Are credit ratings effective on a momentum investment strategy? An empirical study

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Abstract

This dissertation investigates the existence of momentum effect for stocks differentiated by their credit rating, provided by S&P in a sample of 23790 listed companies from the US Market between 1987 and 2017. I analyse two types of credit rating categories, Investment grade and Speculative grade. The average credit ratings form an inverted U-shape across the various momentum portfolios, suggesting that a momentum strategy of buying previous winners and selling previous losers essentially takes long and short positions in firms with the lowest credit risk respectively.

Keywords: Corporate Credit Ratings, Momentum, Portfolio Strategy, Equity price

Resumo

Esta dissertação investiga a existência de efeito momentum para ações diferenciadas por sua classificação de crédito, fornecida pela S&P em uma amostra de 23790 empresas listadas no Mercado dos EUA entre 1987 e 2017. Analiso dois tipos de categorias de classificação de crédito, grau de investimento e grau especulativo. As classificações de crédito médias formam uma forma inversa em U nas várias carteiras de momentum, sugerindo que uma estratégia de momentum de comprar vencedores anteriores e vender perdedores anteriores essencialmente leva posições longas e curtas em empresas com o menor risco de crédito, respectivamente.

Palavras-chave: Corporate Credit Ratings, Momentum, Portfolio Strategy, Equity price

Contents

I. Introduction

In financial markets, there is general belief that securities are efficient in reflecting information of individual stocks. According to the Efficient-market-hypothesis (EMH), stocks always trade at their fair value; therefore, the market price of a stock is equal to its fundamental value. Malkiel (2003) defines an efficient market as a market where portfolio trading opportunities do not arise for above-average risk-adjusted returns. The author documents that stock markets, through the development of information systems that spreads news faster, tends to become more efficient and less predictable. The puzzling topic leads open the discussion whether markets are truly efficient or not, several researches in the industry investigate the predictability and modelling of market movements.

Asset pricing models enrich the literature of stock returns description, Sharpe (1964) provides the Capital asset pricing model (CAPM), which is a core model for asset pricing theories and applications. Fama and French (1992), extend the CAPM in order to develop the three-factor-model (FF3), which considers a market excess return variable along with a size and a value. Fama and French (2015) provide an extension of the previous model, known as the five-factor-model (FF5), which accounts for two additional factors that are respectively an investment and a profitability factor. The two additional variables lead to important empirical evidence: the value factor leads to overfitting in the model, and a four-factor-model without its inclusion has the same predictive power.

Fama (1970) claims that historical prices cannot predict future prices, which explains why the author models' do not include past returns in the development. In the same paper, the author recognizes that a measure of persistency of past return, known as Momentum, is a strong and intriguing anomaly to consider when explaining abnormal returns in generalist portfolio strategies. Following Fama (1970) work, Jegadeesh and Titman (1993) propose a research extension on momentum anomaly, by defining the price momentum factor as the cumulative return of 3 to 12 past month, the authors argue that a momentum trading strategy provide high risk-adjusted returns.

Carhart (1997) takes inspiration from the findings of both Jegadeesh and Titman (1993) and Fama and French (1992). The author creates a four-factor-model, which is an extension of the FF3 that includes the momentum anomaly. Avramov et al (2007) extend the documentation on momentum of Jegadeesh and Titman (1993). The authors argue that momentum effect is present for speculative grade firms, moreover it gradually dissipates with an increasing firms' credit quality for the portfolios built; the link between credit ratings and momentum effect is found to be robust when controlling for variables such as firm size, forecast dispersion, leverage, and cash flow volatility. This dissertation takes a direct inspiration from their work and the objective is to understand if, by extending their findings with more recent data, a momentum-based strategy which sort out companies by credit ratings can provide significant payoffs.

Following the premises that market anomalies related to profit opportunities typically disappears or dissipates over time (Schwert, 2003), the dissertation aims to explore and extend the universe of analysis where Avramov et al. (2007) settled their basements. To provide an educated answer on the topic, controls over momentum-based trading strategies are performed with the scope of understanding different portfolios performances and behaviour according to the credit quality of the portfolio components. It is a main objective of the dissertation to unravel if credit ratings hold significant informativeness for the excess returns generated by the momentum effect.

I find that a momentum investment strategy that consists of selling loser momentum portfolios provide positive excess returns throughout the time frame between January 1987 and February 2017. However, the excess returns are not statistically significant, meaning that the momentum anomaly is not existent. Avramov et al. (2007) momentum investment strategy of buying previous winners and selling previous losers speculative grade portfolios do not provide excess returns when controlling for data from January 2004 onwards, meaning that the effect find by the authors is dissipated.

The other sections of the dissertation are as follows: Section II presents the Literature review, Section III presents the Methodology part, Section IV presents the Data, Section V presents the Empirical results, Section VI presents the Limitations while Section VII presents the Conclusions.

II. Literature Review

The Capital asset pricing model (CAPM) of Sharpe (1964) is the foundation of asset pricing theories, it provides the fair value of individual assets through an intuitive formula. The model prices investments by taking into consideration both time and return. CAPM is built on several assumptions that make the model unable to explain asset returns on many samples, for instance, it ignores the risk appetite of individuals on the market, transaction costs, taxes and short selling operations. Despite such limitations, CAPM model is widely adopted to estimate expected returns of individual assets. It is a widely adopted baseline for asset pricing modelling.

Fama and French (1993) extend the CAPM model by adding a value and a size factor to the equation, the realization is the Fama and French three-factor-model (FF3). Empirical evidence shows that the addition of the two factors contributes to expand the informative power provided by CAPM in describing abnormal returns. The FF3 model generates abnormal returns, which are empirically driven by small companies (Fama, 1998). The use of value-weighted returns, instead of an equally weighted methodology, allows to clear the analysis from anomalies such as asset growth and firms' profitability that are not fully explained by the FF3 model. Fama and French (2015) propose a five-factor-model (FF5) which is a direct extension of the FF3 model. The FF5 model adds a profitability and an investment factor to the FF3 and provides better explanatory power than the predecessor. The FF5 points out a matter of parsimony, since a four-factor-model, which excludes the value factor, has the same predictive power of the FF5. The authors explains that value factor provides a redundant information into the FF5 model because the value anomaly is already explained by both the profitability and the investment factors. Hence, value factor exclusion provides a more parsimonious solution than a FF5 when developing an asset pricing model.

An extensive body of finance literature provides findings on the scope of predicting future stock returns basing on past price information. On the topic, I consider two distinct strategies, namely Momentum and Contrarian strategies. Momentum is classified as a positive-feedback trading strategy, it analyses the persistence of cumulative past returns, and it assumes that past performances tend to be consistent in future. Hence, a momentum strategy considers buying companies with positive excess cumulative past returns. In contrast, Contrarian strategy is a negative-feedback trading strategy, making it the opposite to momentum. In fact, a contrarian strategy, according to cumulative past returns, considers selling the best performers and to buy the worst past performers. Jegadeesh and Titman (1993) and Rouwenhorst (1998) argue that momentum is the continuation of returns, more specifically is the tendency of stocks that have performed well in the past 3 to 12 months to perform well in the next 3 to 12 months. It is stated by Fama (2008) that momentum was one of the anomalies that keep existing while being unexplained by both the FF3 and the CAPM.

Carhart (1997) presents an asset-pricing model by merging Fama and French (1993) and Jegadeesh and Titman (1993) works, therefore, a pricing model of four factor is made by the adding of momentum to the FF3 model. The author, by analysing a sample of mutual funds, concludes that the momentum addition to the asset-pricing model provides more explanatory power than previous models. In particular, the pricing model is capable of explaining mutual funds returns better than the CAPM. The model is adopted in order to explain individual stock or portfolio returns in frameworks that do not consider the universe of mutual funds.

De Bondt and Thaler (1985), according to the view that individuals overreact to information, show that stock prices also overreact to information. The authors point that there is a profitable trading opportunity by selling past winners and buying past losers. Poorly performing stocks for 3 to 5 years over-perform stocks that have a positive performance for the same timeframe. However, the empirical evidence suggests that long term losers are, in fact, significantly outperforming long term losers only on January months. Jegadeesh (1990) and Lehmann (1990) propose a short-term contrarian strategy which consists in picking portfolios that underperformed in the past weeks and past months. The authors argue that the strategy is capable to generate consistent excess returns, however, performances on the market are significantly reduced due to the high transaction costs nature of the strategy itself. Such suspicion is supported by the findings of Jegadeesh (1991), the results lead to the conclusion that short-term return reversals are related to bid-ask spreads, evidencing support on the interpretation.

Momentum anomaly, as documented by Jegadeesh and Titman (1993), is one of the most debated anomalies by the finance literature. Their findings concludes that a Momentum based strategy of buying past winners and selling past losers provides significant risk-adjusted returns proving that a weak form of market efficiency is violated. In addition, the authors argue that momentum strategy driven profits are subject to dissipation in the two years following the holding period. Barroso and Santa Clara (2015) report that momentum returns are negatively correlated with market and value factors, the authors show that momentum strategy generates positive risk-adjusted excess returns. In addition, the authors find that momentum volatility has predictive power over both lower returns and higher volatility.

Grobys et al. (2018), conduct an expanded analysis of the above-mentioned work. The authors extend the research on risk-managed momentum strategies on an industry level. The authors argue that both hedged and non-hedged industry momentum strategies are subject to optionality effect, meaning that the strategies are unaffected by a time-varying beta.

Conrad and Kaul (1998) provide momentum explanations based on the efficient market hypothesis. The authors find that both momentum and contrarian strategies provide positive market excess returns, moreover, momentum have high excess returns on a mid-term horizon (3-12 months). Daniel and Moskowitz (2016) demonstrate that momentum returns are sensitive to market crashes, especially during market reversals following sustained periods of bearish market. The effect is known as the optionality effect, which states that the behaviour of momentum strategies in a bearish market environment resembles the one of call options having on the market as underlying asset.

Unlike previous literature, Moskowitz and Griblatt (1999) adopt an alternative take on momentum strategy; in fact, instead of focusing on stock price momentum, they built a momentum portfolio by buying stocks into winning industries and shorting stocks representative of losing industries, both equally impacting the structure of the portfolio originated in mentioned way. The authors' conclusion is that momentum effect is an industry driven anomaly. In addition, Grundy and Martin (2001) argue that industry momentum strategies lead to profitability the month after the formation period.

Momentum also captured the interest of institutional investors, as demonstrated by the findings of Fung and Hsieh (2001). The authors argue that trend followers' behaviour leads to a non-linear option-like trading strategy. More specifically, a trend follower strategy has similar characteristics to a lookback straddle option. In conclusion it is shown that trend-following strategies have positive skewness and there is correlation between long volatility and trend following.

Bouchaud et al. (2006) derive the P&L of trend following strategies and evidence that it has an asymmetrically right skewed distribution. The authors also argue that trend followers are more likely to lose than gain on the market, such conclusion is reached through the analysis of the probabilities of incurring in a winning trade, known as the hit ratio. In particular, the hit ratio is roughly 50% in a low volatility environment, however, it drops quickly when the volatility increase, meaning that the more volatile the market is, the more likely is to incur in a zero to negative P&L.

Dao et al. (2016) deepens the study on the link between a trend-following strategy and the term structure of realized volatility, their findings show that, in a scenario in which long-term volatility is greater than short-term volatility, a trend following strategy turns out to be profitable. Hence, the challenge for a profitable trend following strategy is to perform risk management operations with the objective to obtain a positive skewness and a positive convexity. Moreover, Dao et al. (2016) explore the hedging properties of a portfolio created from a trend following strategy, arguing that it has similar payoffs to a portfolio composed of equally weighted at-the-money strangles. The authors' findings show that the strangle portfolio pays a fixed price for the short-term volatility, while the trend following portfolio is positively exposed to it. The authors conclude that options provide a better hedge on the market, nevertheless, a trend following strategy is a much cheaper solution in order to hedge long only exposures.

Chan et al. (1996) suggests a behavioural model in order to understand momentum anomaly, the documented model shows that investors under-react to fundamentals, and, as a result, momentum arises. The findings suggest that the markets respond only gradually to new information. Chui et al. (2010) expose the absence of momentum returns on the Japanese market while North America, Europe and Asia Pacific registered strong momentum returns, the implications on why Japan has no momentum effect are attributed to the low individualism of Japanese investors.

Chordia and Shivakumar (2002) further explain the momentum anomaly by controlling it for event windows, momentum strategies are explained by parsimonious sets of macroeconomic variables and, moreover, provide large payoffs during expansion periods but momentum effect is non-existent during recessions. Avramov et al. (2007) finds that there is a robust link between momentum and credit ratings, more specifically, momentum payoffs are noticeable on speculative grade firms, while the momentum effect dissipates for investment grade firms, the findings confirm that the momentum strategy is significant only during expansion business cycles. In contrary, Wang et al. (2015), by analysing the Taiwanese market, document that there is no momentum effect and credit ratings are not relevant when constructing a momentum-based strategy.

McLean and Pontiff (2016) argue that anomalies tend to disappear after their discovery. More specifically, the authors denote that anomalies return predictability lose efficiency ex-post to a literature publication, meaning that investors become informed after anomalies acknowledgment, which leads to price correction.

An extended batch of literature comprehend the information efficiency provided by credit ratings and credit rating agencies (CRAs), for instance, Blume et al. (1998) discover that CRAs become more stringent in evaluating parameters that lead to the assignment of the rating to individual companies; according to their findings, that leads to an overall downgrade of the market credit quality. Baghai et al. (2014) support the aforementioned results, they expose that, due to more conservative ratings assigned, companies are less likely to issue debt and increase leverage, which leads to a more conservative management of the companies involved. Hung et al. (2022) add new findings on the economic consequences of the global dominance of Credit rating agencies. The authors argue that there is a direct relationship between global market power of CRAs and conservative assessment of credit ratings, furthermore, empirical evidence suggest that market power of CRAs can strengthen their reputation concerns, which leads to issue stringent ratings and such trend fuel the increase of false warnings on default risks.

The main research question I am aiming to answer in this dissertation is the following: *Are credit ratings able to provide effective information when constructing a momentum portfolio strategy? How do credit rating-oriented stock picking affect portfolio performances?*

The expectations, given the literature discussed above, are that credit ratings are less informative than in previous literature. The more conservative nature of CRAs and the gradual awareness of investors on the momentum anomaly led to the supposition that a momentum investment strategy does not consist in buying and selling prevalently investment grade type of firms. I presume that mixed compositions will result from the credit quality of the firms inside the momentum portfolios.

III. Methodology

The research design aims to provide an answer whether or not credit ratings are informative when creating portfolios through momentum strategies. As demonstrated by Avramov et al. (2007), the strategy is profitable only when considering speculative grade firms, which are a minor component of the market capitalization.

Returns are a normalized measure of performance that will allow different assets and portfolios to be compared. In accordance with Meucci (2010), there are two mathematical notions adopted from both the academical and professional fields: linear and logarithmic returns. By considering a stock having price P_t at the end of the month *t*, then having price P_{t-1} for end of the month *t-1*, linear returns L_t are then defined as follows:

$$L_t \equiv \frac{V_t}{V_{t-1}} - 1$$

In contrast, log returns C_t for the end of the month *t* of a stock price P_t will be as follows:

$$C_t \equiv \ln\left(\frac{P_t}{P_{t-1}}\right)$$

While both provide the same numerical result, they reach the same results through two different understandings of returns. Linear returns are calculated at the end of the frequency period. Logarithmic returns a continuously cumulated throughout time. For simplicity, this dissertation uses logarithmic returns, since cumulated returns are realized simply as a sum of the individual period log-returns.

Momentum is defined as the pace at which a price would change. The industry defines two types of strategies that revolve around the use of given notion. A positive-feedback approach is the trading strategy that implies persistency of past returns for the next trading periods, consisting in buying past winners and selling past losers. Contrarian portfolio strategies are the exact opposite, known as negative-feedback trading strategies, their underlying assumption is that past returns will not hold in future. Therefore, by assuming that stocks will have contrary performances from the past, previous winners are sold while previous losers are bought.

Momentum portfolio performances are constructed following Jegadeesh and Titman (1993). Portfolio momentum strategies are noted as follows: a strategy that select stocks basing on cumulative returns on past J months and hold for K months is considered a J-month / K-month strategy. At the beginning of each month t, stocks are ranked in ten decile portfolios based on their cumulative returns for past n-months. In accordance with these rankings, ten equally weighted decile portfolios are formed. The portfolios are hold for K-months. The top decile portfolio is called "winner" portfolio while the bottom performer is called "loser" portfolio. Below is shown the mathematical expression that shows how portfolio returns are obtained, in line with Meucci (2010) notations and Jegadeesh and Titman (1993) methodology. Considering that stock returns are calculated as log returns, where *K* represent the number of cumulative periods for which the cumulative returns are calculated at time *t*, the expression is as follows:

$$C_t^K \equiv \ln\left(\frac{V_{t+k}}{V_t}\right) = C_t + C_{t+1} + \cdots + C_{t+k-1}$$

The formula above formula, proposed by Meucci (2010), is applied twice for each momentum investment strategy. Firstly, the formula is applied to calculate cumulative returns of individual stocks for the J months of construction period; secondly, same calculation is adopted for the realized returns of each portfolio. Basing on the formation period, the top 10% performing stocks are assigned to the winner portfolio (P10). On the other hand, the stocks which have the worst performances in the formation period are assigned to the loser portfolio (P1).

IV. Data

The goal of the dissertation is to extract empirical evidence of credit rating explanatory power on momentum strategy, that is, the paper will extend the analysis conducted by Avramov et al. (2007) which takes the work conducted by Jegadeesh and Titman (1993) as reference for the data treatment.

Monthly returns data are extracted for stocks listed in the CRSP Database, the stocks considered for the dissertation pertain to NYSE, DOW JONES and NASDAQ indices. Furthermore, in line with the cleaning procedures performed by Avramov et al. (2007), further criteria are applied in order to filter data to be included in the research sample, that said, stocks are included in the database of analysis only if they have, at minimum, 6 consecutive monthly return observations. For each month analyzed, I also exclude from the analysis penny stocks, in specific, stocks belonging to the lowest percentile by market capitalization are removed from the dataset analyzed.

To ensure that the results are not driven by illiquid stocks into the sample, I do remove stocks which, for two or more consecutive months, generate returns equal to zero. The filtering procedure leads to a universe of 23,790 listed companies, uniquely distinguished by permno, for a period between January 1987 and February 2017, period for which credit ratings are available from COMPUSTAT databases. This results in 362 months which will be investigated. The ratings extracted are provided from Standard & Poor's, the decision of taking their ratings is driven by two reasons: in first place, it is driven by the motivation that Standard and Poor's is the credit rating agencies with the oldest data available, allowing therefore to analyze a more accurate universe throughout time. Moreover, Avramov et al (2007) made use of S&P data available from COMPUSTAT, that allows to get a more direct comparison with their results. The addition of credit ratings to the procedure leads to a universe of 6,357 rated companies out of 23,790.

Ratings of Standard and Poor's accounts for 22 unique ratings, starting from a AAA rating (top rating), and concluding to a D rating (default). In line with Avramov et al (2007), I convert Standard and Poor's ratings into numerical scale: AAA rating is 1, AA+ rating is 2, and continues until D rating with 22.[1] In accordance to the numerical notation, a score of 10 (BBB-

[1] The entire scope of ratings is listed as per the following: AAA = 1, AA+ = 2, AA = 3, AA- = 4, A+ = 5, A = 6, A- = 7, BBB+ = 8, BBB = 9, BBB- = 10, BB+ = 11, BB = 12, BB- = 13, B+ = 14, B = 15, B- = 16, CCC+ = 17, CCC = 18, CCC- = 19, CC = 20, C = 21, D = 22.

or better) or below is representing an investment grade firm, on the other hand, firms with a score of 11 (BB+ or worse) or above are considered speculative grade.

In order to form and make use of momentum variable, I follow the definition of momentum documented by Jegadeesh and Titman (1993). Momentum is seen as the cumulative return of past months. Decile portfolios are constructed and ranked by following cumulative past returns of their potential components for the past 3, 6, 9 and 12 months. At the start of each month t, stocks are assigned to 10 ordinally ranked portfolios based on cumulative returns for formation periods of respectively the past 3, 6, 9, and 12 months. The stocks that represent portfolio 1 (P1), the loser portfolio, are the 10% worst performers for the given formation period, on the other hand, portfolio 10 (P10), is composed by the top 10% companies in terms of cumulative returns for the same formation period.

In order to make the portfolios of investment grade and speculative grade categories representative of their credit quality, I exclude from the decile portfolios of the two categories, stocks that incur in a downgrade or an upgrade during their formation period.

Table I provides descriptive statistics for the sample of monthly log-returns of all the firms, investment grade and speculative grade firms. The comparison across categories shows that the results for the information of the stock are somewhat similar, controlling through different sub-sample time periods does not produce visible changes throughout the diverse categories. It is important to notice that in Table I - Panel C, which highlights the results for the big financial crisis timeframe, Speculative Grade firms contribute for a lower standard deviation than the sample average (31.54% against 31.77% of the whole sample for the same time frame), the reverse observation could be made for all of the other time frames.

The mean monthly portfolio returns, both equally and value weighted, show that the speculative grade sub sample contributes for higher positive returns throughout the entire time analysis. However, the results are somewhat similar for both investment grade and speculative grade samples. In regards to credit ratings, Table I - Panel A shows that the average credit rating for investment grade firms is 7.21 (A-) while for speculative grade is 13.89 (B+) and the mean credit rating among all the firms is 10.49 (BBB-/BB+).

Table I
Return and Size characteristics of the firms

Table I presents descriptive statistics of monthly stock returns for the companies for stocks rated by Standard and Poor's and listed on CRSP database. For each month t, stocks of NYSE, NASDAQ, and DOW JONES indexes are extracted on the CRSP database. Stocks that, at the end of month t-1, are smaller than the smallest NYSE size percentile. Monthly returns are log-returns between t and t-1 stock monthly prices. Return descriptive results are obtained from the time series of each stock, then the results are averaged across all of the stocks for the analysis. Value weighted mean of returns is obtained as the cross sectional mean of individual stocks monthly return time series which are then cross sectionally weighted accordingly to the stock market capitalization size at the time t. Standard deviation, skewness and excess kurtosis are computed for each stock and then averaged across all stocks, said descriptive statistics come from the equal weighted mean. Equally weighted mean, value weighted mean and standard deviation are the % monthly value. Rating mean is obtained as the cross sectional mean off all the stocks ratings in each month t, it is represented by the conventional numerical score described as such as before in the paragraph. Panel A shows the statistics above described in a sample period from January 1987 to February 2017. Panel B, C and D show the information above listed for different time frames: Panel B sample period is January 1987 to December 2002, Panel C sample period is January 2003 to December 2008, finally, Panel D sample period is January 2009 to February 2017.

Panel A: ***Whole period of Analysis***

	All Firms	Investment Grade	Speculative Grade
Return - equally weighted mean (%)	1.75%	2.10%	1.37%
Return - value weighted mean (%)	1.54%	1.25%	1.87%
Return - standard deviation (%)	31.77%	31.48%	32.07%
Return - skewness	0.83	0.86	0.79
Return – excess kurtosis	3.11	3.17	3.04
Rating - mean	10.49	7.21	13.95

Panel B: ***Tech Crisis Analysis***

	All Firms	Investment Grade	Speculative Grade
Return - equally weighted mean (%)	2.96%	3.27%	2.61%
Return - value weighted mean (%)	1.86%	1.66%	2.10%
Return - standard deviation (%)	35.50%	34.91%	36.15%
Return - skewness	0.78	0.84	0.72
Return – excess kurtosis	2.35	2.46	2.23
Rating - mean	10.41	7.21	13.89

Table I - *Continued*

Panel C: ***Big Crisis Analysis***

	All Firms	Investment Grade	Speculative Grade
Return - equally weighted mean (%)	2.05%	2.41%	1.72%
Return - value weighted mean (%)	0.62%	0.31%	0.93%
Return - standard deviation (%)	31.77%	32.01%	31.54%
Return – skewness	0.71	0.71	0.70
Return – excess kurtosis	2.81	2.81	2.81
Rating – mean	10.89	7.34	14.01

Panel D: ***Post Big Crisis Analysis***

	All Firms	Investment Grade	Speculative Grade
Return - equally weighted mean (%)	0.59%	0.99%	0.14%
Return - value weighted mean (%)	1.88%	1.49%	2.33%
Return - standard deviation (%)	28.38%	28.07%	28.71%
Return – skewness	0.90	0.93	0.88
Return – excess kurtosis	3.94	3.98	3.90
Rating – mean	10.33	7.14	13.96

V. Results

The starting point in order to detect an association between momentum trading strategies and credit rating is to explore the average numerical rating for each of the 10 momentum portfolios, built over J formation periods of respectively 3, 6, 9 and 12 months. Table II – Panel A shows the results for the entire time frame of analysis, Table II – Panel B, C, and D represents different time frame sub-samples. Assuming persistency on the findings of Avramov et al. (2007), I expect to see extreme winner and loser portfolios to be composed heavily by companies with lower credit quality.

Table II
Credit Rating Score of Momentum Portfolio over Formation Period

Stocks of the universe of analysis whose returns are retrieved from CRSP and are rated from Standard and Poor's for the same month t are ranked into decile portfolios in accordance to the return performance during the formation period. During the portfolio formation period screening, stocks that do not possess a rating issued by Standard and Poor's are excluded for the realization of the table results. Are excluded from the table results stocks that, at the end of month t-1, are smaller than the lowest NYSE size percentile. Table II shows the cross-sectional monthly average credit rating score for each decile portfolio during the respective formation period J = 3, 6, 9, and 12 months. The rating assigned by Standard and Poor's is obtained from COMPUSTAT, it is updated on a quarterly basis. Following Avramov et al. (2007) the ratings are transformed in numerical scores as follows: AAA = 1, AA+ = 2, AA = 3, AA- = 4, A+ = 5, A = 6, A- = 7, BBB+ = 8, BBB = 9, BBB- = 10, BB+ = 11, BB = 12, BB- = 13, B+ = 14, B = 15, B- = 16, CCC+ = 17, CCC = 18, CCC- = 19, CC = 20, C = 21, D = 22. The Sample Period of panel A is January 1987 to February 2017. Panel B sample period is January 1987 to December 2002. Panel C sample period is January 2003 to December 2008. Panel D sample period is January 2009 to February 2017.

Panel A: ***Whole Time Period***

	J = 3	**J = 6**	**J = 9**	**J = 12**
P10	9.64	9.57	9.76	9.95
P9	9.92	9.86	9.73	9.60
P8	9.79	9.77	9.76	9.77
P7	9.87	9.85	9.76	9.77
P6	9.76	9.81	9.75	9.78
P5	9.97	10.00	9.83	9.85
P4	9.81	9.73	10.03	9.83
P3	9.82	9.72	9.70	9.84
P2	9.55	9.63	9.55	9.49
P1	10.02	10.04	9.99	9.79

Table II - *Continued*

Panel B: ***Tech Crisis Period***

	J = 3	J = 6	J = 9	J = 12
P10	9.60	9.38	9.61	10.10
P9	9.07	9.03	9.13	8.75
P8	8.91	8.91	8.86	8.52
P7	9.02	8.84	8.61	8.48
P6	8.65	9.00	8.64	8.73
P5	9.29	9.23	8.92	8.76
P4	8.71	8.83	8.82	9.33
P3	9.09	8.79	9.09	9.42
P2	8.82	9.15	9.40	9.30
P1	10.22	10.36	10.24	9.92

Panel C: ***Big Crisis Period***

	J = 3	J = 6	J = 9	J = 12
P10	9.54	9.68	9.78	9.79
P9	10.25	10.10	10.05	9.78
P8	9.78	9.75	9.76	10.10
P7	9.89	9.89	9.75	9.88
P6	9.91	9.77	9.93	9.69
P5	10.13	10.52	9.90	10.19
P4	10.25	10.01	10.77	10.29
P3	10.09	10.09	9.79	10.03
P2	9.84	9.58	9.48	9.05
P1	9.78	9.87	9.58	9.47

Panel D: ***Post Big Crisis Period***

	J = 3	J = 6	J = 9	J = 12
P10	9.74	9.71	9.91	9.88
P9	10.31	10.36	10.05	10.20
P8	10.27	10.26	10.26	10.20
P7	10.26	10.26	10.28	10.24
P6	10.18	10.17	10.06	10.35
P5	10.21	9.98	10.19	10.11
P4	10.08	10.03	10.10	9.76
P3	10.06	10.07	10.04	9.96
P2	9.91	10.12	9.74	9.98
P1	9.96	9.80	10.00	9.88

Table II – Panel B, which refers to the time period analyzed by Avramov et al. (2007), shows that extreme winner and loser portfolios are composed by higher credit risk stocks. In specific, the extreme loser and winner portfolio, namely P1 and P10, are the two portfolios with the highest credit rating score throughout all the formation periods analyzed. The findings I provide are also consistent in evidencing that middle portfolios have the lowest credit score. It is evident from Table II - Panel B that the average credit rating across the different momentum portfolios forms a U-shape, meaning that winner and loser portfolios, as in Avramov et al. (2007), are composed mostly by companies with lower credit quality than other decile portfolios.

The empirical evidence in more recent data, Table II - Panel C and D, shows that the pattern argued by Avramov et al. (2007), does not persist. In fact, the results show that the credit rating anomaly over momentum portfolio does not provide clear guidance on portfolio origination. Table II - Panel D provides an interesting pattern shift, in fact among all the decile portfolios P1 and P10 portfolios are composed, on average, by firms with the best credit quality among the created portfolios. The average worst credit quality is evidenced between P7 and P9, which are mid-to-winner portfolios. Indeed, the mean credit rating score for the sub-sample of most recent data analyzed leads to an inverted U-shape across the various momentum portfolios, indicating that momentum extreme winner and extreme loser portfolios are overall composed by firms with the best credit quality.

Table III provide the average credit rating score for the decile momentum portfolios throughout their holding period. The factor K represents the holding period of the portfolios, and it starts at the month following the last of the holding period J. The empirical findings that I document show that there is no significant difference between the average credit score of the momentum portfolios before the formation and during the investment period. The analysis for the different timeframes in Table III – Panel B, C, and D lead to the somewhat identical conclusion of the findings of Table II. Hence, it is demonstrated from the results that the average credit rating , for the time period from January 1987 to December 2002, show that the highest average credit score is found in winner and loser portfolios (P1 and P10), at the same time, the average score gradually lowers until it reaches the lowest value for the mid portfolios; by drawing a line that ordinally connects portfolios from P1 to P10 the average credit score takes on a U-shape curve. The trend reverts to an inverted U-Shape when analyzing from January 2009 to February 2017, which is the most recent time frame presented. The average credit rating of momentum portfolios is therefore stable for momentum strategies from 3 to 12 months.

Table III
Credit Rating Score of Momentum Portfolio over Holding Period

Stocks of the universe of analysis whose returns are retrieved from CRSP and are rated from Standard and Poor's for the same month t are ranked into decile portfolios in accordance to the return performance during the formation period. During the portfolio formation period screening, stocks that do not possess a rating issued by Standard and Poor's are excluded for the realization of the table results. Are excluded from the table results stocks that, at the end of month t-1, are smaller than the lowest NYSE size percentile. Table III shows the cross-sectional monthly average credit rating score for each decile portfolio throughout the respective holding period K = 3, 6, 9, and 12 months. The rating assigned by Standard and Poor's is obtained from COMPUSTAT, it is updated on a quarterly basis. Standard and Poor's ratings are converted in numerical scores as explained in Table II. The Sample Period of panel A is January 1987 to February 2017. Panel B sample period is January 1987 to December 2002. Panel C sample period is January 2003 to December 2008. Panel D sample period is January 2009 to February 2017.

Panel A: *Whole Time Period*

	K = 3	**K = 6**	**K= 9**	**K = 12**
P10	9.89	9.85	9.87	9.69
P9	9.55	9.61	9.41	9.44
P8	9.79	9.64	9.65	9.70
P7	9.75	9.68	9.94	9.75
P6	9.96	9.96	9.72	9.75
P5	9.74	9.74	9.75	9.68
P4	9.84	9.75	9.62	9.58
P3	9.74	9.75	9.63	9.54
P2	9.83	9.65	9.57	9.51
P1	9.61	9.55	9.69	9.76

Panel B: ***Tech Crisis Period***

	K = 3	**K = 6**	**K = 9**	**K = 12**
P10	10.02	9.97	9.94	9.70
P9	8.80	9.19	8.95	8.89
P8	9.11	8.54	8.88	8.95
P7	8.61	8.97	8.80	9.10
P6	9.30	9.12	8.98	8.79
P5	8.57	8.88	8.68	8.94
P4	9.00	8.81	8.60	8.56
P3	8.96	8.97	8.91	8.57
P2	9.13	9.01	9.11	8.72
P1	9.47	9.27	9.42	9.74

Table III - *Continued*

Panel C: ***Big Crisis Period***

	K = 3	K = 6	K = 9	K = 12
P10	9.72	9.90	9.83	9.67
P9	9.82	9.66	9.69	9.71
P8	10.22	10.27	10.04	10.26
P7	10.29	9.99	10.78	10.36
P6	10.14	10.50	9.77	10.12
P5	9.88	9.83	10.04	9.69
P4	9.80	9.72	9.64	9.73
P3	9.65	9.73	9.57	9.74
P2	10.11	9.81	9.66	9.52
P1	9.70	9.72	9.81	9.63

Panel D: ***Post Big Crisis Period***

	K = 3	K = 6	K = 9	K = 12
P10	9.90	9.54	9.82	9.68
P9	9.91	10.02	9.62	9.77
P8	9.90	9.99	9.95	9.85
P7	10.00	9.93	9.98	9.73
P6	10.19	9.97	10.09	10.03
P5	10.19	10.08	10.02	10.14
P4	10.27	10.22	10.14	9.99
P3	10.24	10.23	10.10	9.95
P2	10.17	10.10	9.91	10.17
P1	9.75	9.78	9.94	9.89

Table IV presents monthly returns for loser portfolio (P1), winner portfolio (P10) and a zero-investment strategy, which is a long position into the winner portfolio and a short position in the loser portfolio (P10 – P1). The construction of the momentum portfolios takes reference from Jegadeesh and Titman (1993). Hence, each of the investment strategies are represented by two factors, respectively J and K. Origination of the portfolios is established on the formation period, represented by the J-months of period. Next, extreme winner, extreme loser, and zero investment strategy portfolios performances are calculated for the K-months of holding period. I calculate holding period returns starting from the period next to the formation period end.

As in Jegadeesh and Titman (1993), J-K combinations of respectively 3, 6, 9, and 12 months are developed. For instance, in Table IV - Panel A, for which the research period is set from

January 1987 to February 2017, a strategy consisting into forming the portfolios after 9 months and holding them for 6 months results in J=9 and K=6. The formation period is the period in between January 1987 and September 1987. In mentioned period are formed P1, P10, and the zero investment strategy portfolios. Hence, starting from October 1987 until March 1988 the holding period for said portfolios takes place.

The results shown in Table IV – Panel A suggests a clear pattern over momentum investment strategies. In particular the investment strategy of buying winners and selling losers is profitable among all the J-K combinations. Evidence shows that previously mentioned profitability is generated almost entirely by the negative performance of the loser portfolios. In supporting said statement, it emerges from the table results that the greater performances are originated by J-K combinations of higher holding periods. In specific, for Table IV - Panel A, the investment strategy with the largest payoff consists in selling the loser portfolio originated after 3 months of formation and then hold for 12 months, said strategy provides a positive mean payoff of 6.61% without considering incurring costs of transaction or similar.

The results shown in Table IV – Panel B, C, and D, which provide an insight for the different time sub-samples of analysis, evidence that the previously mentioned strategy is consistent among different fragmentation of the whole time period of analysis. That is, momentum investment strategies of loser portfolios for longer holding periods, 9 or 12 months, generate the largest negative payoffs among the sample analyzed. Furthermore, a statistical test of significance is performed on each J-K portfolio mean monthly returns, the test is executed in order to ensure that the results are statistically significant. According to the t-stat, the payoffs for the zero-investment strategy which hold the position for 9 and 12 months are significant for a 5% level throughout the full period of analysis (Table IV – Panel A).

The portfolio returns from January 2003 to December 2008, shown in Table IV – Panel C, are not statistically significant for all the J-K portfolio combinations, meaning that for the time-frame there is evidence of no momentum effect.

In regards to Table IV results, I find that the zero-investment strategies for whichever J-K portfolio combination provides positive payoffs that are mainly driven by selling the loser portfolio. The portfolio returns are also statistically significant for a 5% level only for 9 and 12 months of holding period.

Table IV
Returns of Relative Strength Portfolios

Relative strength momentum portfolios are formed following a formation period of J months and held for K months. The respective values of J and K for each portfolio strategy are shown in the first column for J and in the first row for K. Stocks are ranked basing on their cumulative past J-month returns, extreme winner and extreme loser firms are respectively assigned to P10 and P1 portfolios. P10 and P1 are realized as an equal weighted combination of stocks pertaining to them. Table IV shows the average monthly return (in % values) realized after K-months of holding period. Portfolios in the table are realized immediately after the lagged returns are realized to assign stock into the portfolios. Panel A sample period is January 1987 to February 2017, Panel B sample period is January 1987 to December 2002, Panel C sample period is January 2003 to December 2008, finally, Panel D sample period is January 2009 to February 2017. T-stats are shown in parenthesis for each J-K momentum strategy portfolio combination below the respective monthly percentage average return. T-stat suggesting interesting results are marked as * if with 5% confidence level and ** if with 1% confidence level.

Panel A: J-K Momentum Portfolios - *Whole Time Period*

J	**K =**	**3**	**6**	**9**	**12**
3	**P10**	-0.47	-0.37	-0.34	-0.34
		(0.21)	(0.33)	(0.44)	(0.58)
	P1	-2.11	-4.19	-5.66	-1.65
		(0.90)	(1.64)	(2.19)*	(2.52)*
	P10-P1	1.65	3.45	4.64	1.31
		(0.92)	(1.67)	(2.05)*	(2.27)*
6	**P10**	0.03	-0.02	-0.12	-0.18
		(0.02)	(0.02)	(0.11)	(0.31)
	P1	-2.60	-2.43	-3.39	-1.91
		(1.03)	(1.78)	(2.40)*	(2.70)**
	P10-P1	2.63	2.41	3.26	1.73
		(1.40)	(2.29)*	(2.77)**	(2.82)**
9	**P10**	0.19	0.09	0.01	-0.09
		(0.09)	(0.12)	(0.01)	(0.16)
	P1	-2.71	-1.65	-2.22	-1.99
		(1.06)	(1.76)	(2.33)*	(2.68)**
	P10-P1	2.91	1.75	2.23	1.90
		(1.52)	(2.43)*	(2.89)**	(3.16)**
12	**P10**	0.15	0.01	-0.05	-0.15
		(0.07)	(0.02)	(0.09)	(0.27)
	P1	-2.66	-1.19	-1.65	-2.01
		(1.02)	(1.67)	(2.23)*	(2.51)*
	P10-P1	2.81	1.20	1.60	1.87
		(0.82)	(0.84)	(0.85)	(0.77)

Table IV – *Continued*

Panel B: J-K Momentum Portfolios – *Tech Crisis Period*

J	K =	3	6	9	12
3	**P10**	-0.45	-0.59	-0.76	-0.29
		(0.21)	(0.33)	(0.40)	(0.57)
	P1	-2.36	-4.80	-6.59	-1.93
		(1.06)	(2.06)*	(2.88)**	(3.30)**
	P10-P1	1.90	4.20	5.82	1.64
		(0.97)	(1.96)*	(2.44)*	(2.75)**
6	**P10**	0.22	0.23	0.15	-0.12
		(0.11)	(0.25)	(0.16)	(0.22)
	P1	-2.79	-2.76	-4.01	-2.27
		(1.13)	(2.18)*	(3.19)**	(3.44)**
	P10-P1	3.01	2.99	4.16	2.15
		(1.68)	(3.07)**	(3.66)**	(3.47)**
9	**P10**	0.52	0.33	0.24	0.03
		(0.26)	(0.52)	(0.40)	(0.07)
	P1	-3.11	-1.92	-2.60	-2.27
		(1.32)	(2.40)*	(3.17)**	(3.38)**
	P10-P1	3.63	2.25	2.84	3.07
		(2.16)	(3.86)**	(4.24)**	(4.43)**
12	**P10**	0.45	0.18	0.07	-0.05
		(0.21)	(0.38)	(0.16)	(0.10)
	P1	-2.97	-1.35	-1.91	-2.24
		(1.27)	(2.17)*	(2.89)**	(3.07)**
	P10-P1	3.42	1.54	1.98	2.20
		(2.13)*	(3.14)**	(3.62)**	(3.58)**

Table IV – *Continued*

Panel C: J-K Momentum Portfolios – *Big Crisis Period*

J	K =	3	6	9	12
3	P10	-0.57	-1.19	-1.72	-0.53
		(0.23)	(0.38)	(0.54)	(0.66)
	P1	-1.96	-3.50	-3.96	-1.03
		(0.72)	(1.15)	(1.23)	(1.24)
	P10-P1	1.38	2.30	2.24	0.50
		(0.88)	(1.09)	(0.99)	(0.84)
6	P10	-0.30	-0.48	-0.77	-0.49
		(0.11)	(0.29)	(0.46)	(0.61)
	P1	-2.65	-2.04	-2.33	-1.15
		(1.02)	(1.31)	(1.36)	(1.38)
	P10-P1	2.35	1.56	1.56	0.66
		(1.27)	(1.33)	(1.27)	(1.09)
9	P10	-0.24	-0.35	-0.50	-0.49
		(0.09)	(0.31)	(0.46)	(0.63)
	P1	-2.59	-1.37	-1.55	-1.32
		(0.88)	(1.16)	(1.30)	(1.46)
	P10-P1	2.34	1.02	1.05	0.83
		(1.18)	(1.23)	(1.26)	(1.22)
12	P10	-0.36	-0.34	-0.44	-0.55
		(0.12)	(0.40)	(0.53)	(0.72)
	P1	-2.59	-1.01	-1.20	-1.45
		(0.82)	(1.13)	(1.30)	(1.46)
	P10-P1	2.23	0.68	0.76	0.91
		(0.97)	(1.02)	(1.07)	(1.10)

Table IV – *Continued*

Panel D: J-K Momentum Portfolios – *Post Big Crisis Period*

J	K =	3	6	9	12
3	**P10**	-0.40	-0.31	-0.28	-0.26
		(0.20)	(0.28)	(0.41)	(0.51)
	P1	-1.81	-1.85	-1.83	-1.71
		(0.82)	(1.52)	(2.30)*	(2.98)**
	P10-P1	1.42	1.54	1.54	1.45
		(0.87)	(1.74)	(2.58)**	(3.15)**
6	**P10**	0.01	-0.04	-0.02	-0.02
		(0.03)	(0.04)	(0.03)	(0.04)
	P1	-2.20	-2.17	-2.14	-1.97
		(0.87)	(1.64)	(2.43)*	(3.14)**
	P10-P1	2.20	2.12	2.12	1.95
		(1.10)	(2.18)*	(3.14)**	(3.88)**
9	**P10**	0.01	0.11	0.06	0.06
		(0.01)	(0.12)	(0.11)	(0.14)
	P1	-2.14	-2.15	-2.13	-2.10
		(0.86)	(1.58)	(2.38)*	(3.14)**
	P10-P1	2.16	2.26	2.20	2.16
		(1.02)	(2.10)*	(2.96)**	(3.86)**
12	**P10**	0.08	0.05	0.13	0.06
		(0.04)	(0.05)	(0.21)	(0.13)
	P1	-2.21	-2.14	-2.16	-2.12
		(0.87)	(1.58)	(2.40)*	(3.05)**
	P10-P1	2.29	2.19	2.29	2.18
		(1.04)	(1.85)	(2.84)**	(3.42)**

Table V shows the J-K combination portfolios for the two categories of credit rating (Speculative and Investment grade). The two distinct types of portfolios therefore do only consider firms that represent the respective category of credit quality. Are then excluded from the portfolios origination companies that, during the formation period, receive a downgrade (upgrade) such that the company shift from investment (speculative) grade to speculative (investment) grade.

The findings that I provide in Table V show that positive payoffs are, on average, provided by the zero-investment strategy for each of the credit rating categories, more specifically, the zero-investment strategy for the J=9, K=3 combination portfolio present the largest payoffs (1.88% and 2.26% monthly return for Investment Grade and Speculative Grade portfolios respectively).

J-K portfolio combinations for larger holding periods than 3 months leads the payoffs to be not statistically significant for any level (t-stat presented in parenthesis below each portfolio). The control of the portfolio formation for the Credit rating category evidence that larger payoffs are provided for momentum portfolios of investment grade type of firms, suggesting that said category drives the momentum phenomenon.

Table V
J-K Combination Portfolios for Credit Rating Category

Relative strength momentum portfolios are formed following a formation period of J months and held for K months. The respective values of J and K for each portfolio strategy are shown in the first column for J and in the first row for K. For each J-K Combination are presented the winner portfolio (P10), the loser portfolio (P1) and the zero-investment strategy (P10–P1). For each portfolio are presented the mean monthly return (in % values) and, below it, the respective t-stat (shown in parenthesis). The J-K Combination of relative strength portfolios are realized for both respectively Speculative and Investment credit rating categories. Speculative Grade portfolio is constructed using only companies that, during the Formation Period, have a credit rating score equal or above 11 (BB+ or worse). Investment Grade portfolio is constructed with companies that, during the Formation period, have a credit rating score equal or below 10 (BBB- or better). Companies are kept into the portfolios if a rating upgrade or downgrade occur during the holding period, meanwhile, they are excluded from the table results if the credit rating variation occur during the Formation period. Table V sample period is January 1987 to February 2017. T-stat suggesting interesting results are marked as * if with 5% confidence level and ** if with 1% confidence level.

	Speculative Grade Portfolio					***Investment Grade Portfolio***				
J	**K =**	**3**	**6**	**9**	**12**	**K =**	**3**	**6**	**9**	**12**
3	**P10**	-0.19	-0.21	-0.28	-0.46	**P10**	-0.48	-0.44	-0.65	-0.95
		(0.33)	(0.24)	(0.25)	(0.34)		(0.82)	(0.51)	(0.58)	(0.71)
	P1	-1.64	-1.37	-1.83	-1.95	**P1**	-1.64	-1.46	-2.03	-2.38
		(2.25)*	(1.26)	(1.28)	(1.13)		(1.82)	(1.40)	(1.50)	(1.43)
	P10-P1	1.45	1.16	1.55	1.49	**P10-P1**	1.16	1.02	1.39	1.43
		(2.21)*	(1.19)	(1.22)	(0.97)		(2.58)*	(1.07)	(1.13)	(0.96)
6	**P10**	0.00	-0.02	-0.16	-0.30	**P10**	-0.20	-0.19	-0.36	-0.67
		(0.01)	(0.02)	(0.15)	(0.22)		(0.36)	(0.23)	(0.34)	(0.53)
	P1	-1.88	-1.51	-1.89	-1.82	**P1**	-2.05	-1.79	-2.37	-2.67
		(2.40)*	(1.29)	(1.23)	(0.96)		(2.77)**	(1.60)	(1.60)	(1.45)
	P10-P1	1.88	1.49	1.74	1.53	**P10-P1**	1.85	1.60	2.01	2.00
		(2.78)**	(1.48)	(1.32)	(0.95)		(2.83)**	(1.63)	(1.57)	(1.29)
9	**P10**	0.11	-0.06	-0.11	-0.16	**P10**	0.07	-0.07	-0.20	-0.41
		(0.19)	(0.07)	(0.10)	(0.13)		(0.12)	(0.08)	(0.19)	(0.33)
	P1	-1.78	-1.44	-1.69	-1.76	**P1**	-2.19	-1.85	-2.39	-2.62
		(2.17)*	(1.15)	(1.02)	(0.86)		(2.79)**	(1.54)	(1.51)	(1.33)
	P10-P1	1.88	1.39	1.57	1.60	**P10-P1**	2.26	1.78	2.18	2.21
		(2.71)**	(1.32)	(1.15)	(0.95)		(3.35)**	(1.75)	(1.66)	(1.38)
12	**P10**	0.00	-0.08	-0.06	-0.09	**P10**	-0.23	-0.25	-0.30	-0.51
		(0.01)	(0.09)	(0.06)	(0.06)		(0.38)	(0.29)	(0.28)	(0.42)
	P1	-1.80	-1.36	-1.66	-1.77	**P1**	-2.18	-1.80	-2.19	-2.47
		(2.11)*	(1.05)	(0.95)	(0.82)		(2.68)**	(1.45)	(1.32)	(1.19)
	P10-P1	1.80	1.28	1.60	1.68	**P10-P1**	1.96	1.55	1.89	1.96
		(2.51)*	(1.19)	(1.12)	(0.96)		(2.79)**	(1.47)	(1.40)	(1.19)

VI. Limitations and Further Research

Given the results discussed so far, there are many questions and possibilities left for research in the future. One useful exercise might be, continuing with this methodology, is to control the results for periods of recession. During a recession, across the economy deviations of several economic activities spreads and can drive the results for several months of analysis, further literature suggestions can be oriented in exploring the credit rating effect on momentum strategies for different business cycles, for example, by focusing on January effect or expansionary and recessionary business cycles, as proposed by Wang et al. (2015).

A further research could extend the model built by Carhart (1997), the Fama and French three model which adds the momentum effect, such model can be explored with the addition of credit rating scores acting as a control variable, the credit rating variable controls can be fragmented into 3 or more sub-groups as proposed by Avramov et al. (2007), such as the decile momentum portfolios for three credit rating groups or the tercile momentum portfolios for ten credit rating groups.

Throughout the analysis of the results, portfolios do not consider transaction costs. There is a strong support from the literature that effects on the markets are the results of mispricing. Persistence of mispricing assume that the costs limit arbitrage maneuvers, with the objective of maintaining the markets efficient, as argued by Scholes (1972), Shiller (1984), Pontiff (2006). The existence of a momentum effect can be the result of a mispricing phenomenon, transaction costs allow to binding costs that limit arbitrage opportunities, this statement is supported by Lesmond et al. (2004), which argues that there is cross-sectional relationship between transaction costs and momentum payoffs.

VII. Conclusions

The purpose of the study is to identify whether the momentum anomaly in the United States does still exist and if the credit ratings provide informativeness and orientation in the application of momentum investment trading strategies. In order to provide an educate answer on the topic, following Jegadeesh and Titman (1993) methodology, I created J-K combinations of momentum-based investment strategy portfolios.

The dissertation does find that momentum effect does not provide positive nor significant payoffs when buying the winner portfolio. In fact, for each J-K combination, winner portfolios are not statistically significant for even a 10% level. The payoff along the different J-K combinations is brought mainly by the zero-investment strategies, which generate positive significant payoffs for a 5% level for all the formation periods J and when the holding period K is equal to 6, or 12 months.

Portfolios of different credit risk, namely Investment grade and Speculative grade momentum portfolios, does not present a clear divergence in their results, Investment grade portfolios provide somewhat greater payoffs, especially for portfolios with larger formation periods (9 and 12 months). Hence, it can be stated that investment grade type of firms slightly contributes more than speculative grade firms in driving the momentum effect. Moreover, in both Investment grade and Speculative grade portfolios, significant (for a 5% level) and positive payoffs are originated only by the zero investment strategy for every combination of J-months of formation period and 3 months of holding period.

The behavior of the average credit score of momentum portfolios does resemble an inverted U-shape which means that momentum strategy of buying previous winners and selling previous losers consists in taking long and short position on firms with the highest credit quality.

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