.10	-0.06	(-1.43)
5 (high)	0.23	0.17	0.16	0.15	0.16	-0.07	(-1.07)

Table 3-7 – Two-Way Dependent Sorts in UP vs DOWN Markets (cont'd)

Panel B: Rated vs Non-rated firms

Raw Returns								Raw Returns							
Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5) - (1)		Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5) - (1)	
Rated Firms, UP State								Non-Rated Firms, UP State							
1 (low)	0.01	0.04	0.06	0.07	0.07	0.07	(4.48)	1 (low)	0.01	0.04	0.06	0.07	0.08	0.07	(6.75)
2	0.04	0.06	0.06	0.06	0.06	0.02	(2.21)	2	0.03	0.05	0.06	0.06	0.06	0.03	(3.95)
3	0.04	0.06	0.06	0.05	0.06	0.02	(1.89)	3	0.04	0.04	0.04	0.04	0.05	0.02	(2.37)
4	0.04	0.06	0.06	0.06	0.06	0.02	(2.43)	4	0.03	0.04	0.05	0.06	0.06	0.03	(4.37)
5 (high)	0.00	0.04	0.06	0.06	0.08	0.07	(5.46)	5 (high)	0.01	0.04	0.05	0.07	0.08	0.07	(7.22)
Rated Firms, DOWN State								Non-Rated Firms, DOWN State							
1 (low)	0.25	0.19	0.15	0.14	0.15	-0.10	(-1.41)	1 (low)	0.24	0.16	0.15	0.16	0.14	-0.10	(-1.37)
2	0.15	0.11	0.10	0.09	0.11	-0.04	(-0.90)	2	0.14	0.12	0.11	0.10	0.10	-0.05	(-1.58)
3	0.12	0.09	0.08	0.08	0.09	-0.04	(-1.17)	3	0.10	0.08	0.07	0.07	0.07	-0.03	(-1.20)
4	0.15	0.11	0.10	0.11	0.10	-0.05	(-1.15)	4	0.15	0.12	0.10	0.09	0.09	-0.05	(-1.55)
5 (high)	0.23	0.18	0.17	0.15	0.14	-0.10	(-1.27)	5 (high)	0.23	0.15	0.16	0.15	0.17	-0.06	(-0.93)

Table 3-7 – Two-Way Dependent Sorts in UP vs DOWN Markets (cont'd)

Panel C: IG vs NIG firms

Raw Returns								Raw Returns							
Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5) - (1)		Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5) - (1)	
IG Firms, UP State								NIG Firms, UP State							
1 (low)	0.03	0.06	0.06	0.06	0.07	0.04	(3.38)	1 (low)	-0.02	0.03	0.04	0.05	0.09	0.11	(4.32)
2	0.05	0.06	0.06	0.06	0.06	0.01	(0.95)	2	0.01	0.03	0.06	0.06	0.06	0.06	(3.39)
3	0.05	0.06	0.06	0.05	0.05	0.01	(0.77)	3	0.02	0.04	0.05	0.05	0.07	0.05	(3.06)
4	0.05	0.06	0.06	0.06	0.06	0.01	(0.95)	4	-0.01	0.03	0.05	0.08	0.07	0.08	(4.59)
5 (high)	0.04	0.06	0.06	0.07	0.07	0.03	(3.03)	5 (high)	-0.05	0.02	0.04	0.05	0.10	0.14	(6.17)
IG Firms, DOWN State								NIG Firms, DOWN State							
1 (low)	0.18	0.14	0.11	0.11	0.10	-0.08	(-1.53)	1 (low)	0.28	0.27	0.23	0.17	0.21	-0.07	(-0.97)
2	0.11	0.10	0.09	0.08	0.09	-0.03	(-0.94)	2	0.20	0.17	0.12	0.15	0.15	-0.06	(-0.77)
3	0.11	0.09	0.07	0.07	0.08	-0.04	(-1.25)	3	0.17	0.15	0.13	0.12	0.13	-0.05	(-0.83)
4	0.13	0.09	0.09	0.09	0.08	-0.04	(-1.63)	4	0.20	0.16	0.17	0.16	0.15	-0.04	(-0.69)
5 (high)	0.17	0.14	0.12	0.11	0.09	-0.08	(-1.75)	5 (high)	0.29	0.23	0.24	0.19	0.19	-0.10	(-1.03)

Table 3-8 – Two-Way Dependent Sort: Screen vs No Screen

Each month firms are sorted by the same two-way dependent sort as in Table 7. The top half of each panel reports the results of these sorts drawn from all of the firms in each sub-sample with no price screen and there is no gap-month between the formation and holding periods. The bottom half of each panel reports the results of these sorts drawn from all of the firms in each sub-sample priced at \$1 or higher at the time of portfolio formation (and there is a gap-month included between formation and holding periods). Presented are the mean returns of each individual portfolio as well as the momentum strategy portfolio which is the difference between portfolios (5) and (1). Panel A presents the results of entire sample. Panel B presents the results of the rated firm sample and the non-rated firm sample. Panel C presents the results of the investment grade sample and the non-investment grade sample. *t*-statistics are reported in parentheses. Statistically significant results (at 5%) are bolded.

Panel A: All firms

Raw Returns							
Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5) - (1)	
All Firms, No Gap - No Screen							
1 (low)	0.94	1.11	1.36	1.34	1.51	0.57	(1.61)
2	0.97	1.09	1.14	1.07	1.11	0.14	(0.80)
3	0.93	0.95	0.88	0.86	0.92	-0.01	(-0.08)
4	1.03	1.08	1.02	1.10	1.13	0.10	(0.56)
5 (high)	0.84	1.12	1.24	1.37	1.57	0.72	(2.10)
All Firms, 1-month Gap - \$1 Screen							
1 (low)	0.80	1.07	1.29	1.33	1.54	0.75	(2.64)
2	0.87	1.03	1.14	1.11	1.17	0.30	(1.88)
3	0.83	0.91	0.86	0.86	0.98	0.15	(1.20)
4	0.93	1.05	1.04	1.15	1.22	0.30	(1.82)
5 (high)	0.73	1.08	1.24	1.39	1.56	0.82	(2.97)

Table 3-8 – Two-Way Dependent Sort: Screen vs No Screen (cont'd)

Panel B: Rated vs Non-rated firms

Raw Returns							Raw Returns								
Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5) - (1)	Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5) - (1)		
Rated Firms, No Gap - No Screen							Non-Rated Firms, No Gap - No Screen								
1 (low)	0.84	1.10	1.30	1.21	1.41	0.56	(1.38)	1 (low)	0.97	1.09	1.30	1.46	1.51	0.53	(1.55)
2	1.04	1.15	1.11	1.03	1.04	-0.01	(-0.05)	2	0.97	1.02	1.07	1.08	1.16	0.19	(1.08)
3	0.95	1.09	1.03	0.94	0.93	-0.02	(-0.11)	3	0.88	0.82	0.81	0.77	0.92	0.04	(0.31)
4	1.05	1.15	1.05	1.12	1.08	0.03	(0.17)	4	1.02	1.01	1.00	1.08	1.13	0.11	(0.62)
5 (high)	0.67	1.07	1.21	1.25	1.40	0.73	(1.97)	5 (high)	0.96	1.08	1.21	1.44	1.62	0.66	(1.87)
Rated Firms, 1-month Gap - \$1 Screen							Non-Rated Firms, 1-month Gap - \$1 Screen								
1 (low)	0.76	1.09	1.20	1.29	1.43	0.65	(1.93)	1 (low)	0.81	1.02	1.22	1.40	1.53	0.72	(2.65)
2	0.96	1.08	1.10	1.06	1.13	0.17	(0.92)	2	0.84	1.00	1.09	1.12	1.18	0.34	(2.26)
3	0.88	1.05	1.01	0.94	1.00	0.12	(0.72)	3	0.79	0.80	0.81	0.79	0.97	0.18	(1.55)
4	0.97	1.11	1.06	1.17	1.16	0.19	(0.96)	4	0.88	0.97	0.99	1.10	1.20	0.32	(2.07)
5 (high)	0.70	1.10	1.24	1.30	1.45	0.75	(2.24)	5 (high)	0.75	1.03	1.20	1.44	1.59	0.83	(3.25)

Table 3-8 – Two-Way Dependent Sort: Screen vs No Screen (cont'd)

Panel C: IG vs NIG firms

Raw Returns								Raw Returns							
Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5) - (1)		Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5) - (1)	
IG Firms, No Gap - No Screen								NIG Firms, No Gap - No Screen							
1 (low)	1.02	1.22	1.18	1.15	1.19	0.14	(0.53)	1 (low)	0.57	1.16	1.27	1.08	1.91	1.36	(1.95)
2	1.10	1.19	1.05	0.98	0.99	-0.11	(-0.65)	2	0.69	0.75	1.14	1.31	1.24	0.55	(1.57)
3	1.04	1.07	0.99	0.91	0.90	-0.13	(-0.80)	3	0.92	1.06	1.00	1.00	1.18	0.27	(0.89)
4	1.16	1.12	1.02	1.01	0.94	-0.22	(-1.19)	4	0.51	0.88	1.03	1.55	1.36	0.84	(2.41)
5 (high)	1.08	1.16	1.14	1.17	1.14	0.06	(0.22)	5 (high)	-0.07	0.95	1.15	1.16	1.76	1.82	(3.48)
IG Firms, 1-month Gap - \$1 Screen								NIG Firms, 1-month Gap - \$1 Screen							
1 (low)	0.90	1.18	1.14	1.19	1.27	0.33	(1.37)	1 (low)	0.58	1.13	1.16	1.18	1.86	1.30	(2.61)
2	1.04	1.12	1.06	1.01	1.08	0.04	(0.23)	2	0.67	0.84	1.12	1.24	1.29	0.63	(1.83)
3	0.97	1.04	0.98	0.90	0.96	-0.01	(-0.05)	3	0.71	1.03	1.00	0.99	1.28	0.57	(2.10)
4	1.06	1.07	1.06	1.04	1.05	-0.01	(-0.06)	4	0.45	0.93	1.09	1.54	1.36	0.91	(2.72)
5 (high)	0.98	1.18	1.17	1.22	1.24	0.26	(1.03)	5 (high)	0.13	1.00	1.22	1.23	1.87	1.74	(3.86)

Table 3-9 – Monthly Returns Regressed on Lagged-Market Return

Each month t , momentum portfolios are formed based on their 6-month formation period return. The momentum strategy portfolio is defined as the winner portfolio (top decile) minus the loser portfolio (bottom decile) and its 6-month cumulative return (t to $t+5$) is then regressed on the lagged 36-month market return ($t-36$ to $t-1$) and the lagged 36-month market return squared. The regressions are also repeated for the CAPM- and Fama-French-adjusted 6-month cumulative returns. The coefficients of these regressions are reported. t -statistics are reported in parentheses below. Panel A presents the results of entire sample. Panel B presents the results of the rated firm sample and the non-rated firm sample. Panel C presents the results of the investment grade sample and the non-investment grade sample. Statistically significant results (at 5%) are bolded.

Panel A: All, Rated vs Non-Rated

All Firms				
	Intercept	LAGMKT	LAGMKT ²	Adjusted R ²
Raw return	-1.10 (-0.29)	33.86 (2.21)	-22.68 (-1.71)	17.82
CAPM-adjusted	-0.84 (-0.22)	33.68 (2.21)	-22.63 (-1.72)	17.72
Fama-French-adjusted	-0.85 (-0.22)	33.47 (2.20)	-22.48 (-1.71)	17.52
Rated Firms				
	Intercept	LAGMKT	LAGMKT ²	Adjusted R ²
Raw return	-4.02 (-0.84)	37.90 (1.96)	-21.38 (-1.22)	16.36
CAPM-adjusted	-3.54 (-0.74)	37.56 (1.96)	-21.29 (-1.24)	16.29
Fama-French-adjusted	-3.25 (-0.68)	36.99 (1.92)	-21.20 (-1.23)	15.70
Non-Rated Firms				
	Intercept	LAGMKT	LAGMKT ²	Adjusted R ²
Raw return	0.18 (0.05)	32.11 (2.38)	-23.23 (-2.01)	17.44
CAPM-adjusted	0.34 (0.10)	32.00 (2.38)	-23.20 (-2.02)	17.34
Fama-French-adjusted	0.24 (0.07)	31.86 (2.38)	-23.00 (-2.00)	17.30

Table 3-9 – Monthly Returns Regressed on Lagged-Market Return (cont'd)

Panel B: IG vs NIG

IG Firms				
	Intercept	LAGMKT	LAGMKT ²	Adjusted R ²
Raw return	-2.74 (-0.91)	22.13 (1.83)	-14.34 (-1.23)	9.79
CAPM-adjusted	-2.37 (-0.79)	21.87 (1.83)	-14.27 (-1.24)	9.70
Fama-French-adjusted	-2.32 (-0.77)	21.71 (1.82)	-14.22 (-1.24)	9.52
NIG Firms				
	Intercept	LAGMKT	LAGMKT ²	Adjusted R ²
Raw return	-3.46 (-0.59)	49.94 (2.16)	-24.96 (-1.17)	17.29
CAPM-adjusted	-3.02 (-0.51)	49.63 (2.16)	-24.87 (-1.18)	17.17
Fama-French-adjusted	-2.49 (-0.42)	48.55 (2.11)	-24.69 (-1.18)	16.36

Table 3-10 – Momentum Returns and Return Dispersion

$$MOM_t = \beta_0 + \beta_1 RRD_{1-3} + \varepsilon_t$$

$$MOM_t = \beta_0 + \beta_1 RD_{1-3} + \beta_2 MKT_{1-36} + \varepsilon_t$$

Each month t , momentum portfolios are formed based on their 6-month formation period return as they were in Table 11. The resulting time-series of returns is then regressed on the two models above. Where RRD is the 3-month lagged residual return dispersion, RD is the 3-month lagged return dispersion and MKT is the 36-month lagged market return. These regressions are repeated for both the raw momentum returns as the dependent variable and the change-in-momentum as the dependent variable. The change-in-momentum is defined as the raw momentum return from the portfolio formed at t minus the raw momentum return from the portfolio formed at $t-9$. The coefficients of these regressions are reported, with their t -statistics are reported in parentheses below. Panel A presents the results of entire sample. Panel B presents the results of the rated firm sample and the non-rated firm sample. Panel C presents the results of the investment grade sample and the non-investment grade sample. Statistically significant results (at 5%) are bolded.

Panel A: All firms

	INT	RRD(1-3)	R ²	INT	RD(1-3)	MKT(1-36)	R ²
All Firms							
MOM(t)	0.77 (3.13)	-0.33 (-2.06)	0.03	1.32 (3.41)	-0.42 (-2.43)	0.02 (2.15)	0.15
ΔMOM(t,t-9)	0.00 (0.00)	-0.56 (-2.45)	0.04	1.80 (2.66)	-0.67 (-2.89)	0.01 (0.49)	0.07

Panel B: Rated vs Non-Rated firms

	INT	RRD(1-3)	R ²	INT	RD(1-3)	MKT(1-36)	R ²
Rated Firms							
MOM(t)	0.65 (2.28)	-0.30 (-1.46)	0.02	1.03 (2.14)	-0.40 (-1.97)	0.02 (2.18)	0.13
ΔMOM(t,t-9)	0.03 (0.06)	-0.63 (-2.73)	0.03	2.03 (2.61)	-0.77 (-3.01)	0.01 (0.64)	0.07
Non-Rated Firms							
MOM(t)	0.84 (3.66)	-0.33 (-2.22)	0.03	1.47 (3.91)	-0.42 (-2.54)	0.02 (2.05)	0.14
ΔMOM(t,t-9)	-0.02 (-0.05)	-0.50 (-1.96)	0.03	1.62 (2.32)	-0.59 (-2.47)	0.01 (0.39)	0.06

Table 3-10 – Momentum Returns and Return Dispersion (cont'd)

$$MOM_t = \beta_0 + \beta_1 RRD_{1-3} + \varepsilon_t$$

$$MOM_t = \beta_0 + \beta_1 RD_{1-3} + \beta_2 MKT_{1-36} + \varepsilon_t$$

Panel C: IG vs NIG firms

	INT	RRD(1-3)	R ²	INT	RD(1-3)	MKT(1-36)	R ²
IG Firms							
MOM(t)	0.34 (1.45)	-0.23 (-1.71)	0.02	0.74 (1.89)	-0.32 (-2.20)	0.02 (2.02)	0.10
Δ MOM(t,t-9)	0.01 (0.02)	-0.57 (-3.11)	0.04	1.84 (3.16)	-0.69 (-3.30)	0.01 (0.62)	0.08
NIG Firms							
MOM(t)	1.29 (3.29)	-0.24 (-0.84)	0.01	1.04 (1.82)	-0.35 (-1.28)	0.03 (2.42)	0.12
Δ MOM(t,t-9)	0.04 (0.07)	-0.82 (-2.58)	0.03	2.41 (2.25)	-0.96 (-2.87)	0.01 (0.74)	0.07

Table 3-11 – Combined Economic and Market State Model

$$MOM_t = \beta_0 + \beta_1 RRD_{1-3} + \beta_2 MKT_{1-36} + \beta_3 DEF_{t-1} + \beta_4 DIV_{t-1} + \beta_5 TERM_{t-1} + \beta_6 YLD_{t-1} + \varepsilon_t$$

Each month t , momentum portfolios are formed based on their 6-month formation period return as they were in Table 11. The resulting time-series of returns is then regressed on the model above. Where RRD is the 3-month lagged residual return dispersion, MKT is the 36-month lagged market return, DEF is the lagged default spread, DIV is the lagged market dividend yield, TERM is the lagged term spread and YLD is the lagged yield on 3-month T-bills. Again, the regression is repeated for the raw momentum returns as the dependent variable and the change-in-momentum as the dependent variable. The coefficients of these regressions are reported, with their t -statistics are reported in parentheses below. Statistically significant results (at 5%) are bolded.

Panel A: All, Rated, and Non-rated firms

	β_0	<i>RRD</i>	<i>MKT</i>	<i>DEF</i>	<i>DIV</i>	<i>TERM</i>	<i>YLD</i>	<i>F-stat</i>	R^2
All Firms									
MOM(t)	22.05 (4.33)	-2.00 (-2.55)	0.02 (0.53)	-17.84 (-3.27)	-3.08 (-1.10)	1.11 (0.88)	1.04 (1.09)	4.65 (0.00)	0.39
Δ MOM(t,t-9)	22.02 (2.15)	-2.75 (-1.31)	-0.01 (-0.19)	-22.31 (-2.61)	-0.71 (-0.13)	1.57 (0.81)	-0.42 (-0.21)	3.07 (0.01)	0.18
Rated Firms									
MOM(t)	28.18 (4.56)	-1.92 (-2.54)	0.02 (0.44)	-20.04 (-3.24)	-3.71 (-1.05)	0.13 (0.08)	0.78 (0.70)	5.17 (0.00)	0.37
Δ MOM(t,t-9)	29.32 (2.52)	-2.81 (-1.48)	-0.01 (-0.13)	-28.87 (-3.10)	0.23 (0.04)	1.17 (0.50)	-0.95 (-0.44)	5.09 (0.00)	0.20
Non-Rated Firms									
MOM(t)	20.17 (4.15)	-1.86 (-2.17)	0.02 (0.52)	-17.14 (-3.32)	-2.31 (-0.92)	1.28 (1.13)	0.92 (1.03)	4.16 (0.00)	0.37
Δ MOM(t,t-9)	18.86 (1.93)	-2.47 (-1.08)	-0.02 (-0.26)	-19.80 (-2.37)	-0.92 (-0.18)	1.75 (0.94)	-0.21 (-0.11)	2.41 (0.04)	0.16

Table 3-11 – Combined Economic and Market State Model (cont'd)

$$MOM_t = \beta_0 + \beta_1 RRD_{1-3} + \beta_2 MKT_{1-36} + \beta_3 DEF_{t-1} + \beta_4 DIV_{t-1} + \beta_5 TERM_{t-1} + \beta_6 YLD_{t-1} + \varepsilon_t$$

Panel B: IG and NIG firms

	β_0	<i>RRD</i>	<i>MKT</i>	<i>DEF</i>	<i>DIV</i>	<i>TERM</i>	<i>YLD</i>	<i>F-stat</i>	<i>R</i> ²
IG Firms									
MOM(t)	23.15 (4.38)	-1.55 (-2.19)	0.00 (0.02)	-15.15 (-3.48)	-2.85 (-1.10)	-0.51 (-0.38)	0.39 (0.50)	5.47 (0.00)	0.30
Δ MOM(t,t-9)	27.71 (3.10)	-2.55 (-1.68)	-0.03 (-0.52)	-26.57 (-3.96)	0.19 (0.04)	0.83 (0.45)	-0.72 (-0.45)	6.68 (0.00)	0.24
NIG Firms									
MOM(t)	34.22 (4.14)	-1.90 (-1.78)	0.05 (0.84)	-24.36 (-2.80)	-6.68 (-1.28)	1.45 (0.61)	2.01 (1.15)	5.57 (0.00)	0.36
Δ MOM(t,t-9)	31.05 (2.10)	-3.93 (-1.61)	0.02 (0.17)	-31.39 (-2.46)	-0.33 (-0.04)	1.61 (0.51)	-0.96 (-0.33)	4.34 (0.00)	0.16

Chapter 4: Momentum and Life Expectancy

4.1 Introduction

In an efficient market, it should be impossible to systematically outperform the market on a risk-adjusted basis. Yet, momentum strategies appear to do just that. As such, the presence and persistence of positive risk-adjusted returns would seem to challenge the concept of efficient markets, one of the very foundations for much of financial theory.

Based on existing literature, it would appear that the more commonly held belief is that momentum is in fact an irrational behavioural result. While there are numerous theories from both the risk-based¹⁵ and behavioural-based¹⁶ camps, the bulk of the empirical work appears to support the behavioural theories. What we know empirically from numerous papers¹⁷ about the cross-section momentum firms is that they are smaller, and have a lower analyst following (with greater dispersion in their forecasts), lower credit ratings, greater idiosyncratic volatility¹⁸, greater trading volume as well as greater return and cashflow volatility. Much of these findings are cited as proxies for uncertainty supporting an explanation of underreaction due to this uncertainty.

And while this interpretation is certainly reasonable, there is an alternate interpretation, one that is not necessarily at odds with the market return dispersion results discussed in the previous chapter. These determinants may instead be proxying for the health of the firm, or more accurately, its lack of health and the probability that it will not survive. Chen (2011) comes to this same

¹⁵ See Conrad and Kaul (1998); Berk, Green and Naik (1999); Johnson (2002); and Sagi and Seasholes (2007).

¹⁶ See Barberis, Schleifer and Vishny (1998); Daniel, Hirshleifer and Subramanyam (1998); Hong and Stein (1999); George and Hwang (2004); Grinblatt and Han (2005); and Vanyanos and Woolley (2013).

¹⁷ Hong, Lim and Stein (2000); Arena, Haggard and Yen (2008); Avramov et al (2007); Jian, Lee and Zhang (2005); Zhang (2006); Sagi and Seasholes (2007); Lee and Swaminathan (2000)

¹⁸ This is according to Arena, Haggard and Yen (2008); whereas McLean (2010) finds no relationship between momentum returns and idiosyncratic volatility (ivol). The results would appear to differ depending on how ivol is defined.

conclusion regarding the cross-sectional determinants of the book-to-market effect. Firms with a strong book-to-market effect share many of the same characteristics listed here. In his paper, Chen establishes an empirical link between many of these determinants and the delisting probability of a firm. Using the inverse of the delisting probability as a proxy for the life expectancy of a firm, he shows how life expectancy can rationally explain variation in the strength of the book-to-market effect among firms of varying size.

A finite life expectancy may be a point of contention for some, given that firms are typically thought to have infinite lives. I address this point and elaborate in Section 4.2, but for now suffice it to say not all firms survive – some do cease to exist. And, therefore, at least some firms do have finite life expectancies, even short ones. This, in turn, implies variation in these life expectancies across firms.

In this paper I take a similar approach and explore the possible role of a firm's life expectancy in the explanation of momentum. Based on a very simple version of the same model employed by Chen (2011), which was in turn based on the model of Pastor and Veronesi (2003), I present a case where the life expectancies of firms assigned to momentum portfolios can affect the strength of the subsequent momentum returns. Similar to Conrad and Kaul (1998), in this case, momentum is the result of the cross-sectional variation in expected returns. Quite simply, on average the winner portfolio has a greater expected return than the loser portfolio, and, therefore, a winner-minus-loser portfolio would have a net positive expected return and would tend to earn positive realized returns over time. Portfolios are formed by sorting firms by their past realized returns. If we refer to the “efficiency” of this sorting as to how well sorting by realized returns also sorts by expected returns, then, according to my model, controlling for the life expectancy of firms should increase/decrease this “efficiency” and, therefore, subsequent profits. Firms with lower life

expectancies would tend to be sorted more efficiently relative to their longer-lived counterparts and should, therefore, experience greater momentum returns.

Using Chen's (2011) delisting probability logit model, I obtain the firms' delisting probabilities and, using these probabilities as a proxy for firm life expectancy, I find an empirical relationship between life expectancy and momentum. I find that momentum is much stronger among firms with a lower life expectancy. Momentum in the lowest quintile group outperforms momentum in the highest, by 4.6% over 6-months, or 9.4% annually. This is consistent with the predictions of the model I present. This finding also opens up the possibility that previous empirical work on momentum was misinterpreted.

My main contribution is providing an alternative interpretation for much of the existing empirical work on momentum. I do not claim to disprove current behavioural theories; however, this levels the playing field between behavioural-based and risk-based in that both can be interpreted as consistent with existing empirical evidence. The literature no longer seems as lopsided. Another contribution is presenting a framework which is consistent with both the cross-sectional evidence of momentum firms, as well as the evidence on the time-varying nature of momentum. Many papers focus on one or the other. I also establish a previously undocumented empirical link between momentum and life expectancy which is both economically and statistically significant. This result is potentially related to the work on credit-rating in Avramov et al (2007) as far as credit-rating proxies for delisting probability. Avramov et al find that momentum is concentrated in the lowest credit quality firms. However, I am able to extend their analysis beyond *just* firms with credit ratings. In addition to this, I also establish another previously undocumented empirical link between momentum and Chicago Board Options Exchange Volatility Index (VIX) as a proposed proxy for market uncertainty.

The rest of the paper proceeds as follows. Section 4.2 discusses the existing related literature and presents the model and its implications. Section 4.3 presents empirical evidence. Section 4.4 concludes.

4.2 Rationale and Motivation

CS (2002) claim that momentum is related to the macroeconomic state. They find that momentum can be predicted from a set of macroeconomic factors and that momentum is only positive during economic expansion. Cooper, Gutierrez and Hammeed (2004) (hereafter CGH) dispute Chordia and Shivakumar's findings and argue that market states are a better predictor. They find that the 36-month lagged market return is a better predictor and that, somewhat similar to Chordia and Shivakumar, momentum is only profitable following market "up" states.

Even though CGH interpret their findings as evidence towards a behavioural explanation, their results may be consistent with those presented here. Given that "down" markets are typically fewer/shorter than "up" states, the lack of profitable momentum may be due more to the change from "up" to "down" than to the fact that it's a "down" state. Consistent with this argument, Daniel and Moskowitz (2013) examine momentum "crashes" and find that these occur as the market transitions into negative or down markets. They point out that high beta portfolios formed during times of positive market returns, would be expected to underperform in a negative market. I argue that the same could be true in a negative to positive transition; however, the longer "up" markets give more time for momentum to recover as opposed to the shorter "down" markets.

In response to such a lack of consensus regarding the factors driving momentum, a number of both rational and behavioural theories/models have been proposed to explain the existence of momentum. I discuss some of these models below.

Conrad and Kaul (1998) suggest that momentum profits are simply the product of buying “high mean” stocks and selling “low mean” stocks, resulting in positive profits on average. They decompose momentum returns into what they refer to as the “time-series predictability” component and the “cross-sectional variation” component and argue that momentum returns may be due entirely to the cross-sectional variation in unconditional mean returns of stocks. The idea is that if stock returns follow a random walk with drift, and even the time-varying changes in that drift is unpredictable, then there would be no time-series predictability; however, a momentum strategy could still earn positive returns due to cross-sectional dispersion. Past winners would tend to include more stocks with higher unconditional mean returns, on average, as compared to past losers. Therefore, momentum strategies would result in the long positions having higher unconditional means relative to the short positions, which in turn, would result in positive returns of the combined portfolio. Conrad and Kaul’s empirical work indicates that only the cross-sectional variation component contributes positively to momentum returns.

Behavioural-Based Models

Barberis, Shleifer and Vishny (1998) present a model of investor behaviour which contains both the underreaction and overreaction of investors to new information. Conservatism causes investors to underreact over the short- to medium-term and momentum is a consequence of this underreaction. In Daniel, Hirshleifer and Subramanyam (1998), individuals tend to attribute positive outcomes to their own abilities and negative outcomes to their environment, or luck. When they interpret outcomes as positive, their overconfidence in stock-picking ability translates into overconfidence in these “winners” and they bid up the prices of these stocks, overreacting to this news.

Grinblatt and Han (2005) argue that momentum is the result of prospect theory and mental accounting, combining to create the disposition effect. Investors' reluctance to sell past losers causes a delay in the incorporation of new information into prices, leading to underreaction, resulting in momentum. The psychological concept of anchoring is used as an explanation for momentum in George and Hwang (2004). Looking at 52-week highs, the authors find that momentum is stronger as firms approach their 52-week high.

Hong and Stein (1999) divide investors into two groups: informed and uninformed traders. Trading by the informed group is not enough to fully incorporate the new information into prices and so the market underreacts to this new information. The uninformed group slowly continues to push prices up (down) as they follow the lead of the informed group.

Typically in these behavioural theories, momentum is at least partially driven by investors' underreaction and uncertainty is thought to exacerbate this underreaction, leading to greater momentum returns. Until now, these behavioural theories have found empirical support through the cross-sectional determinants of momentum and their perceived relation to uncertainty at the firm-level.

Discussion of Existing Cross-Sectional Determinant Empirical Work

In this section I discuss much of the existing empirical findings related to momentum. Many of the individual cross-sectional determinants identified empirically in past papers have typically been used to support the notion of irrational behavioural explanations for momentum. And while convincing, the interpretation can shift once life expectancy is introduced. Many of the findings discussed below also discuss a firm with a shorter life expectancy. The strength of this explanation is that it takes in much of the previous work and unifies it under one theory. Typically, behavioural theories have difficulty accounting for one empirical result or another. For example,

uncertainty measures are routinely used to support the overconfidence explanation. The overconfidence bias is stronger in the face of uncertainty. The evidence supports this as momentum does increase in relation to typical proxies for uncertainty. However, momentum is also negatively related to market volatility¹⁹. Market volatility and increased trading have been interpreted as the result of uncertainty in the market. If this is the case, then momentum should be increasing with market volatility, but it does not.

Hong, Lim and Stein (2000) establish an empirical link between momentum and both firm size and analyst coverage. They find that momentum is stronger among smaller firms and those with less analyst coverage and argue that smaller firms with less coverage would experience slower information dissemination to the public. This is consistent with the behavioural model of Hong and Stein (1999) that suggests that momentum may be due to an initial under reaction to new information which could be due to slower information dissemination. However, size and analyst coverage are also found to be positively related to life expectancy by Chen (2011). This in turn, implies a negative relationship according to the rational explanation presented in this paper, so while these findings are consistent with the behavioural model, they are also consistent with the rational explanation momentum at the same time.

The role of idiosyncratic or firm-specific volatility's relationship appears to be more ambiguous. Arena, Haggard and Yan (2008) find a positive relationship, whereas McLean (2010) finds that no relationship exists. Idiosyncratic volatility is found to be negatively related to life expectancy by Chen (2011) and should, therefore, have a positive relationship with momentum, consistent with Arena, Haggard and Yan. The idea of idiosyncratic volatility in these cases, however, may be somewhat of a misnomer. Its calculation requires specification of an underlying

¹⁹ See Wang and Xu (2015).

market model. If this is not the true underlying model, then values calculated may represent something else entirely.

Among credit-rated firms, credit quality seems to have a dramatic effect on momentum returns. Avramov et al (2007) claim that momentum is only positive among low credit quality firms (non-investment grade). Their findings are that momentum is non-existent among firms with an investment grade credit rating. Assuming that credit quality is a proxy for life expectancy as a measure of firm health among rated firms; this too is consistent with my predictions. An important distinction here is that this result is among rated firms. They also find that rated firms and non-rated firms earn similar momentum returns. Given that non-rated firms still earn momentum, this is not a credit rating story exclusively, and credit ratings are most likely proxying for something else at work. It may be that Avramov et al, were capturing this life expectancy effect in their findings. One important contribution of this paper is that it extends the analysis to non-rated firms as well, as credit rating is not a requirement for conclusion.

Jian, Lee and Zhang (2005) and Zhang (2006) look at proxies for information uncertainty and conclude that there is a positive relationship between information uncertainty and momentum returns. One such proxy is cash flow volatility; this result is also confirmed by Sagi and Seasholes (2007) in their empirical work. In another possibly related finding, Lee and Swaminathan (2000) find that momentum is stronger among more heavily traded stocks. I suggest this may be related because one interpretation of this finding is that the higher trading volume may be due to diverging opinions among investors and therefore consensus and equilibrium are more difficult to reach. In such an interpretation, trading volume may indicate uncertainty regarding firm value. None of these measures are used to model life expectancy as it is determined in this paper; however, I think it is reasonable to assume that these results are nonetheless consistent in terms of life expectancy.

Uncertainty in general, should have a negative impact on life expectancy in a risk-averse world. In particular, the volatility measures (returns, cash flow) would be negatively related to life expectancy (and therefore positively to momentum) as an increase in these measures implies and increase in the probability of insolvency at some point, overall.

While these characteristics of momentum firms have been studied piece-by-piece and the interpretations have sometimes varied from study to study, taken altogether in the big picture, they begin to paint a picture of a firm facing great uncertainty and volatility and therefore, a shorter life expectancy. It's possible that each of these determinants may have been found to increase momentum, not through their relation to stock return uncertainty and their resulting psychological impact on investor behaviour, but through their relation to a firm's life expectancy. Sorting by these determinants may actually sort by life expectancy to some degree and thereby magnifying the mechanism by which firms are sorted by their expected returns during the formation period.

Market Volatility

In contrast to the cross-sectional determinants at the firm-level, there are also a number of important related findings that pertain to the market overall, as opposed to firm-specific cross-sectional determinants. One of my predictions is that as the dispersion among returns increases, it is likely that idiosyncratic returns are increasing relative to their systematic counterparts (in the event that expected returns are relatively stable/consistent in the short-term), which would dampen the sorting effect of past returns and lead to more random portfolio assignment in terms of expected returns. This would lead to a decrease in momentum. There are a number of existing papers that confirm this prediction.

SS (2010) find that momentum is negatively related to return dispersion in the market, both in terms of the cross-sectional standard deviation of returns, as well as a residual measure that also

controls for market returns overall. Wang and Xu (2015) find that momentum is greater following low market volatility. Again, assuming relative stability in expected returns, lower market volatility could mean lower unpredictable idiosyncratic returns and thus strengthen the sorting effect of past returns (the correlation between past returns and expected returns). Huang (2013) constructs what he calls the momentum gap measure which measures the difference between the winner and loser formation period returns, which is another measure of dispersion, just at the more extreme ends. A larger momentum gap implies more extreme returns in the winner and loser portfolios' past returns, and the more extreme the return the more likely it is driven by idiosyncratic returns. This increase in idiosyncratic returns hampers the correlation between past returns and expected returns and would thus lead to lower momentum returns.

Life Expectancy Model and Implications

Rational Momentum as Variation in Expected Returns

In contrast to much of the previous work arguing for rational momentum²⁰, the case presented does not rely on any special mechanism driving price continuation, but rather, it depends on cross-sectional variation in expected returns. To put it in simple terms, the winner portfolio tends to outperform the loser because the former is riskier and therefore earns more. The key here is the efficiency of the sorting procedure first mentioned in Section 4.1. How efficiently does sorting by past realized return (over the formation period) also sort by expected return? The difference between realized returns and expected returns is idiosyncratic or firm-specific returns. The introduction of idiosyncratic returns adds noise to the sorting procedure and reduces the

²⁰ See Berk, Green and Naik (1999); Johnson (2002); and, Sagi and Seasholes (2007).

efficiency. The greater the idiosyncratic returns the lesser the degree to which firms can be sorted on the expected returns by sorting on their realized returns.

To illustrate, consider a firm's realized return, $r_{i,t}$:

$$r_{i,t} = \mu_{i,t} + \varepsilon_{i,t} \quad (7)$$

This realized return is comprised of its expected return, $\mu_{i,t}$, and its firm-specific return, $\varepsilon_{i,t}$, over any period, t . Assuming that a firm's expected return is relatively stable²¹ over the short- to medium-term (e.g. over the formation and holding periods of the momentum strategy), it is natural that high- μ (above average) firms in period $t-1$ would tend towards above average returns in period t , and vice versa for low- μ firms, given that:

$$E[\varepsilon_{i,t}] = 0 \quad (8)$$

$$E[\varepsilon_{i,t} | \mu_{i,t}] = 0 \quad (9)$$

Therefore, in a perfectly rational efficient market, so-called momentum would be a natural result of sorting by realized returns (past returns). On average, the winner portfolio that outperformed the loser over the formation period will tend to outperform the loser again over the holding period. This cross-sectional difference would be systematic.

One potential pitfall with this, is that in the momentum strategies we are dealing with the extreme ends of the realized return spectrum; the average absolute firm-specific returns of these two extreme portfolios would likely be quite high. While the realized expected returns of the winner portfolio would be greater than those of the loser, on average. This is because the firm-specific returns are independent of their expected returns (as per equation 2), and hence they have the potential to bring lower- μ (higher- μ) firms into the winner (loser) portfolio and introduce a

²¹ It is not necessary that the firm's actual expected return remains stable, but merely that a firm's expected return's relative ranking remains somewhat stable over this horizon.

great deal of noise, if their absolute value is high enough. If the noise is too great over period $t-1$, the cross-sectional differences in mean returns of the two extreme portfolios may be undetectable over period t . In such a case, any difference in subsequent raw returns in the following period (the holding period) would be unsystematic and imply, at least over the following holding period, that the market is not rational and/or efficient. In other words, a behavioural explanation is much more likely.

So momentum is either systematic or unsystematic; either the expected returns, μ , are driving momentum, or it's the firm-specific returns, ε . If the cause is rational (i.e. systematic), then "strengthening" the systematic component (relative to the unsystematic) during portfolio formation should increase the efficiency of the sorting procedure and magnify the outcome (i.e. momentum returns in the holding period). On the other hand, if "strengthening" the systematic component has no effect, then it is far more likely that the cause is behavioural in nature (i.e. unsystematic).

Ultimately it's the level of idiosyncratic returns or "noise" that determines the efficiency of the sorting procedure and through that, subsequent momentum returns in an efficient market. In the following subsection, I show one way it may be possible to manipulate the efficiency of the sorting effect by decreasing the relative weight of firm-specific returns is through exploiting life expectancy.

Finite Life Expectancy

Do firms have a finite life expectancy? Some readers may find it difficult to accept the concept of a firm's life expectancy, in that it implies a finite life. Firms are often assumed to have infinite lives – in fact, this is an underlying requirement for the popular dividend discount model.

For the purposes of this study, stock exchange delisting for cause represents the firm's end-of-life. And while it could very well be true that many – if not most – firms have life expectancies so long that they are essentially “infinite” for our intents and purposes, it is also true that some firms do delist. Some firms also cease operations and some even liquidate. The point is that the concept of finite life expectancies – even short life expectancies – is feasible.

The measure I employ is that of Chen (2011). It is the probability of delisting that is determined by a probabilistic model of delisting using actual delisting data. The model does not require that all firms have short finite lives; only that there is cross-sectional variation in these probabilities.

Model

Following Chen (2011), I begin with a simple model relating a firm's share price to the book value of its assets. The firm is an all-equity non-dividend paying firm with a certain finite life of τ years. Expressing a firm's stock price as a function of its continuously compounded book value, price P can be expressed as:

$$P = B e^{(g-\mu)\tau} \quad (10)$$

where B is the firm's book value of assets, g is the assets' long-term average expected growth rate (the firm's return on assets), μ is the firm's required rate of return, and τ is the firm's life expectancy in years. If P is efficiently priced, then g , μ , and τ represent their true unobservable values. In this model, g does not necessarily equal the next period's expected growth; instead, it is the life-time average of all future expected growth rates. Under this interpretation, neither g nor μ need to be stated explicitly.

The intuition requires no specification of the underlying pricing model that determines μ . The only informal restriction placed on μ , is that while time-variation in expected returns is

permitted, μ is relatively stable (on average) over the shorter horizon of roughly 12 months (i.e. there would typically very little change in μ over the formation period and the holding period in a momentum strategy).

Assuming that the market is efficient so that stocks are accurately priced, any deviation from μ in realized returns would be due to firm specific shocks that cause changes in their expected growth rate, g . Appendix A shows that the realized return, $r = \ln(P_t/P_{t-1})$, over one period $t-1$ to t can be rearranged to be expressed as²²:

$$r = \Delta g \bar{\tau} + \mu \quad (11)$$

where Δg is the change in the expected growth rate from time $t-1$ to t (and $\bar{\tau} = \tau - 1$). Given that realized returns consist of a systematic portion and an idiosyncratic portion, with respect to equation (5), the systematic portion (or expected return) is represented by μ and the idiosyncratic portion by $\Delta g \bar{\tau}$. This would imply that for a given change in the expected growth rate (Δg) and a given expected return (μ), firms with longer life expectancies (τ) would have a relatively larger idiosyncratic component ($\Delta g \bar{\tau}$) to their realized returns. Conversely, all else being equal, firms with shorter life expectancies would have a smaller idiosyncratic component. This also means that, all else being equal, the realized returns of shorter-lived firms would be dictated to a greater extent by their expected return component μ , relative to longer-lived firms.

In the context of momentum strategies where firms are sorted by their past returns, equation (5) represents their past returns; the realized return of the firm over the formation period. The placement of shorter-lived firms (within the winner/loser portfolios) would depend to a greater extent on their expected return as compared to their longer-lived counterparts, and would thus be

²² For the derivation of this equation, see Appendix A.

more systematic. The placement of these longer-lived firms would depend more on their unpredictable idiosyncratic risk and would therefore be more random. Thus, the expected return of the winner (loser) portfolio of the shorter-lived firms should be greater (lesser) than for longer-lived firms, whose placement in the portfolios is more dependent on their random idiosyncratic returns.

Grundy and Martin (2001) point out that by sorting on past returns, we are guaranteed to see a difference in the factor exposure influence between the winner and loser portfolios. The question is whether this difference is detectable and significant enough to drive momentum. Grundy and Martin claim that it is not; however, their results are conditional on the factor pricing model they use, which may very well be misspecified and invalidate their results. Although testing the *absolute* magnitude of these returns to determine significance is not possible without knowing the correct factor pricing model, by exploiting the idiosyncratic risk's relationship with life expectancy, we may be able to detect the significance of this mechanism by looking at its *relative* magnitude.

In other words, if the mechanism by which sorting on past returns generated future returns is the cross-sectional variation in expected returns/factor exposures between the two extreme portfolios, manipulating this mechanism should also manipulate the momentum returns. And so, while measuring absolute risk-adjusted returns requires a factor model, measuring changes in the unadjusted returns requires no such model. By **manipulating** the average life expectancies of the winner/loser portfolios, we can look for changes in momentum returns.

Implications

Let's assume that momentum is the result of the cross-sectional variation of expected returns. This cross-sectional variation is then the result of sorting by past returns over the formation period, which is an imperfect proxy for expected returns over the formation period. According to equation (5), the extent to which the noise corrupts the proxy is captured by $\Delta g\bar{r}$. If $\Delta g\bar{r}$ were to equal zero, then past returns, r , would be a perfect proxy for expected returns, μ . The overall implication is, therefore, that as the unsystematic noise in firm-level returns increases, the efficiency of sorting by expected return *through* the sorting of past returns (i.e., the correlation between past returns and expected returns) decreases. As the correlation decreases, the randomness of the sorting increases and the expected returns of the winner and loser portfolios converge lowering future momentum raw returns. This leads to the following two testable implications:

- 1) Firms sorted by life expectancy should experience different levels of raw momentum returns, with the lowest life expectancy group experiencing the highest returns.
- 2) As firm-level return dispersion across the market increases, to the extent that such an increase is due to firm-specific returns increasing, subsequent raw momentum returns should decrease.

The second implication already has substantial evidence supporting this concept. Return dispersion, market volatility and the gap between the past returns of the winner and loser portfolios have all been shown to negatively related to subsequent momentum returns.

4.3 Empirical Analysis

Data and Methodology

My sample includes all nonfinancial US common stocks listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX) and the NASDAQ Stock Market (with a shared code of 10 or 11 on CRSP) over the period of 1981-2013²³. The data includes returns, delisting codes, fundamental data, institutional ownership information and analyst estimates. Return²⁴ and delisting data is obtained from CRSP; financial statement fundamental data is obtained from Compustat; institutional ownership data is obtained from Thomson Reuters; and, analyst estimates are obtained from the Institutional Brokers' Estimate System (IBES). Stock returns are adjusted to correct for delisting bias according to Shumway (1997) and Shumway and Warther (1999).

The main empirical analysis studies the momentum returns of a dependent double-sorted momentum strategy. Each month, firms are first sorted by estimated life expectancy, and then by past return (i.e., formation period return). The life expectancy of a firm is not directly observable, and, therefore, must first be estimated.

Life Expectancy

For the purposes of this paper, a firm's life expectancy is proxied by its probability of delisting for cause²⁵ within 1-year. This is the same definition as in Chen (2011). Chen

²³ 1981 was chosen as a starting point as this was also the beginning year on which the logit model was based. It is after 1981 that Chen (2011) claims that delistings for cause increases significantly. In the event that this was a significant break, then the resulting logistic model is more applicable to post-1981 data.

²⁴ Individual and market index returns.

²⁵ As defined by CRSP. This typically includes firms that liquidate or no longer meet listing requirements.

distinguishes between delisting for mergers & acquisitions²⁶ and delisting for cause²⁷, arguing that delisting for cause is more representative of the end of a firm. Technically, these values are all expectancies; they are the expectations of the markets. Since the market's expectation of a firm's delisting probability is unobservable, I use the logistic regression model from Chen (2011) to estimate firms' delisting probabilities. A firm's implied life expectancy is then defined as the inverse of its estimated delisting probability (e.g., if delisting probability = 0.5, then life expectancy = 1/0.5)

In each month t , I estimate the probability of delisting for every firm i (indirectly) using Chen's (2011) Fama-MacBeth logit regression model²⁸. The logistic regression model yields the predicted values which are then transformed²⁹ into the probability estimates.

The model parameter estimates are as follows:

$$\begin{aligned} \theta_{i,t} = & -0.91\text{Size}_{i,t} + 0.15\text{Nasdaq}_{i,t} + 0.10\text{Analysts}_{i,t-1} + 0.06\text{O-score}_{i,t} \\ & + 0.34\text{O-dummy}_{i,t} + 0.96\text{Ivol}_{i,t} + 0.72\text{IO}_{i,t-1} \\ & + 1.52\text{Lev}_{i,t-1} - 0.95\text{ROE}_{i,t-1} - 0.11\text{BM}_{i,t-1} \\ & - 0.17\text{Age}_{i,t}, \end{aligned} \tag{12}$$

where $\theta_{i,t}$ is the predicted value from the model for firm i at time t , $\text{Size}_{i,t}$ is the natural log of firm i 's market cap at time t , $\text{Nasdaq}_{i,t}$ is a dummy variable equal to 1 if firm i is listed on the NASDAQ exchange (and 0 otherwise), $\text{Analysts}_{i,t-1}$ is the natural log of the number analysts covering firm i at $t-1$, $\text{O-score}_{i,t}$ is the Ohlson (1980) O-score³⁰ at time t , $\text{O-dummy}_{i,t}$ is a dummy variable equal to 1 if firm i has a missing³¹ O-score at time t (and 0 otherwise), $\text{Ivol}_{i,t}$ is firm i 's

²⁶ CRSP delisting codes: 200 – 399.

²⁷ CRSP delisting codes: 400 – 599.

²⁸ The parameters are the averages of all the monthly cross-sectional parameter estimates.

²⁹ Predicted values from logistic models are not probabilities themselves, but functions of those probabilities. Therefore, the raw outputted predicted values need to be transformed first.

³⁰ See the appendix A for the Ohlson (1980) model estimates.

³¹ Missing O-scores are set to -0.78 as per Chen (2011).

idiosyncratic volatility (annualized standard deviation of daily beta-excess returns over the past 365 days) at t , $IO_{i,t-1}$ is firm i 's percentage of institutional ownership at $t-1$, $Lev_{i,t-1}$ is firm i 's total liabilities to total assets ratio at $t-1$, $ROE_{i,t-1}$ is the return on equity (income before extraordinary items divided by book equity from the previous period) of firm i at $t-1$, $BM_{i,t-1}$ is firm i 's book-to-market ratio at time $t-1$, and $Age_{i,t}$ is firm i 's CRSP-age (number of years since it was listed on the CRSP database) at time t . Following Chen's methodology, all independent variables are winsorized (at 1% and 99%).

Probabilities of delisting ($\gamma_{i,t}$) are then obtained from the transformation of the predicted values, $\theta_{i,t}$:

$$\gamma_{i,t} = \frac{1}{1 + e^{-\theta_{i,t}}}, \quad (13)$$

where $\gamma_{i,t}$ is the probability that, as of time t , firm i will delist within the next 12-months, and $\theta_{i,t}$ is the predicted value from (3) for firm i in month t . In turn, life expectancies are obtained from the inverse of the estimated probabilities (e.g. $1/\gamma_{i,t}$).

Momentum Returns

The formation period return is the second sorting criteria; it is the buy-and-hold return over the formation period, which include the J -months prior to the holding period (or $J + 1$ months prior including a skip-month) in a J/K momentum strategy³². In this case, $J = 6$ and a skip-month is included (in order to mitigate the impact of the bid-ask bounce), therefore, the formation period for month t is months $t-7$ to $t-2$ ($t-1$ is the skip-month).

³² The J/K in a J/K momentum strategy refers to the formation period length (J) and the holding period length (K).

Momentum portfolios are then formed based on stock rankings by life expectancy and formation period return through a dependent double-sort. Each month t , all NYSE firms in my sample (with a price greater than \$1 as of month t) are sorted by their implied life expectancy, $1/\gamma_{i,t}$, and assigned into quintiles. The remaining non-NYSE firms are then assigned to the appropriate quintile based on the NYSE cut-off values. Within each delisting probability quintile, all stocks are then ranked according to their formation period returns over $t-7$ to $t-1$ and assigned into quintiles based on these rankings. A momentum portfolio is then created for each combination of life expectancy quintile and formation period return quintile, resulting in 25 separate momentum portfolios. The momentum strategy portfolios³³ consist of long positions in the high past-return portfolio and equally short positions in the low past-return portfolio within each life expectancy quintile. The result of this double-sort is 5 separate momentum strategy portfolios (one for each life expectancy quintile). All portfolios are equally-weighted.

Holding period returns are calculated for each momentum strategy portfolio. As with the formation period returns, holding period returns are also buy-and-hold returns. The holding period consists of the K -months following portfolio formation. K equals 6 in this case; therefore, the holding period for each momentum strategy portfolio formed in month t is t to $t+6$ (end of $t+5$). This method results in overlapping returns; therefore, the t -statistics of mean returns are estimated with heteroskedastic- and autocorrelation-consistent standard errors. The momentum strategy returns are calculated and averaged for each life expectancy quintile and compared across quintiles.

³³ I distinguish between momentum portfolios and momentum strategy portfolios. Momentum portfolios are any individual portfolio that results from the sorting strategy (e.g. winner portfolio or loser portfolio), whereas momentum strategy portfolios are the combined winner-minus-loser portfolios (or high-minus-low portfolios).

Return Dispersion

The second implication of the model is that future momentum returns will decrease (increase) as return dispersion prior to portfolio formation increases (decreases). In other words, the model implies a negative relationship between return dispersion and momentum returns.

In order to test this, I follow the methodology of SS (2010). I estimate the momentum returns as described above, except in this case it is a single-sort strategy with only one momentum strategy portfolio formed each month. Those momentum returns are then regressed on measures of return dispersion. According to this model, the resulting coefficient on return dispersion measure should be negative and statistically significant.

SS (2010) define two return dispersion measures. The first is what the authors call simply “return dispersion” (RD) and it is the cross-sectional standard deviation of returns across 100 portfolios formed on book-to-market and size (ten book-to-market deciles by ten size deciles). The 6-month monthly buy-and-hold returns of the momentum strategy are regressed on this RD measure and the lagged market return over the past 36-months. The process is repeated, using the change in momentum from t to $t-9$ as the dependent variable.

The second Stivers and Sun measure is the “relative return dispersion” (RRD). This measure is the monthly residual from RD regressed on the absolute value of the market and a dummy indicating the market return was negative multiplied by the absolute return of the market:

$$RD_t = \delta_0 + \delta_1 |R_{M,t}| + \delta_2 D_t^- |R_{M,t}| + \varepsilon_t . \quad (14)$$

In this case, ε_t is RRD_t . Then, both the 6-month buy-and-hold momentum return and the change in momentum (t to $t-9$) are regressed, separately, on the RRD measure.

Summary Statistics

The summary statistics of the separate delisting probability quintiles in terms of implied life expectancy are presented in Table 1. There is quite a significant range in implied life expectancies from the lowest group to the highest. The mean life expectancy for the lowest delisting probability quintile is 909.1 years compared to a mean of 4.5 years for the highest probability quintile. While the concept of a 900 year old firm may seem abstract, the focus of this paper is more on the relative differences between the various groups and, therefore, it is the ranking and ages relative to one another that are important.

Table 2 shows the mean 6-month compounded raw and risk-adjusted returns (CAPM and Fama-French 3-factor) of typical single-sort momentum strategy with a 6-month formation period, gap-month, and 6-month holding period; as well as the mean returns of the winner and loser portfolios individually. These values will serve as a baseline for comparison with conditional strategies presented in this paper. The risk-adjusted returns, adjusted for the CAPM and Fama-French 3-factor model are mainly presented to demonstrate that these models do estimate positive alphas. The focus of this paper is mainly on the behaviour of the raw returns as opposed speculation on the correct underlying pricing model. The mean 6-month raw momentum return is approximately 4.1%, although the variation is quite large (the same is true of each of the other portfolios).

Main Results

Table 3 presents the results of the two-way dependent sort in which the firms are first sorted into life expectancy quintiles and then into formation period return quintiles. The momentum strategy definition and timing are as described above. 25 individual portfolios are constructed from each combination of life expectancy quintile and past return quintile. The mean return of each

portfolio, as well as the mean difference between the winner and loser portfolios for each life expectancy quintile and the overall difference between the strategy returns between the lowest and higher life expectancy quintiles are reported.

If positive raw momentum returns are the result of cross-sectional differences in expected returns due to sorting by past returns, then we would expect these raw momentum returns to increase as life expectancy decreases, due to the sorting mechanism being stronger in portfolios with lower life expectancies. The results of Table 3 Panel A indicate that this is indeed the case. The 6-month compounded momentum strategy returns of each life expectancy quintile are reported and the raw returns clearly decrease monotonically as life expectancy increases. The raw returns of every life expectancy quintile are significant except among quintile with the longest expected life. The lowest life expectancy quintile earns a 6-month compounded momentum return of 6.5% on average, compared to 1.9% for the highest life expectancy quintile. The difference between the two quintiles (high vs low) is 4.6% and is also statistically significant.

The momentum strategies in Panel A employ a \$1 price screen, which is typical in the momentum literature. The price screen means that any firm that is priced below \$1 at the time of portfolio formation is excluded. As a check, Panel B shows the results with a \$5 price screen, which is also used in momentum occasionally. The results appear to be even stronger under this price screen. The lowest life quintile's mean 6-month return is now 8.3% and the difference between high and low quintiles has increased to 6.3%. The overall pattern of results does not differ, however, between the two price screens. The life quintiles 1 through 4 are still economically and statistically significant, while life quintile 5 remains statistically insignificant.

Overall, these findings are consistent with Avramov et al (2007)'s result among credit-rated firms; momentum does not appear to be significant among the highest rated firms, or in other

words, among the most financially healthy/stable firms. The difference between these two “extreme” ends of the life expectancy spectrum appears to be driven by both the winner and loser portfolios of both quintiles, with the winner (loser) quintile decreasing (increasing) with life expectancy.

The mean 6-month cumulative returns of the three lower life expectancy quintiles are also greater than that of the single-sort strategy which was 4.0%. The strategy return of the lowest quintile is much greater than overall single-sort strategy with a 6.5% 6-month cumulative return (with the \$1 price screen). It would appear that sorting by life expectancy can also enhance raw momentum returns (compared to a traditional single-sort strategy).

Robustness Tests

Although it is not just the mean returns themselves, but also the pattern of mean returns that is quite strong, I examine the possibility that these results could be influenced by the very extreme end of the life expectancy spectrum. There are firms with life expectancies so low that they are expected to delist during the overall momentum horizon. The extreme uncertainty facing these firms may lead to unusual (yet, strong) returns behaviours. To verify that this is not the case, I have repeated the analysis with a sample that excludes firms with a life expectancy of 1.5 years or less. Results are presented in Table 4. As can be seen, the results of this additional screen are very close to those of Panel A of Table 3. There is a slight increase in the means of the lower life expectancy quintiles, but overall the results are consistent.

I also take a look at the results using different numbers of quantiles for the double-sorting. Table 5 presents the results of a 10 by 5 sort (Panel A), a 5 by 10 sort (Panel B), and a 10 by 10 sort (Panel C). The overall pattern of increasing mean raw momentum returns with decreasing life expectancies holds, and all differences between the top and bottom life expectancy groups are

positive and statistically significant. The 10 by 10 sort yields the highest difference at 6.7%. In both the 10 by 5 and 10 by 10 sorts, the highest life expectancy group earns statistically insignificant returns (although all momentum strategies in the 5 by 10 sort yield economically and statistically significant returns), with the lowest return being from the 10 by 5 sort which earns just a 1.3% 6-month compounded return.

Return Dispersion and Momentum

Another prediction of the model is that momentum returns should increase (decrease) as the dispersion in the cross-section of market returns decreases (increases). As discussed earlier, the reasoning behind this is that the strength of the expected return sorting mechanism is determined by the relative magnitude of the idiosyncratic return component versus that of the expected return component that comprise the realized returns. If the expected returns of firms are relatively stable over the intermediate horizon, larger changes in the cross-sectional return dispersion of all the firms would be more likely due to changes in the idiosyncratic returns, on average. As the idiosyncratic returns increase, relative to the expected return component, the return dispersion, especially among the extreme ends of the past-return spectrum, should increase as well. Increasing dispersion caused by increasing idiosyncratic return proportions leads to more random assignment with respect to expected returns in winner and loser portfolios, and thus subsequent raw momentum returns should decrease.

Using the SS (2010) measures of return dispersion and relative return dispersion, I regress the momentum returns of my sample on these dispersion measures. Return dispersion (RD) is

defined as the cross-sectional standard deviation of all stock returns.³⁴ Relative return dispersion (RRD) is the residual from the original RD measure regressed on absolute value of the market return. The 3-month moving average for both RD and RRD are the independent variables used in the regression of raw momentum returns.

The results are presented in Table 6. Panel A provides the results of the momentum strategy returns. Both measures, RD and RRD, have negative coefficients for both the raw momentum returns and the change in momentum from time t to $t-9$, with the results for the change in momentum being statistically significant. This negative relationship is consistent with the model predictions. The lack of statistical significance in the regression of raw returns may indicate that there is some other missing factor that determines the absolute magnitude of raw momentum returns; however, what is also important here is the directional influence of return dispersion over part of the formation period. The results indicate that, relative to prior momentum, an increase in return dispersion leads to a relative reduction in subsequent momentum returns. In this context, it would appear that increased idiosyncratic returns, as measured by the cross-sectional return dispersion, do decrease the expected return sorting mechanism of sorting by past returns, by increasing the randomness of the sorting procedure.

Panels B and C present the results of the same regressions, but on the winner portfolio (P5) and loser portfolio (P1), separately. While the regression coefficients of the change in return regression for the winner portfolio are both negative, the RD measures do not appear to be statistically significant in explaining the relative returns of either portfolio on its own. It does not

³⁴ More specifically, it is the cross-sectional standard deviation of the 100 size and book-to-market portfolios generously made available by Kenneth French through his website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

appear that the statistically significant relationship of the combined portfolio is driven solely by either the winner or loser portfolio.

These findings are consistent with SS's (2010) original findings, and appear to be consistent with those of Huang (2013) as well. Huang (2013) coins what the author refers to as the "momentum gap" – the difference between the returns of the winner and loser portfolio's formation period returns. Taken as another measure of dispersion in returns across the market and thus an indirect measure of the relative strength of idiosyncratic returns, these findings also seem to support the cross-sectional variation in expected returns explanation of raw momentum returns.

Table 7 presents the results of change in momentum returns (from $t-9$ to t) regressed onto the RD and RRD moving average measures ($t-1$ to $t-3$) on each life expectancy quintile. In every case, each dispersion measure is negative and significant. Of particular note, is that the coefficient estimates appear to be increasing (in negative value) with life expectancy to some degree. The pattern is not monotonic; however, the magnitudes of the higher life quintiles are greater than those of the lower life quintiles. This could be due to the relatively greater sensitivity to growth shocks of the longer-lived firms. Greater dispersion is even more likely to come from greater idiosyncratic variation among these groups, thereby weakening the sorting efficiency of the momentum strategies.

Market-Level Uncertainty

The negative RD relationship from SS (2010), along with the negative market volatility relationship from Wang and Xu (2015) and the negative momentum gap relationship from Huang (2013) can be interpreted as evidence of a negative relationship between momentum returns and market-level uncertainty, which, as previously stated, is inconsistent with prevailing behavioural-based theories of momentum. In this section, I further test this relationship with an additional proxy

for market-level uncertainty. The Chicago Board Options Exchange's Volatility Index (VIX) is also referred to as the "fear index" and has been previously used as a proxy for market uncertainty³⁵.

Table 8 presents the results of various regressions where the monthly momentum returns are regressed on VIX levels. The table presents a number of model specifications – all of which include the VIX level from the previous month and/or the VIX level squared. The squared VIX variable is included in the event that the relationship is not a linear one. Some of the specifications also control for the lagged market return and the lagged moving average of the RD measure (as defined in the previous section).

Overall, the evidence indicates a strong negative relationship between momentum returns and the level of the VIX. In every regression specification, at least one of the VIX variables (VIX or VIX²) is negative and statistically significant. This is true even after controlling for both the lagged market return and the lagged RD. When both the VIX level and the squared VIX level are included the squared level appears to subsume the explanatory power of the VIX level, indicating a nonlinear relationship – the negative impact on momentum returns is much greater at higher levels of the VIX. Another striking feature of these results is that none the coefficients on the lagged market return nor those of the lagged RD measure are statistically significant. The inclusion of a VIX variable appears to subsume any explanatory power that these variables had. This may call into doubt the previous interpretation of CGH (2004) and even that of SS (2010) that these variables as market state variables help explain the time-variation in momentum returns.

The results of Table 8 add more support to the idea that momentum is negatively related to market-level uncertainty through its proxy (VIX). While this result is not consistent with

³⁵ See Connelly, Stivers and Sun (2005); Drechsler and Yaron (2011); and Bekaert, Hoerova and Lo Duca (2013).

behavioural explanations, it is consistent with the explanation proposed in this chapter. The greater the uncertainty in the market as a whole, the greater the likelihood of more noise in the prices or returns of the stocks in the market. As the noise in these returns increases, the relative weight of their expected returns (in relation to the realized returns) decreases and the sorting efficiency also decreases – firms are more and more likely to be sorted randomly when sorted on realized returns as opposed to sorting based on their expected returns. This potentially leads to a reduction in the subsequent momentum returns going forward.

4.4 Conclusion

The idea that momentum is a rational response in an efficient market is still very much alive. In fact, much of the evidence against it can be just as easily interpreted as evidence for it, when examined through the lens of life expectancy.

By conditioning on life expectancy, I am able to change the overall momentum returns and demonstrate how firms with shorter expected lives experience greater momentum than their more expectantly long-lived counterparts. It would also appear that momentum is no longer even significant among the firms with the longest life expectancies. This provides support for the rational explanation that momentum is due to cross-sectional variation in expected returns in winner/loser portfolios that results from sorting by past returns, through life expectancy's theoretical impact on the effect of such sorting. It also provides indirect support for the theory of efficient markets. The implication of this explanation is that there are no predictable returns to momentum beyond expected returns. While the raw momentum profits may continue to be positive, that is likely due to the risk borne by taking on such a strategy that is typically long in a riskier portfolio and short in another.

This indirect evidence does not conclusively prove these claims, of course. But it brings them back in the realm of possibility. At the very least, it weakens the confidence in behavioural explanations. Just in terms of quantity, there appear to be far more papers in support of a behavioural explanation of momentum. However, this idea of life expectancy's impact on momentum suggests that a new interpretation is in order for much of this work. In fact, one of the most compelling factors supporting the life expectancy explanation is the volume of research with which these findings are consistent. To the best of my knowledge, no other momentum explanation can claim to be as consistent with the same quantity of empirical work.

The possibility that momentum may not be what we think it is, and that markets are indeed efficient (at least weak-form efficient) should be enough to warrant further investigation. Market efficiency is too important a concept to ignore. An additional implication of this reasoning is that our popular asset pricing models may well be misspecified. If this is the case, there may be an additional risk factor waiting to be discovered.

Table 4-1 – Summary Statistics: Life Expectancies by Delisting Probability

Each month, the delisting probability of each firm is estimated from the Chen (2011) logit regression model. Firms are then assigned to quintiles based on their estimated delisting probabilities, using the quintile cut-offs of the NYSE firms. The implied life expectancy is calculated as 1/delisting probability. Summary statistics of the life expectancies of the sample firms by delisting probability quintiles are provided below. Values are reported as estimated life expectancies.

Prob Quantile	Life Expectancy				
	Mean	Median	StDev	Skewness	Kurtosis
1	909.1	1277.1	862.1	9.0	290.2
2	246.9	316.5	314.5	3.3	42.2
3	102.6	132.3	126.9	3.4	58.1
4	44.4	56.2	54.9	2.7	21.8
5	4.5	8.3	4.1	1.6	4.6

Table 4-2 – Mean Momentum Returns (Traditional Single-Sort)

This table provides summary statistics on the raw and adjusted returns of a traditional momentum strategy (sorted only on past returns) from all the firms in the overall sample. The momentum strategy is a straight-forward 6/6 strategy: firms are ranked each month t on their 6-month formation period return over $t-7$ to $t-1$ and a momentum portfolio (P5-P1) that is long the winner portfolio (P5) and short the loser portfolio (P1) is formed and held for 6-months, from t to $t+6$.

		N	Mean	(t-stat)	Max	Min	Std
Raw	P5-P1	1167	4.06	(11.36)	41.25	-63.45	12.21
	P5	1167	6.67	(11.58)	83.62	-51.78	19.68
	P1	1167	3.01	(3.96)	179.53	-52.14	25.93
CAPM	P5-P1	1152	4.43	(12.31)	40.29	-61.41	12.22
	P5	1152	2.05	(6.60)	61.19	-24.09	10.56
	P1	1152	-2.13	-(4.56)	94.23	-30.70	15.87
FF3	P5-P1	1152	4.98	(13.89)	49.64	-58.85	12.16
	P5	1152	1.91	(10.51)	28.48	-21.08	6.18
	P1	1152	-2.93	-(8.13)	81.33	-26.79	12.24

Table 4-3 – Momentum by Life Expectancy

Each month t , all firms in the sample are subject to a dependent double sort: firms are first assigned to quintiles based on their implied life expectancy and then each life expectancy quintile is then sorted into quintiles based on cumulative past return ($t-7$ to $t-1$). The sorting procedure results in 25 individual portfolios. The mean cumulative 6-month holding period return (t to $t+6$) is reported for each portfolio. The mean difference between the high (winner) and low (loser) past return quintiles for each life expectancy quintile is also reported, along with the overall difference between the low (and second lowest) and high life expectancy quintiles (with t -statistics in parentheses). The mean difference between the high (winner) and low (loser) past return quintiles is also known as the mean momentum strategy return and the overall difference is the difference in strategy returns between the life expectancy quintiles. t -statistics are reported in parentheses (corrected for heteroskedasticity and autocorrelation of an automatically determined lag length). Statistically significant results (at 5%) are bolded.

Panel A		Past Returns (\$1 price screen)						
Life Expectancy	1 (low)	2	3	4	5 (high)	Difference (5) - (1)		
5 (High)	6.238	6.420	6.287	6.485	8.132	1.894	(1.619)	
4	5.626	7.075	7.577	7.492	9.354	3.728	(2.812)	
3	5.749	7.268	7.464	7.948	10.011	4.262	(3.021)	
2	5.100	7.325	8.054	8.821	10.419	5.319	(4.406)	
1 (low)	5.787	7.688	9.350	10.160	12.252	6.465	(4.718)	
Difference (1) - (5)						4.571	(3.773)	
Panel B		Past Returns (\$5 price screen)						
Life Expectancy	1 (low)	2	3	4	5 (high)	Difference (5) - (1)		
5 (High)	5.965	6.403	6.250	6.424	7.946	1.981	(1.687)	
4	5.517	7.077	7.595	7.478	9.313	3.795	(2.880)	
3	5.552	7.249	7.467	7.941	10.020	4.468	(3.270)	
2	4.732	7.114	7.962	8.696	10.360	5.627	(5.031)	
1 (low)	3.019	6.259	8.015	9.232	11.326	8.307	(6.664)	
Difference (1) - (5)						6.326	(6.338)	

Table 4-4 – Momentum by Life Expectancy: Life Expectancy > 1.5 years

Similar to Table 3, except firms with implied life expectancies less than 1.5 years have been excluded. Each month t , all firms in the sample *with an implied life expectancy greater than 1.5 years* are subject to a dependent double sort: firms are first assigned to quintiles based on their implied life expectancy and then each life expectancy quintile is then sorted into quintiles based on cumulative past return ($t-7$ to $t-1$). The sorting procedure results in 25 individual portfolios. The mean cumulative 6-month holding period return (t to $t+6$) is reported for each portfolio. The mean difference between the high (winner) and low (loser) past return quintiles for each life expectancy quintile is also reported, along with the overall difference between the low (and second lowest) and high life expectancy quintiles (with t -statistics in parentheses). The mean difference between the high (winner) and low (loser) past return quintiles is also known as the mean momentum strategy return and the overall difference is the difference in strategy returns between the life expectancy quintiles.

Life Expectancy	Past Returns (\$1 price screen)					Difference	
	1 (low)	2	3	4	5 (high)	(5) - (1)	
5 (High)	6.237	6.425	6.295	6.480	8.149	1.911	(1.637)
4	5.623	7.047	7.601	7.440	9.352	3.730	(2.800)
3	5.692	7.289	7.521	7.932	10.010	4.318	(3.095)
2	5.140	7.275	8.011	8.771	10.388	5.247	(4.299)
1 (low)	5.722	7.771	9.430	10.222	12.446	6.724	(5.064)
Difference (1) - (5)						4.813	(4.146)

Table 4-5 – Momentum by Life Expectancy: Alternative Quintiles

Each month t , all firms in the sample are subject to a dependent double sort: firms are first assigned to quintiles based on their implied life expectancy and then each life expectancy quintile is then sorted into quintiles based on cumulative past return ($t-7$ to $t-1$). The sorting procedure results in 50/50/100 individual portfolios. The mean cumulative 6-month holding period return (t to $t+6$) is reported for each portfolio. The mean difference between the high (winner) and low (loser) past return quintiles for each life expectancy quintile is also reported, along with the overall difference between the low (and second lowest) and high life expectancy quintiles (with t -statistics in parentheses). The mean difference between the high (winner) and low (loser) past return quintiles is also known as the mean momentum strategy return and the overall difference is the difference in strategy returns between the life expectancy quintiles. t -statistics are reported in parentheses (corrected for heteroskedasticity and autocorrelation of an automatically determined lag length). Statistically significant results (at 5%) are bolded.

Panel A		Past Returns					Difference	
Life Expectancy	1 (low)	2	3	4	5 (high)	(5) - (1)		
10 (high)	6.541	5.944	6.168	6.265	7.827	1.286	(1.174)	
9	5.964	6.915	6.421	6.660	8.564	2.599	(1.931)	
8	6.029	6.954	7.182	7.191	8.536	2.507	(1.908)	
7	5.238	7.128	7.990	7.673	10.246	5.008	(3.467)	
6	6.297	7.051	7.434	7.689	9.869	3.573	(2.481)	
5	5.346	7.360	7.800	7.849	10.158	4.813	(3.460)	
4	5.414	7.536	7.809	8.758	10.284	4.870	(3.631)	
3	5.037	7.122	8.012	8.629	10.745	5.708	(4.722)	
2	4.856	7.398	8.493	9.698	10.981	6.125	(4.307)	
1 (low)	6.070	7.877	9.777	10.498	13.045	6.975	(5.211)	
Difference (1) - (10)						5.689	(4.822)	

Table 4-5 – Momentum by Life Expectancy: Alternative Quantiles (cont'd)

Panel B												
	Past Returns											
Life Expectancy	1 (low)	2	3	4	5	6	7	8	9	10 (high)	Difference (10) - (1)	
5 (High)	6.083	6.403	6.256	6.602	6.348	6.242	6.342	6.622	7.082	9.256	3.173	(1.993)
4	5.400	5.860	6.794	7.296	7.755	7.442	7.510	7.375	8.152	10.594	5.193	(3.057)
3	4.908	6.495	7.093	7.481	7.678	7.366	7.968	7.884	9.035	11.034	6.126	(3.350)
2	4.257	6.044	7.001	7.551	7.746	8.277	8.647	8.885	9.958	10.837	6.580	(4.343)
1 (low)	5.169	6.278	7.244	8.301	9.277	9.583	9.880	10.569	11.755	13.133	7.965	(4.718)
Difference (1) - (5)											4.792	(3.040)
Panel C												
	Past Returns											
Life Expectancy	1 (low)	2	3	4	5	6	7	8	9	10 (high)	Difference (10) - (1)	
10 (high)	6.849	6.237	5.714	6.186	6.173	6.179	6.333	6.193	7.364	8.264	1.415	(0.935)
9	5.627	6.304	6.865	6.969	6.403	6.462	7.001	6.307	7.145	10.016	4.388	(2.365)
8	6.075	6.011	6.640	7.222	7.270	7.098	7.215	7.167	7.548	9.602	3.527	(2.031)
7	4.696	5.821	6.678	7.588	8.358	7.599	7.823	7.471	9.326	11.194	6.498	(3.657)
6	5.723	6.900	6.543	7.532	7.664	7.210	7.420	7.963	8.684	11.126	5.403	(2.662)
5	4.364	6.376	7.157	7.552	7.528	8.084	8.242	7.444	9.176	11.193	6.830	(3.734)
4	5.101	5.733	7.376	7.683	7.349	8.257	8.708	8.828	10.009	10.554	5.453	(3.302)
3	3.792	6.312	6.780	7.465	7.416	8.598	8.622	8.622	10.334	11.167	7.375	(4.954)
2	3.854	5.860	7.201	7.618	8.446	8.541	9.474	9.919	9.977	12.005	8.151	(4.536)
1 (low)	5.531	6.617	7.470	8.278	9.369	10.187	10.113	10.887	12.473	13.608	8.077	(4.702)
Difference (1) - (10)											6.662	(4.060)

Table 4-6 – Momentum and Return Dispersion

This table presents the regression estimates from the following regressions:

$$r_t = \beta_0 + \beta_1 RRD_{1-3} + \varepsilon_t \quad r_t = \beta_0 + \beta_1 RD_{1-3} + \beta_2 MKT_{1-36} + \varepsilon_t$$

$$\Delta r_{(t,t-9)} = \beta_0 + \beta_1 RRD_{1-3} + \varepsilon_t \quad \Delta r_{(t,t-9)} = \beta_0 + \beta_1 RD_{1-3} + \beta_2 MKT_{1-36} + \varepsilon_t$$

The dependent variable is either the return in month t , r_t , or the change in return from month $t-9$ to month t , $\Delta r_{(t,t-9)}$, which is regressed onto either the lagged 3-month moving average of the relative return dispersion (RRD), or onto the lagged 3-month moving average of the return dispersion (RD) and the lagged 36-month average market return. Panel A presents the combined strategy (P5-P1) results, Panel B presents the winner portfolio (P5) results, and Panel C presents the loser portfolio (P1) results. t -statistics are reported in parentheses (corrected for heteroskedasticity and autocorrelation of an automatically determined lag length). Statistically significant results (at 5%) are bolded.

Panel A

Return	P5-P1				
	Cons	RD(1-3)	Mkt(1-36)	Cons	RRD(1-3)
r_t	0.054 (1.645)	-1.909 -(1.482)	0.107 (2.528)	0.041 (2.906)	-1.619 -(1.009)
$\Delta r_{(t,t-9)}$	0.089 (2.467)	-2.970 -(2.557)	0.001 (0.024)	0.000 -(0.042)	-2.337 -(2.768)

Panel B

Return	P5				
	Cons	RD(1-3)	Mkt(1-36)	Cons	RRD(1-3)
r_t	0.175 (3.615)	-1.311 -(1.272)	-0.099 -(1.480)	0.093 (5.064)	-2.126 -(2.310)
$\Delta r_{(t,t-9)}$	0.165 (1.815)	-2.749 -(1.118)	-0.204 -(2.438)	-0.004 -(0.219)	-4.426 -(1.584)

Panel C

Return	P1				
	Cons	RD(1-3)	Mkt(1-36)	Cons	RRD(1-3)
r_t	0.125 (1.853)	1.009 (0.427)	-0.237 -(2.455)	0.055 (2.355)	-0.195 -(0.073)
$\Delta r_{(t,t-9)}$	0.059 (0.487)	0.840 (0.226)	-0.211 -(1.815)	-0.004 -(0.166)	-1.548 -(0.461)

Table 4-7 – Momentum and Return Dispersion by Life Expectancy

This table presents the regression estimates from the following regressions:

$$\Delta r_{(t,t-9)} = \beta_0 + \beta_1 RRD_{1-3} + \varepsilon_t \quad \Delta r_{(t,t-9)} = \beta_0 + \beta_1 RD_{1-3} + \beta_2 MKT_{1-36} + \varepsilon_t$$

The dependent variable change in return from month $t-9$ to month t , $\Delta r_{(t,t-9)}$, of the combined strategy portfolio (P5-P1). The dependent variable is regressed onto either the lagged 3-month moving average of the relative return dispersion (RRD), or onto the lagged 3-month moving average of the return dispersion (RD) and the lagged 36-month average market return. The regressions are run separately for each life expectancy quintile. t -statistics are reported in parentheses (corrected for heteroskedasticity and autocorrelation of an automatically determined lag length). Statistically significant results (at 5%) are bolded.

Life Expectancy	Cons	RD(1-3)	Mkt(1-36)	Cons	RRD(1-3)
5 (high)	0.162	-4.865	-0.036	0.000	-5.042
	(3.43)	-(3.46)	-(0.81)	(0.01)	-(2.83)
4	0.182	-5.599	-0.035	-0.002	-5.894
	(3.62)	-(3.49)	-(0.65)	-(0.12)	-(3.39)
3	0.179	-5.635	-0.023	-0.001	-5.883
	(4.52)	-(4.72)	-(0.46)	-(0.08)	-(4.25)
2	0.084	-2.696	-0.010	-0.002	-2.404
	(2.62)	-(2.92)	-(0.20)	-(0.19)	-(3.68)
1 (low)	0.086	-2.828	-0.005	-0.002	-2.243
	(1.88)	-(2.00)	-(0.12)	-(0.21)	-(2.07)

Table 4-8 – Momentum and Market-Level Uncertainty (VIX)

This table presents the regression estimates from a series of regressions that regresses the monthly momentum returns on various independent variables. VIX is the level of the VIX in the previous month, VIX² is the squared level of the VIX in the previous month, Mkt(1-36) is the lagged 3-year market return (previous 36 months), and RD(1-3) is the moving average of the return dispersion measure over the previous 3-months. *t*-statistics are reported in parentheses (corrected for heteroskedasticity and autocorrelation of an automatically determined lag length). Statistically significant results (at 5%) are bolded.

Specification	Cons	VIX	VIX ²	Mkt(1-36)	RD(1-3)
1	0.169 (3.36)	-0.680 (-2.50)			
2	0.096 (5.84)		-1.379 (-3.64)		
3	0.005 (0.08)	0.758 (1.58)	-2.709 (-3.36)		
4	0.176 (3.60)	-0.585 (-2.17)		-0.245 (-1.65)	
5	0.109 (4.99)		-1.238 (-3.90)	-0.185 (-1.35)	
6	0.023 (0.33)	0.705 (1.37)	-2.486 (-2.80)	-0.167 (-1.27)	
7	0.175 (4.06)	-0.587 (-2.48)		-0.247 (-1.54)	0.018 (0.06)
8	0.113 (4.43)		-1.230 (-3.71)	-0.0178 (-1.26)	-0.059 (-0.27)
9	0.021 (0.30)	0.829 (1.31)	-2.685 (-2.58)	-0.139 (-0.99)	-0.195 (-0.78)

APPENDIX A – Derivation of the realized return over the holding period

$$P = B e^{(g-\mu)\tau}$$

g_{old} represents the expected long-term growth rate at the beginning of the period.

$$P_0 = B_0 e^{(g_{old}-\mu)\tau}$$

At the end of the period (the formation period), the firm experiences a firm-specific shock which results in a new long-term expected growth rate, g_{new} . At the end of this period, the new price, P_1 is:

$$\begin{aligned} P_1 &= B_1 e^{(g_{new}-\mu)(\tau-1)} \\ P_1 &= (B_0 e^{g_{old}}) e^{(g_{new}-\mu)(\tau-1)} \\ P_1 &= B_0 e^{(g_{new}-\mu)(\tau-1)+g_{old}} \end{aligned}$$

The realized return over the formation period is calculated as $r = \ln(P_1/P_0)$:

$$\begin{aligned} r &= \ln \frac{P_1}{P_0} = \ln \frac{B_0 e^{(g_{new}-\mu)(\tau-1)+g_{old}}}{B_0 e^{(g_{old}-\mu)\tau}} \\ r &= \ln e^{(g_{new}-\mu)(\tau-1)+g_{old}} e^{-(g_{old}-\mu)\tau} \\ r &= (g_{new} - \mu)(\tau - 1) + g_{old} - (g_{old} - \mu)\tau \\ r &= g_{new}(\tau - 1) + \mu - \mu\tau - g_{old}(\tau - 1) + \mu\tau \\ r &= (g_{new} - g_{old})(\tau - 1) + \mu \\ r &= \Delta_g \bar{\tau} + \mu \end{aligned}$$

where $\bar{\tau} = (\tau - 1)$

APPENDIX B – Ohlson O-score

$$\begin{aligned} O\text{-score} = & -1.32 - 0.47 \ln(\text{total assets}) + 6.03 \frac{\text{total liabilities}}{\text{total assets}} - 1.43 \frac{\text{working capital}}{\text{total assets}} \\ & + 0.076 \frac{\text{current liabilities}}{\text{current assets}} \\ & - 1.72(1 \text{ if total liabilities} > \text{total assets, 0 otherwise}) - 2.37 \frac{\text{net income}}{\text{total assets}} \\ & - 1.83 \frac{\text{funds from operations}}{\text{total liabilities}} \\ & + 0.285(1 \text{ if a net loss for the last two years, 0 otherwise}) \\ & - 0.521 \frac{\text{net income}_t - \text{net income}_{t-1}}{|\text{net income}_t| + |\text{net income}_{t-1}|} \end{aligned}$$

Chapter 5: Conclusion

One of the most striking features of momentum behaviour is that the overall performance of momentum has drastically declined over the more recent time-period – to the point that some variations of momentum strategies now fail to produce economically or statistically significant returns. While it is always possible that momentum, as an anomaly, may cease to exist one day, it is also possible that this weaker performance is the result of the turbulent times during 2009. Daniel and Moskowitz (2013) study “momentum crashes” and find that, while infrequent, they can have drastic effects on the overall returns of momentum strategies. One such (very significant) crash occurred in 2009. The question is, then, is the apparently changing nature of momentum a consequence of these “crashes” or is momentum truly changing.

The issue of whether or not momentum is a rational result or one driven by the irrational behaviour of investors is an important one. And one that is not likely to be settled definitively due to the joint hypothesis problem. We cannot know whether the presence of abnormal returns is a sign of market inefficiency or model misspecification. Rather, we must rely on indirect evidence. And consensus regarding the nature of momentum will be built based on the reasonableness of the theory/explanation and its consistency with the indirect evidence.

Presently, the consensus appears to be building towards the acceptance of behavioural-based theories. These theories or models are very intuitive and relatable. In addition, much of the empirical cross-sectional findings certainly seem to support these theories. Yet, difficult questions still remain. Why is momentum negatively related to past volatility? Why does momentum experience occasional but extreme “crashes”? While the idea that these sub-phenomena could be driven by irrational investor behaviour would certainly not be surprising, it still remains to be seen

how this behaviour could be reconciled with the original behaviour that potentially drives momentum. In other words, there is currently no satisfactory *unifying* behavioural theory.

The explanation put forth in Chapter 4 offers a credible risk-based theory counter-argument to the underreaction behavioural-based theories. While I believe that the risk-based explanation is consistent with more of the existing evidence, both explanations remain plausible. Much of the evidence supporting either explanation can also be attributed to the other side as well. In a way, we are getting close to being back to square one. The challenge in the future is to search for more convincing evidence that more clearly favours one side over the other.

The possibility of rational momentum within the context of an efficient market has strong implications regarding existing asset pricing models. One such implication is that if momentum were indeed rational but still generated “abnormal” returns – according to our asset pricing models – then the models must be misspecified. Is there a missing factor? The addition of the momentum factor to the Fama-French 3-factor model to create the Carhart 4-factor model was in response to just such a question. However, even with the Carhart 4-factor model, we are not necessarily any closer to that answer. Why might momentum be a priced risk factor? What does it proxy? We will not truly understand the nature of stock returns until we at least know the risks for which they are compensating. The search for this missing factor (or some other alternative specification) could very well be rewarding in the future.

Finally, the concept of a firm’s life expectancy and its implications on the firm’s return behaviour is intriguing. Chen (2011) has already connected it the price-to-book effect anomaly and now it may also be part of the explanation of the momentum anomaly. The potential exists that it may be more involved in driving or at least explaining other “anomalies” as well. Avramov et al (2013) links credit-rating with many anomalies. At the very least, the concept of life

expectancy may extend Avramov et al's findings to non-rated firms. Or, it may be found that the credit-rating does in fact proxy for life expectancy and it is actually a firm's limited life expectancy that drives these results. We may yet see that these anomalies are not in fact anomalies, but rational return behaviour.

And there is more work to be done on the life expectancy measure itself (the probability of delisting). Chen introduces the idea, but more rigorous work on fine-tuning the measure could potentially increase its accuracy, and therefore, usefulness. The concept is tangentially related to default and bankruptcy measures which have been studied quite extensively. The idea of life expectancy, however, can extend the concept beyond to firms without debt (or significant levels of debt).

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