



Momentum and credit ratings – a persistent relationship

Rodrigo Santos Neves

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Henriques Machado Meira

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Abstract

This thesis investigates and broadens the relationship between momentum and credit rating. Momentum profitability is reliant upon low-grade firms and is non-existent for high-grade firms. Momentum payoffs from 1981 to 2021 are generated by low-rated firms that account for less than 5% of the market capitalization of rated firms. The average credit rating of the winner and loser portfolio over the formation period are higher compared to the other 8 portfolios and create a U-shaped curve. The average credit rating of the portfolios for residual momentum forms a flatter U-shaped curve compared with normal momentum, concluding that it takes fewer extreme positions compared with the original momentum. This thesis adds to the literature as it shows that these results are robust to the fact that credit rating agencies have, over time, become more conservative. Holding firm characteristics constant, I find that credit rating agencies have become more conservative by two notches after 1995 in comparison with the period between 1985 to 1995. This fact has no substantial impact for the relationship between momentum profitability and credit rating as they are still generated by low-rated firms that account for less than 2% of the market capitalization of rated firms.

Keywords: Credit ratings, momentum, residual momentum, credit rating agencies

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Resumo

Esta tese investiga e alarga a relação entre a estratégia *momentum* e a classificação de crédito. A rentabilidade do *momentum* depende das empresas de baixa classificação de crédito e não existe para as empresas de alta classificação. A rentabilidade do *momentum* de 1981 a 2021 é gerada por empresas de baixa classificação que representam menos de 5% da capitalização bolsista das empresas com classificação. A classificação média de crédito da carteira vencedora e da carteira perdedora durante o período de formação é superior à das outras 8 carteiras e cria uma curva em forma de U. A notação média de crédito das carteiras para o *momentum* residual forma uma curva em U menos achatada em comparação com o *momentum* original, concluindo que o *momentum* residual toma menos posições extremas em comparação com o *momentum* original. Esta tese contribui para a literatura, na medida em que mostra que estes resultados são robustos face ao facto de as agências de atribuição de classificação de crédito se terem tornado, ao longo do tempo, mais conservadoras. Mantendo as características das empresas constantes, concluo que as agências de atribuição de classificação de crédito se tornaram mais conservadoras em dois níveis após 1995 em comparação com o período de 1985 até 1995. Este facto não tem um impacto substancial na relação entre a rentabilidade de *momentum* e a classificação de crédito, uma vez que estas continuam a ser geradas por empresas com classificações baixas, que representam menos de 2% da capitalização bolsista das empresas com classificações.

Keywords: Classificação de crédito, momentum, momentum residual, agências de classificação de crédito

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Introduction

Momentum has been put forward by Jegadeesh and Titman (1993) who demonstrate that a strategy where one buys the past best performers (winners) and short the worst past performers (losers) can earn substantial abnormal returns. Thus, it is a violation of the weak form market efficiency proposed by Fama and French (1996) which, in that same year, demonstrate that momentum is the only anomaly unexplained by Fama and French (1993) three factor model.

Momentum has been thoroughly researched since Jegadeesh and Titman (2001, 2002) who find that the profitability of the momentum strategy is still in place years after their first discovery. Therefore, there have been put out behavioural and risk-based attempts of explanations to this anomaly.¹

Credit ratings have been a source of information for financial agents on the credit risk of a country, a firm or an individual issue. Ratings are issued by independent Credit Rating Agencies (CRAs) of the main CRAs are Moody's, Standard & Poor's (S&P) or Fitch which base the credit rating allocation on a set of indicators of the financial health of a firm, namely, financial indicators, business activity, and several types of risks that can impact the ability to repay to its creditors.

Avramov (2007) finds a peculiar relationship between the momentum strategy and credit ratings suggesting that momentum payoffs are driven by low grade firms, that account for less than 4% of the overall market capitalization of rated firms. The author also demonstrates that if I exclude this set of companies the returns of the momentum strategy disappear. This study uses data up to 2006. Therefore, I provide in this thesis an update on the work of Avramov (2007).

Blitz (2011) provides a solution that reduces the time exposure to common risk factors of momentum creating a strategy called residual momentum. The main difference in comparison to standard momentum is that it ranks stocks based on past residual returns instead of its past returns.² Residual returns are the portion of stock returns unexplained by the three Fama and French common risk factors thus representing the stock's performance after accounting for market influence. Blitz (2011) states that this strategy

¹ See for example Barberis and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998), Hong, Lim, and Stein (2000), Chordia and Shivakumar (2002), Grinblatt and Han (2002), Avramov and Chordia (2005), among others.

² Momentum as in Jegadeesh and Titman (1993)

does not improve returns but rather improves the sharpe ratio. The author refers that the strategy reduces the exposure to the worst rated stocks but does not provide details into it. This thesis develops further into this topic to find the relationship between residual momentum and credit ratings in comparison with original momentum.

Baghai, Servaes and Tamayo (2014) find that Credit Rating Agencies (CRAs) after being under scrutiny due to the global financial crisis have become more conservative which means that, holding firm characteristics constant, average ratings have dropped by three notches over the period of 1985 to 2009. This finding has impact on the study developed by Avramov (2007) once it relies on the assumption that the firm characteristics of a company rated BB in 2005 are the same as of a company rated BB in 1984. In this thesis, I try to perform the analysis performed by Avramov (2007) relaxing this limitation mentioned by using the same approach as Baghai, Servaes and Tamayo (2014) to compute the predicted ratings.

I also expand the work of Avramov (2007) by answering the following questions: (1) Does the relationship between credit ratings and momentum hold expanding the dataset used? (2) Blitz (2011) mentions that residual momentum reduces the exposure of the strategy to extreme observations. What is then the relationship between residual momentum and credit ratings? (3) As suggested by Baghai, Servaes and Tamayo (2014), the credit ratings standards have changed across the timeframe of this study. As this fact has substantial implications of the assumptions needed to answer the first two questions, if I incorporate it will the relationship between credit ratings and momentum change? I answer these questions using a dataset of monthly data from the CRSP database considering all American primary stocks listed on the New York (NYSE), American (AMEX), and Nasdaq stock markets. From these, I take only the ones that are rated by S&P. I use a dataset that contains monthly credit rating data of American companies rated from S&P. The sample period covers January 1981 until December 2021. Firstly, I compute the average credit rating over the formation period for the portfolios that are formed as in Jegadeesh and Titman (1993) and find that they form, for all the formation periods used in the literature, a U-shaped curve, which means that, on average, the companies within the extreme portfolios have a worst credit rating than the others. These results are in line with Avramov (2007) and show that the relationship the author has put forward holds if we expand the dataset from 2006 to 2021. Further, I sequentially drop the companies with the worst credit rating from the dataset and find that momentum

profitability is driven by low rated firms that account for less than 5% of the market capitalization of rated firms.

I replicate the methodology used by Avramov (2007) described above to residual momentum and find that the average credit rating over the formation period forms a flatter U-shaped curve compared to the curve formed with “original” momentum.

Lastly, I add to the literature since I incorporate the findings of Baghai, Servaes and Tamayo (2014) to relax the assumption which Avramov (2007) relies upon which is that a company with a credit rating of BB in 1985 has the same characteristics of company rated BB in 2007. Using a set of financial characteristics, I perform a regression analysis for the period between 1985 to 1995 using the credit rating as independent variable and financial ratios as dependent variables to predict the credit ratings of firms after 1995. I find that the relationship between momentum profitability and credit ratings holds after incorporating this analysis. Momentum profitability is still driven by low rated firms which account for less than 2% of the market capitalization.

Overall, my evidence is consistent with the prior findings of Avramov (2007) because the relationship between credit ratings and momentum holds, it is the same even after expanding the dataset used. As for residual momentum I add to the literature the relationship between credit ratings and residual momentum returns thus complementing the study by Blitz (2011). This work does not dive into the characteristics of the winner and loser portfolios such as Avramov (2007) but rather tries to expand it to one other strategy and to strengthen it by relaxing the limitation that the standards for credit ratings allocation has changed over time. It also does not dive into the reasons why momentum returns rely on the worst rated stocks.

The thesis is organized as follows. The next section covers the literature review, then I dive into the data and methodology followed by the analysis of the results. Finally, I conclude and show in the Appendix additional information.

Literature review

Ever since its discovery, momentum is highly researched due to its persistence and lack of justifications. Momentum is found by Jegadeesh and Titman (1993) and then Fama and French (1999) demonstrate that it is unexplained by the three-factor model. Momentum is a strategy in which buying past winners and selling past losers earns significant returns.

Jiang *et al.* (2005) and Zhang (2006) suggest that momentum profits are affected by information uncertainty, which is proxied by firm size, firm age, return volatility, cash flow, volatility and analyst forecast dispersion. Avramov (2007) show that the variables used by Jiang *et al.* (2005) and Zhang (2006) do not explain the momentum profitability. Avramov (2007) finds instead that momentum returns are restricted to high credit risk firms. The author discovers that momentum returns are driven by the worst rated stocks and that if I exclude these stocks the momentum returns disappear. However, Avramov (2007) work does not consider the work by Baghai, Servaes and Tamayo (2014) that find that the credit rating agencies have become more conservative, specifically that, holding firm characteristics constant, average ratings have dropped by three notches. This identification is in line with the research done by Alp (2013) whose findings relate to the period of 1985 to 2009. There is no literature yet that incorporates this study in the relationship between credit rating and momentum. It is important to do so as I cannot compare a rating of B in 1986 with a B in 2010 as the literature has proven that they are not equivalent. This fact has substantial effect the work done by Avramov (2007) has he takes the average credit ratings over formation period as well as performs an analysis where observations with a specific credit rating are dropped.

Further, in the opposite direction of Baghai, Servaes and Tamayo (2014 and Altman (2020) mentions that ratings are inflated after the period of quantitative easing or, perhaps, persistent overvaluation of non-financial corporate debt markets since the last financial crisis. Altman (2020) bases his results using the Z-score to assess to assess the likelihood a rating downgrade which is a similar methodology to the one used by Baghai, Servaes and Tamayo (2014).

One limitation to all these works is that Credit Rating Agencies (CRAs) tend to lag the markets in recognizing changes of an issuer and, thereafter, change their ratings (Altman and Rijken (2004, 2006), Loffler (2004, 2005), Beaver, Shakespeare and Soliman (2006), Cantor and Mann (2007), Flandreau, Gaillard and Packer (2009), Cheng and Neamtu (2009), Cornaggia and Cornaggia (2011, 2013), Bruno, Cornaggia and Cornaggia (2013),

Xia (2013)). They do so, according to White (2013), because there is a belief that the appropriate approach is “rating through the cycle”, which means ignoring short run changes in an issuer’s financial position which might reverse.

Another impact which is not studied in this thesis but might impact the credit rating of the companies is the sovereign ceiling channel as documented by Almeida, Cunha, Ferreira and Restrepo (2017) that find that companies reduce their investment and reliance on credit markets following a sovereign rating downgrade. This is identified by using the exogenous variation of the corporate ratings due to the sovereign ceiling policies of CRAs that require that a firm’s rating remains at or below the sovereign rating of their country of domicile.

Bandarchuk and Hilcher (2013) highlight that although numerous studies have shown increased momentum profits when stocks are ranked based on certain characteristics—such as size, R^2 , turnover, age, analyst coverage, analyst forecast dispersion, market-to-book ratio, price, illiquidity, and credit rating—these enhanced returns primarily occur when trading stocks with the most extreme past returns. Once this factor is adjusted for, the momentum profits almost completely vanish.

Grobys (2014) in a study to establish a link between momentum strategies in global equity markets and country specific credit ratings finds that only the momentum strategy which is based on intermediate past returns generate statistically significant profits. Intermediate term momentum is an alternative to the first version of momentum where one sorts the companies based on their past $t - 12$ to $t - 7$ month returns. The author finds that only the winner portfolio appears to be associated with a higher average country specific credit risk in comparison to other portfolios. Also, that neither global asset pricing models nor a conducted world credit risk factor explains this results.

Haga (2015) finds that intermediate term momentum is profitable independent of the credit rating. The author also finds that the difference between intermediate term and short-term momentum is driven by high grade firms. Haga (2015) argues that the reason why intermediate term momentum is significant among low credit risk firms is because of the cognitive dissonance - the slower pace at which investors update their negative ideas about high-grade firms.

Lu, Lee and Yu (2014) study how momentum strategies have different results on different credit rating groups by sorting the companies into three credit rating groups and applying

the momentum strategy in each of those. It complements the findings of Avramov (2007) by also studying the impact of the business cycle and the January effect. The authors find that momentum on the high credit risk group generates positive excess returns. Also, that when the January effect is included, positive momentum only presents itself in low and medium credit risk groups in a 36-month holding period. As for the January effect, Reiganum (1981), Blume and Stambaugh (1983) and Keim (1983) have signs that it is possible that losers can earn large January returns whereas winners do not. This is in line with the finding of Jegadeesh and Titman (1993) and Avramov (2007) which suggest that momentum profits are negative in January.

Blitz *et al.* (2011) suggest a new approach to momentum where instead of ranking the stocks on past returns, they rank on residual returns estimated using the Fama and French three factor model which reduced the exposure of the momentum strategy to the Fama and French factors. This strategy increases risk adjusted profits which are twice as large compared with Jegadeesh and Titman (2001) approach. Blitz *et al.* (2011) mention that their findings are consistent with what Avramov (2007) and that, when sorting companies on residual momentum, the characteristics of decile portfolios of stocks are quite different compared to momentum as in Jegadeesh and Titman (2001).

Data and Methodology

I extract monthly data from the CRSP database considering all American primary stocks listed on the New York (NYSE), American (AMEX), and Nasdaq stock markets. From these, I take only the ones that are rated by Standards & Poor's (S&P). I use a dataset that contains monthly Credit Rating data of American companies rated from S&P. The sample period covers January 1981 until December 2021. The credit ratings are transformed into numerical format, where AAA corresponds to 1 and D corresponds to 22.³ A higher numerical value of credit rating corresponds to low credit risk and vice versa. Ratings above BBB- (10 or below) are considered investment grade whereas the below (11 or above) are considered non-investment grade. I use monthly data from Keneth French's website on the factors: excess market return, size, value, momentum, profitability, and investment.⁴ Monthly returns are computed as follows:

$$r_{i,t} = \ln \left(\frac{P_{i,t}}{P_{i,t-1}} \right)$$

Where $r_{i,t}$ is the return on stock i in month t , $P_{i,t}$ is the price of the stock i in month t . I winsorize at a 3% level on both ends to the simple returns so that my results are not driven nor influenced by extreme returns on the historical data.

Table 1 presents both for the returns data and to the credit ratings dataset.

³ The key for the Credit Ratings is 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.

⁴ https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 1

This table shows the descriptive statistics of the data used in this thesis. The stock prices were obtained from CRSP for the period of 1985 until 2021. Rated firms are the ones rated by S&P whose rating is present in the dataset that contains the time series of the ratings of the companies. Unrated firms are all the other companies. Panel 1 shows the descriptive statistics for the monthly returns from 1985 until 2021. Panel 2 shows the descriptive statistics of the credit ratings assigned by S&P.

Panel 1			
	All Firms	Rated Firms	Unrated Firms
# Companies	6 923	3 008	3 915
# Observations	681 737	338 108	343 629
Average Return	1.28%	1.03%	1.22%
Standard Deviation	0.15	0.11	0.18
Excess Kurtosis	531.43	1.31	450.33
Skewness	8.95	0.03	9.55
Min	-34.23%	-31.58%	-34.23%
Max	1625%	30.56%	1625%
25%	-5.55%	-4.57%	-6.98%
50%	0.51%	0.92%	0.00%
75%	6.83%	6.49%	7.14%
Panel 2			
# Companies			3 008
# Observations			338 108
Average Credit Rating			9.45
Standard Deviation			3.74
Excess Kurtosis			-0.22
Skewness			0.15
Min			1
Max			22
25%			7
50%			9
75%			12

Afterwards, I compute cumulative returns over the formation period using monthly returns:

$$R_{i,t-J,t-1} = \left(\sum_{p=t-J}^{t-1} r_{i,p} \right)$$

Where $R_{i,t-J,t-1}$ is the cumulative return of stock i from the month $t - J$ to the month $t - 1$. Last month returns are excluded from the formation criteria as in Jegadeesh and Titman (1993) to be aligned with the reality in terms of information lags.

There are available ratings for 3 008 stocks which accumulates to 338 108 observations. The average credit rating across the dataset is 9.45 (BBB) with a standard deviation of 3.74 rating categories. Excess Kurtosis is below 0 which means that there are not heavy tails. This is important to the results presented below in this thesis, as extreme results will look even more odd since there are not heavy tails in the dataset.

Descriptive statistics show that 43% of the firms retrieved on CRSP are rated and are those the ones that I work with. The average return for rated in comparison with unrated firms is slightly lower and also presents a lower standard deviation.

For the construction of the momentum strategy, I follow the Jegadeesh and Titman (1993) approach. At any given month t , stocks are ranked according to their cumulative returns over the formation period which is J months prior to t (3, 6, 9 or 12 months) thus meaning, for example, in the case of the 3 months the period between $t - 3$ and $t - 1$. Stocks are then assigned to a portfolio (1 of 10) based on that prior cumulative return. Companies with cumulative returns over the formation period placed on the top 10% of the cumulative returns of all stocks are placed in P10. After that, these portfolios remain as they are constructed for K months being all the positions equally weighted, corresponding to months $t + 1$ to $t + K$. During the formation period, momentum strategy buys the winner portfolio and sells the loser portfolio, which means buying P10 and selling P1. The winner portfolio corresponds to the top decile one and the loser to the bottom decile. At the beginning of the holding period, portfolios are formed as being equal weighted, which means that all the stocks are given the same weight. Therefore, the returns of each portfolio are computed as the equal weighted average return of the stocks that correspond to each portfolio. The monthly strategy returns for a K -month holding period is a simple

average of the returns of the portfolio from the strategy implemented in the current month and previous. Moreover, this strategy closes the positions initiated in the month $t - K$.

I compute the returns of the momentum strategy on rated and unrated firms to check if the results are similar. If so, I can go further into my analysis focusing merely on rated firms. In Table 2, I show that the momentum returns on rated firms are rather similar to the returns across all firms. The average return on a long-short strategy across the companies in my dataset is 0.84% per month whereas for rated firms the average monthly return is 1.05%. These results come from both a formation and holding period of 6 months.

Table 2

For each month t , all NYSE, AMEX and NASDAQ stocks extracted from CRSP are ranked according to their past 6-month cumulative return ($t - 6$ to $t - 1$). Stocks which are priced below \$5 or are smaller than the smallest NYSE size decile are excluded. Portfolios are formed based on what decile the stocks fall and the returns of each portfolio correspond to the equal weighted average of the returns of the stocks inside that portfolio. The momentum strategy corresponds to buying the winner and selling the loser portfolio. Positions are then held for 6 months but there is a lag of 1 month which means that the portfolios are held in the period of $t + 1$ to $t + 6$. Table shows the average monthly returns of the momentum returns for the entire dataset and for rated firms, the ones rated by S&P.

Raw Momentum in Rated and Unrated Firms			
		All Firms	Rated Firms
# Firms		6 923	3 008
Overall	P10-P1	0.84%	1.05%
	P1	0.85%	-0.12%
	P10	1.69%	0.93%

After confirming that the dataset of only rated firms provides similar returns compared to all the firms in the dataset, I go deeper into momentum returns by computing the average momentum returns for different formation periods J (3, 6, 9 and 12 months) and different holding periods K (3, 6, 9 and 12 months). Table 3 shows the results of this analysis. It shows that the best results for the momentum strategy across rated firms comes from a formation period of 9 months and a holding period of also 3 months which derive a return of 1.23%.

Table 3

For each month t , all NYSE, AMEX and NASDAQ stocks extracted from CRSP which are rated by S&P are ranked according to their past 6-month cumulative return ($t - 6$ to $t - 1$). Stocks which are priced below \$5 or are smaller than the smallest NYSE size decile are excluded. Portfolios are formed based on what decile the stocks fall in and the returns of each portfolio correspond to the equal weighted average of the returns of the stocks inside that portfolio. The momentum strategy corresponds to buying the winner and selling the loser portfolio. Positions are then held for 6 months but there is a lag of 1 month which means that the portfolios are held in the period of $t + 1$ to $t + 6$. Table shows the average monthly returns of the momentum returns as well as the winner portfolio returns, and loser portfolio returns for different formation ($J \in \{3,6,9,12\}$) and holding ($K \in \{3,6,9,12\}$) periods. Below the returns I show the p-value which demonstrates the statistical significance of the results.

The “***”, “**”, “*” denote significance at the 1%, 5% and 10% level, respectively.

Returns of Momentum Strategy in Rated Firms					
J=	K=	3	6	9	12
3	P10-P1	0.62%**	0.75%***	0.77%***	0.72%***
		0.010	0.000	0.000	0.000
	P1	0.18%	0.09%	0.09%	0.15%
		0.653	0.819	0.810	0.698
	P10	0.81%**	0.84%**	0.87%**	0.87%**
		0.015	0.012	0.010	0.011
6	P10-P1	1.04%***	1.05%***	0.96%***	0.91%***
		0.002	0.000	0.000	0.000
	P1	-0.11%	-0.12%	-0.05%	0.01%
		0.787	0.770	0.899	0.988
	P10	0.93%***	0.93%***	0.91%***	0.92%***
		0.006	0.007	0.008	0.007
9	P10-P1	1.23%***	1.15%***	1.00%***	0.92%***
		0.000	0.000	0.000	0.000
	P1	-0.44%	-0.38%	-0.26%	-0.18%
		0.292	0.352	0.530	0.659
	P10	0.79%**	0.76%**	0.74%**	0.74%**
		0.020	0.023	0.028	0.027
12	P10-P1	1.22%***	1.15%***	1.04%***	0.95%***
		0.000	0.000	0.002	0.000
	P1	-0.42%	-0.37%	-0.11%	-0.20%
		0.327	0.374	0.787	0.623
	P10	0.80%**	0.78%**	0.93%***	0.75%**
		0.015	0.020	0.006	0.025

I start by following Avramov (2007) approach. This thesis develops further their studies by trying to find a relationship between Credit Ratings and other investment strategies other than pure momentum as in Jegadeesh and Titman (1993), namely, residual momentum as in Blitz *et al.* (2011). Following authors' approach, I exclude stocks that at the beginning of the holding period are priced below \$5 or have a market capitalization that would place them in the bottom NYSE decile to reduce factors that could tweak the results. This is because lower cap stocks are less traded which makes them less liquid. Being less liquid, data quality is reduced, and the prices may not incorporate all the information available.

Avramov (2007) starts by building the momentum portfolios and computes the average numerical credit rating of the portfolios over the formation period. The way to do so is by computing the average credit rating of the stocks that belong to each portfolio across the formation periods. Secondly, the author implements normal momentum while sequentially excluding firms with the highest credit risk thus revealing what type of stocks drive momentum returns. I start by repeating the work of Avramov (2007) work with a larger dataset, until 2021.

Blitz *et al.* (2011) following the research done by Jegadeesh and Titman (1993) propose a different momentum strategy that ranks stocks based on their residual returns rather than on their total returns. By doing so, they reduce the time-varying exposures to the Fama-French Factors. Their strategy yields a Sharpe Ratio almost double that of normal momentum, due to the reduced volatility of this strategy. The methodology is in line with the one followed by Jegadeesh and Titman (1993). The residual returns are computed with the Fama-French 3 Factor Model:

$$(1) r_{i,t} = \alpha_i + \beta_{1,i}MRP_t + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \epsilon_{i,t}$$

Where $r_{i,t}$ is the return on stock i in excess of the risk-free rate, MRP_t , SMB_t and HML_t are the factors from Fama/French Website that correspond to the excess returns on mimicking portfolios for market, size and value in month t and α_i , $\beta_{1,i}$, $\beta_{2,i}$ and $\beta_{3,i}$ are sensitivities to the three risk factors.⁵ Lastly, ϵ_i is the residual return of stock i in month t . Residuals are computed by subtracting the actual return with the estimated stock return for that month using a 36-month rolling regression on the past 36 monthly returns.

⁵ https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Residuals are the portion of stock returns that cannot be explained by common risk factors, representing the stock's unique performance after accounting for market influences. Stocks are ranked according to their last J month cumulative residual returns. To study the link between the residual momentum strategy and credit ratings I will follow the same approach as Avramov (2007) did for normal momentum to have comparable results and to know whether the returns of the residual momentum are also driven by the lower credit rating firms or if, in this case, the exposure to that type of stocks is reduced.

To incorporate Baghai, Servaes and Tamayo (2014) work on how credit rating agencies have evolved I use their approach to predict the credit rating a company would have with the standards of the years before. To do so, I extract financial data from CRSP for the companies that have credit ratings. The data retrieved from CRSP is winsorized at a 3% level at both ends. Descriptive statistics for the data used can be found in table 4. Based on the past credit ratings that the company had and based on its financial characteristics the methodology is the following. Regressing, using regression (2) the financial characteristics on the credit ratings of the companies from January 1985 to December 1995. By doing so, a set of parameters $(\beta_1, \dots, \beta_n)$, is estimated and is used to predict, out of sample, the implied credit ratings of the companies for the period after 1995 using the standards from the latter period.

$$(2)CR_{i,t} = const + \beta_1 * BookLev_{i,t} + \beta_2 * Rent/Assets_{i,t} + \beta_3 * Cash/Assets_{i,t} \\ + \beta_4 * PPE/Assets_{i,t} + \beta_5 * Capex/Assets_{i,t} + \beta_6 * Debt/EBITDA_{i,t} \\ + \beta_7 * IntCov_{i,t} + \beta_8 * Profit_{i,t} + \beta_9 * Size_{i,t}$$

It is a variation of the regression performed by Baghai, Servaes and Tamayo (2014) as I add the constant term (which has no impact in terms of the results) and drop the variables implied volatility and convertible debt to assets as there were many missing values which decrease largely the size of the dataset.

Variables are defined as follows: (i) *BookLev* is long- and short-term debt divided by total assets, (ii) *Rent/Assets* is rental payments divided by total assets, (iii) *Cash/Assets* is cash and short-term investments divided by total assets, (iv) *PPE/Assets* is a measure of tangibility which is property, plant and equipment net of depreciation divided by total assets, (v) *CapEx/Assets* is Capital Expenditures measured by the change in PPE added by depreciation divided by total assets, (vi) *Debt/EBITDA* which is long- and short-term debt divided by EBITDA (earnings before interest, tax, depreciation and amortization),

(vii) *IntCov* is the interest coverage ratio which is EBITDA divided by total interest payments, (viii) *Profit* is a measure of the profitability of the company which is EBITDA divided by total sales, and (iv) *Size* which is the log of the book value of assets, in constant, 2005 US dollars. Data on the Consumer Price Index of the United States of America was retrieved on the Bureau of Labor Statistics of the United States.⁶ The definition of the variables is equivalent to the one used by Baghai, Servaes and Tamayo (2014). The regression has a R^2 of 0.522 which compares to 0.704 from the regression of Baghai, Servaes and Tamayo (2014). All the variables have the expected signal for the exception of profit which is non-significant in my case. In Table 5 I show the summary results of the regression performed.

Table 4

This table shows the descriptive statistics of the data used in this thesis to perform regression (2). The financial data was obtained from CRSP for the period of 1985 until 2021 for the firms that are rated by S&P whose rating is present in the dataset that contains the time series of the ratings of the companies.

	Book Lev	Rent/ Assets	Cash/ Assets	PPE/ Assets	CapEx/ Assets	Debt/ EBITDA	IntCov	Profit	Size
# Companies	2 050	2 050	2 050	2 050	2 050	2 050	2 050	2 050	2 050
Mean	0.34	0.02	0.08	0.35	0.05	3.28	7.89	0.19	8.37
Standard Deviation	0.18	0.02	0.09	0.25	0.05	2.80	8.55	0.13	1.55
Min	0.04	0.00	0.00	0.01	0.00	0.00	0.00	(0.02)	5.54
Max	0.78	0.10	0.35	0.86	0.20	20.01	10.57	0.52	11.79
25%	0.20	0.00	0.02	0.14	0.02	2.80	1.41	0.09	7.24
50%	0.31	0.01	0.05	0.30	0.04	5.09	2.59	0.15	8.24
75%	0.44	0.02	0.11	0.55	0.07	9.33	4.32	0.26	9.45

⁶ <https://www.bls.gov/cpi/data.htm>

Table 5

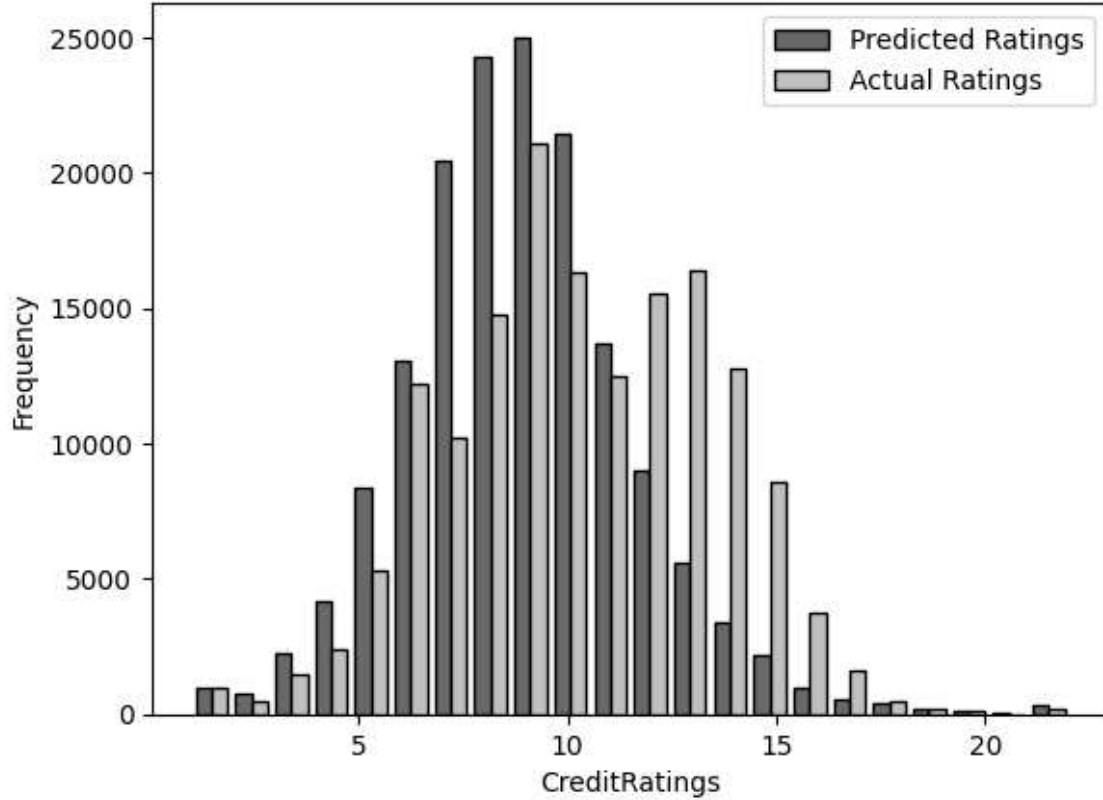
The Table shows the results of regression (2) which regresses the credit ratings on a set of firm financial characteristics which are incorporated in the calculation of the credit rating of a company. The regression is performed using data from 1985 until 1995. The Credit Ratings are S&P Ratings, and the financial data of the companies was extracted from CRSP. Credit Ratings, which are the dependent variable, is the numerical equivalent as defined in this thesis (AAA is 1, AA+ is 2 and D is 22). BookLev is long- and short-term debt divided by total assets; Rent/Assets is rental payments divided by total assets; Cash/Assets is cash and short term investments divided by total assets; Debt/EBITDA is long and short term debt divided by EBITDA; IntCov is EBTIDA divided by total interest payments; Profit is EBITDA divided by total sales; Size is the log of the book value of assets, in constant, 2005 US Dollars; PPE/Assets is property, plant and equipment divided by total assets; Capex/Assets is the change in PPE added by depreciation divided by total assets. The “****”, “***”, “**” denote significance at the 1%, 5% and 10% level, respectively.

OLS	Coef	Std error	t-stat	p-value
const	16.59***	0.15	111.41	0.00
Book_Lev	8.18***	0.11	74.05	0.00
Rent/Assets	11.31***	0.65	17.28	0.00
Cash/Assets	2.42**	0.24	9.99	0.00
Debt/EBITDA	0.00	0.00	1.12	0.26
IntCov	(0.03)***	0.00	(18.07)	0.00
Profit	0.01	0.01	0.79	0.43
Size	(1.17)***	0.02	(76.92)	0.00
PPE/Assets	(2.01)***	0.10	(19.32)	0.00
Capex/Assets	(2.80)***	0.42	(6.60)	0.00

As for the average decrease in credit ratings my results point towards an average 2 notch decrease holding firm characteristics constant. On Graph 1 I show the distribution of the credit ratings from 1995 to 2021 comparing the predicted ratings using the regression mentioned above and the actual ratings of the companies. It becomes clear that using the predicted ratings there is an improvement in terms of the credit rating worthiness of the companies as there are higher columns (which correspond to the frequency of the ratings) to the left side of the graph which correspond to lower (better) credit ratings.

Graph 1

The Graph shows the frequency of each credit rating in the dataset from 1995 to 2021. Predicted ratings are the forecast of the rating of a firm using the parameters that were estimated using regression (2) where credit ratings from 1985 to 1995 are regressed on a set of firm characteristics. Actual ratings are the ratings that were assigned to the companies for the same time (1995 to 2021) which are S&P Ratings.



With the analysis just mentioned I repeat the word done by Avramov (2007) but using the predicted ratings instead of the actual ratings of the companies. With this not only I shorten the timeframe but also the number of companies used. However, since there are still over 2000 companies being used and the timeframe is from 1995 until 2021, I believe the results will still be significant and add to the literature.

Results and Discussion

1. Momentum portfolios over the formation period and the credit rating

a. Momentum as in Jegadeh and Titman (2001)

Firstly, I compute the average credit rating over the formation period across the period in analysis. I check the average credit rating for all the ten portfolios over formation periods of three, six, nine and twelve months. Results are presented in Table 6. The results are in line with Avramov (2007) which shows that the relationship between the composition of the portfolios of the momentum strategy with credit rating still hold. Across all formation periods, the extreme portfolios have on average, the worst rated stocks. For example, by looking at the 6-month formation period the loser portfolio (P1) the average credit rating is 12.6 (BB-) and the winner portfolio (P10) has an average credit rating of 10.98 (BB+) which compares with the middle portfolios such as P5 and P6 which have an average credit rating of 8.44 and 8.26 (BBB). Other intriguing result of this analysis is that when fixing the holding period, meaning looking at the columns, the average credit rating of the 10 portfolios form a U-shape. In the extremes, P1 and P10 have average credit ratings which are higher than the portfolios in between. On the other hand, if I fix the portfolio, looking at the rows, until P5 the credit rating decreases almost monotonically from a formation period of 3 months until 12 months, for example, for portfolio P2 the average credit rating for a formation period of 3 months is 9.65 (BBB-), for a formation period of 6 months is 9.84 (BBB-) and for a formation period of 12 months is 10.00 (BBB-). However, for portfolios P6 to P10 the result is the opposite, the credit rating increases as the formation period increases, for example, for portfolio P10, for a formation period of 3 months the credit rating is 11.27 (BB), for a formation period of 6 months the average credit rating is 10.98 (BB+) and for a formation period of 10 months the average credit rating is 10.51 (BB+). This result is not reported in the literature *per se* but is rather in line with Avramov (2007).

Table 6

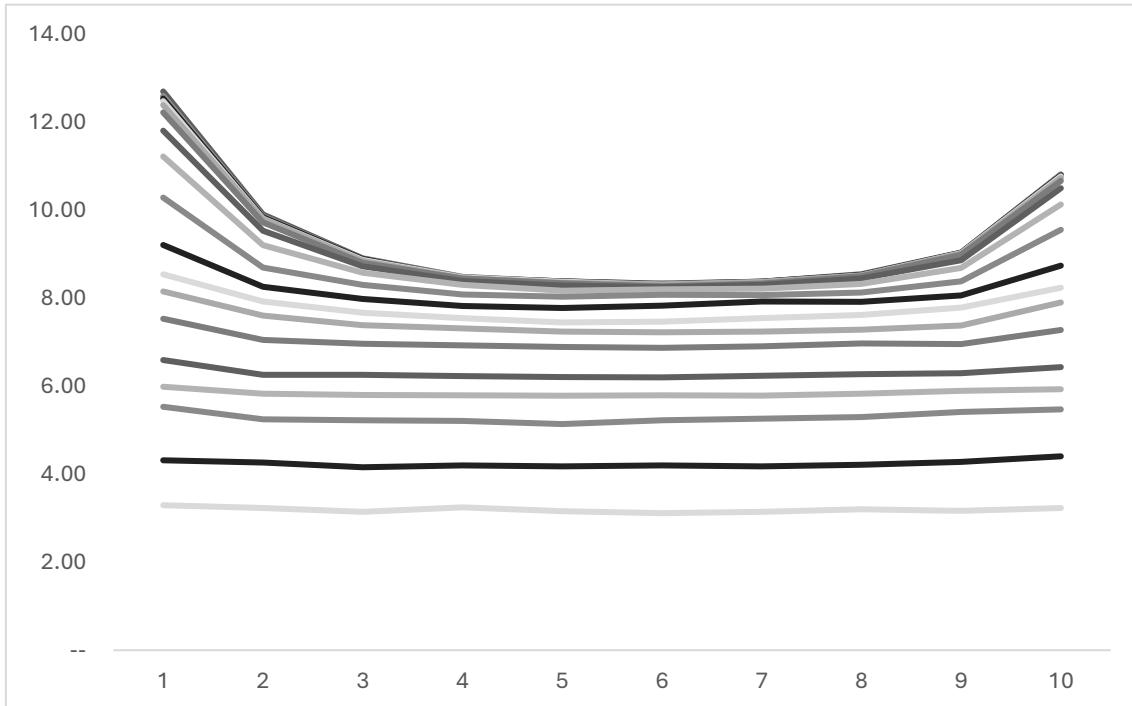
For each month t , stocks which are rated by Standard & Poor's that had residual returns available for the months $t - J$ and $t - 1$ are ranked into 10 portfolios based on past J months cumulative returns. Filtering is done as above, stocks that are priced below \$5 or are smaller than the smallest NYSE decile are excluded. The table shows the average credit rating during formation period J ($J \in \{3,6,9,12\}$). The sample period is from January 1981 to December 2021.

Credit Rating Profile over Formation Period				
	J=3	J=6	J=9	J=12
P1	12.30 (<i>BB-</i>)	12.60 (<i>BB-</i>)	12.82 (<i>BB-</i>)	13.05 (<i>B+</i>)
P2	9.65 (<i>BBB-</i>)	9.84 (<i>BBB-</i>)	9.97 (<i>BBB-</i>)	10.00 (<i>BBB-</i>)
P3	8.85 (<i>BBB</i>)	8.91 (<i>BBB</i>)	9.00 (<i>BBB</i>)	9.01 (<i>BBB-</i>)
P4	8.52 (<i>BBB</i>)	8.52 (<i>BBB</i>)	8.63 (<i>BBB</i>)	8.60 (<i>BBB</i>)
P5	8.34 (<i>BBB</i>)	8.44 (<i>BBB</i>)	8.29 (<i>BBB</i>)	8.40 (<i>BBB</i>)
P6	8.30 (<i>BBB</i>)	8.26 (<i>BBB</i>)	8.25 (<i>BBB</i>)	8.25 (<i>BBB</i>)
P7	8.42 (<i>BBB</i>)	8.39 (<i>BBB</i>)	8.31 (<i>BBB</i>)	8.27 (<i>BBB</i>)
P8	8.65 (<i>BBB</i>)	8.52 (<i>BBB</i>)	8.44 (<i>BBB</i>)	8.44 (<i>BBB</i>)
P9	9.20 (<i>BBB-</i>)	9.07(<i>BBB-</i>)	8.99 (<i>BBB</i>)	8.90 (<i>BBB</i>)
P10	11.27 (<i>BB</i>)	10.98 (<i>BB+</i>)	10.75 (<i>BB+</i>)	10.51 (<i>BB+</i>)

The literature has proven that the companies that drive momentum are the ones with the worst credit rating and that a U-shaped curve is formed over the formation period in terms of the average credit rating of the companies in each of the 10 portfolios which are created as in Jegadesh and Titman (1993). However, nothing has been said about the shape of the curve when the stocks with the worst credit rating are dropped from the dataset. To study this, I check the average credit rating of each portfolio over the formation period when dropping the worst credit rating firms sequentially. First, I drop all the observations with a credit rating of D (22) and sequentially I drop all the observations with a credit rating of C and so on. Meaning that the first iteration has all the companies, the second has all the companies excluding the ones with credit rating of D (22), the third iteration excludes all that have a credit ratings worse than C (21) and it continues until I only use the ones with credit rating better than 4 (AA-). I use a standard formation period of 6 months, but the results are robust to all the formation periods used in the literature (3, 6, 9 and 12 months – Graphs 3-5 in the Appendix). Even when only using observations with a credit rating below 4 (A+) the extreme portfolios had a higher (worst) credit rating than all the portfolios in between. The results are shown in Graph 2.

Graph 2

For each month t , stocks which are rated by Standard & Poor's that had returns available for the months $t - 6$ and $t - 1$ are ranked into 10 portfolios based on past 6 months cumulative returns. Filtering is done as above, stocks that are priced below \$5 or are smaller than the smallest NYSE decile are excluded. Sequentially, for each month t , I drop the companies that have a credit rating worse than x ($x \in \{4, \dots, 22\}$ and starts at 22 going until 4). The graph below shows, on the vertical axis, the average credit rating over the formation period for every iteration of companies dropped. The first line corresponds to the results using all the companies, the second line corresponds to the dataset with companies with a credit rating worse than 22 (D) dropped and so on until the last line which corresponds to the dataset with companies with a credit rating worse than 4 (A+) dropped. The horizontal axis corresponds to the portfolios which are formed (1 is the loser portfolio and 10 corresponds to the winner portfolio).



b. Residual momentum as in Blitz *et al.* (2011)

When using residual momentum, which means creating the portfolios based on past residual cumulative stock returns the results maintain the trend as the normal momentum as can be seen in Table 7 which shows the average credit rating over formation period with residual momentum. The average credit rating of the portfolios forms a U-shape, which means that the extreme portfolios take the worst credit rated stocks, on average. Like the case above, the average credit ratings increase/decrease when increasing/decreasing the formation period. This can be seen for example in the first portfolio (P1) that from a formation period of 3 months to a formation period of 6 months increases the average credit rating from 9.37 (BB) to 9.42 (BB) and when I look at a 9-month formation period the average increases to 9.44 (BB). However, these variations are quite small as for all formation periods they are always inside the same notch. Something intriguing in this case is that the average credit rating decreased compared to momentum as in Jegadeesh and Titman (1993). The justification is that it has less observations as it needs to have 36 past month returns to have one residual, thus decreasing largely the amount of data used to perform this analysis. To check that, on Table 7 I show the credit rating profile over formation period with residual momentum and momentum but using the exact same observation that were used to compute residual momentum. The differences between the average credit ratings when using momentum to residual momentum are not significant as the average credit ratings for all portfolios and across all formation periods lie on the same notch. However, one should mention that the average credit ratings using residual momentum are, in the extremes, lower compared to the one that sorts stocks as in Jegadeesh and Titman (1993) thus corroborating the work of Blitz *et. al* (2011) that mention that residual momentum reduces the exposure to extreme observations in terms of credit ratings. This can also be seen if I look at the maximum credit rating in the extreme portfolios (P1 and P10). In the case of residual momentum, the worst rated stock in the loser portfolio (P1) is a company rated 15 (B) whereas for momentum it is a company rated 16 (B-). The same happens for the winning portfolios (P10) where residual momentum has a company rated 12 (BB) and momentum only has a 13 (BB-).

Table 7

For each month t , stocks that have available past 36 month returns on CRSP, I take their residual return by regressing past 36 month returns on the three Fama and French factors and subtracting its actual return with the predicted value. After that, stocks which are rated by Standard & Poor's that had residual returns available for the months $t - J$ and $t - 1$ are ranked into 10 portfolios based on past J months cumulative residual returns. Filtering is done as above, stocks that are priced below \$5 or are smaller than the smallest NYSE decile are excluded. The table shows the average credit rating during formation period J ($J \in \{3,6,9,12\}$). The sample period is from January 1981 to December 2021. Panel A shows the average credit rating over the formation period by sorting the stocks on their residual cumulative returns. Panel B shows the average credit rating over formation period using the exact same observations but sorting on cumulative returns instead of cumulative residual returns.

Panel A: Credit rating profile over formation period with residual momentum				
	J=3	J=6	J=9	J=12
P1	9.37 (<i>BBB-</i>)	9.42 (<i>BBB-</i>)	9.44 (<i>BBB-</i>)	9.46 (<i>BBB-</i>)
P2	8.10 (<i>BBB</i>)	8.17 (<i>BBB</i>)	8.18 (<i>BBB</i>)	8.19 (<i>BBB</i>)
P3	7.72 (<i>BBB+</i>)	7.79 (<i>BBB+</i>)	7.84 (<i>BBB+</i>)	7.81 (<i>BBB+</i>)
P4	7.53 (<i>BBB+</i>)	7.63 (<i>BBB+</i>)	7.67 (<i>BBB+</i>)	7.68 (<i>BBB+</i>)
P5	7.37 (<i>BBB+</i>)	7.50 (<i>BBB+</i>)	7.48 (<i>BBB+</i>)	7.57 (<i>BBB+</i>)
P6	7.43 (<i>BBB+</i>)	7.45 (<i>BBB+</i>)	7.50 (<i>BBB+</i>)	7.54 (<i>BBB+</i>)
P7	7.38 (<i>BBB+</i>)	7.45 (<i>BBB+</i>)	7.56 (<i>BBB+</i>)	7.54 (<i>BBB+</i>)
P8	7.57 (<i>BBB+</i>)	7.65 (<i>BBB+</i>)	7.61 (<i>BBB+</i>)	7.65 (<i>BBB+</i>)
P9	8.02 (<i>BBB</i>)	8.07 (<i>BBB</i>)	8.01 (<i>BBB</i>)	7.99 (<i>BBB+</i>)
P10	9.17(<i>BBB-</i>)	9.11 (<i>BBB-</i>)	9.13 (<i>BBB-</i>)	9.13 (<i>BBB-</i>)
Panel B: Credit rating profile over formation period with "normal" momentum				
	J=3	J=6	J=9	J=12
P1	9.61 (<i>BBB-</i>)	9.59 (<i>BBB-</i>)	9.70 (<i>BBB-</i>)	9.76 (<i>BBB-</i>)
P2	8.10 (<i>BBB</i>)	8.20 (<i>BBB</i>)	8.24 (<i>BBB</i>)	8.30 (<i>BBB</i>)
P3	7.69 (<i>BBB+</i>)	7.67 (<i>BBB+</i>)	7.76 (<i>BBB+</i>)	7.86 (<i>BBB+</i>)
P4	7.56 (<i>BBB+</i>)	7.51 (<i>BBB+</i>)	7.53 (<i>BBB+</i>)	7.53 (<i>BBB+</i>)
P5	7.34 (<i>BBB+</i>)	7.43 (<i>BBB+</i>)	7.51 (<i>BBB+</i>)	7.41 (<i>BBB+</i>)
P6	7.44 (<i>BBB+</i>)	7.49 (<i>BBB+</i>)	7.39 (<i>BBB+</i>)	7.36 (<i>BBB+</i>)
P7	7.49 (<i>BBB+</i>)	7.44 (<i>BBB+</i>)	7.45 (<i>BBB+</i>)	7.37 (<i>BBB+</i>)
P8	7.63 (<i>BBB+</i>)	7.61 (<i>BBB+</i>)	7.59 (<i>BBB+</i>)	7.61 (<i>BBB+</i>)
P9	8.03 (<i>BBB</i>)	7.96 (<i>BBB+</i>)	8.01 (<i>BBB</i>)	7.79 (<i>BBB+</i>)
P10	9.33 (<i>BBB-</i>)	9.06 (<i>BBB-</i>)	9.04 (<i>BBB-</i>)	8.95 (<i>BBB</i>)

2. Unconditional momentum over different rating subsamples

Until now, and in line with what was suggested by Avramov (2007), I find that both the winner and the loser portfolio are the ones with the highest average credit rating over formation period which suggests that the companies that are driving the momentum returns are the worst rated ones.

In a subsequent study, I try to find what happens to the momentum returns if I start dropping the worst rated firms. In Table 8, I show the average payoffs for momentum strategies as I drop, for every iteration, the worst rated stocks still in the dataset. The second column represents the percentage of market capitalization of the firms still in the dataset, the third column represents the number of firms that were not excluded from the sample and the fourth column represents the percentage of firms in the dataset.

As Avramov (2007) I find that the momentum returns are statistically not significant different from 0 at a 5% level if I use only companies rated from AAA to BB+. It is a sample that accounts for 95.22% of the total market capitalization used in this study but contains only 59.21% of the total companies in the dataset. These values are relatively lower compared with the ones put forward by Avramov (2007). The author finds that returns are non-significant using companies rated AAA to BB which account for 96.62% of the market capitalization of the rated firms in the study and contains 78.84% of the total number of rated firms in the dataset. Differences in values would be expected as the timeframe used is different as well as the dataset. Thus, I can say that the conclusions remain the same and that momentum profits are driven by a subsample of firms which account for less than 5% of the market capitalization of all rated firms.

Table 8

For each month t , all NYSE, AMEX and NASDAQ stocks rated by S&P available on the dataset provided and with available data on CRSP with returns for months $t - 6$ to $t - 1$ are ranked into decile portfolios based on their return during that period. Stocks that are priced below \$5 dollars or are smaller than the smallest NYSE decile are excluded. Portfolio returns are computed monthly by assigning equal weights to the firms in that decile ranking. The momentum strategy corresponds to buying the winner and selling the losing portfolio and holding the position for J months, in this case 6 months. The first row represents monthly returns computed as the equal-weighted average return for the momentum strategy across the time period used (1985 to 2021). The subsequent rows represent the returns for a decreasing sample of stocks obtained by excluding firms with the worst credit ratings. First, column shows the raw average monthly profits for the momentum strategy for each subsample of companies, below the returns there are the t-stats. The second column shows the percentage of the overall sample of rated firms used in this study. The third and fourth columns provide the number of firms in each sample and the corresponding percentage to the total number of firms, respectively. The “***”, “**”, “*” denote significance at the 1%, 5% and 10% level, respectively.

Panel [xx]: Unconditional Momentum over Different Rating Subsamples				
Stock Sample	Momentum Profits	Percent of Total Market Cap	Number of Firms	Percentage of firms
All Firms	1.05%*** 0.00	100.00%	3 008	100.00%
AAA - D	1.01%*** 0.00	99.99%	2 997	99.63%
AAA - C	1.01%*** 0.00	99.99%	2 997	99.63%
AAA - CC	1.01%*** 0.00	99.98%	2 995	99.57%
AAA - CCC-	1.00%*** 0.00	99.98%	2 991	99.43%
AAA - CCC	0.92%*** 0.00	99.97%	2 983	99.17%
AAA - CCC+	0.86%*** 0.00	99.92%	2 970	98.74%
AAA - B-	0.73%*** 0.00	99.70%	2 913	96.84%
AAA - B	0.58%*** 0.01	99.24%	2 770	92.09%
AAA - B+	0.48%** 0.03	98.42%	2 453	81.55%
AAA - BB-	0.49%** 0.03	97.03%	2 106	70.01%
AAA - BB	0.41%* 0.06	95.22%	1 781	59.21%
AAA - BB+	0.33% 0.12	92.86%	1 561	51.89%
AAA - BBB-	0.29% 0.18	88.49%	1 355	45.05%
AAA - BBB	0.26% 0.23	79.89%	1 086	36.10%
AAA - BBB+	0.22% 0.32	70.03%	863	28.69%
AAA - A-	0.27% 0.22	60.08%	667	22.17%
AAA - A	0.21% 0.32	44.28%	419	13.93%
AAA - A+	0.26% 0.29	33.61%	254	8.44%

3. What if Credit Rating Agencies did not become more conservative?

Incorporating the fact that credit rating agencies have become more conservative and following Baghai, Servaes and Tamayo (2014) approach to predict credit ratings for the period after 1995 I repeat the study to check if both my results and Avramov (2007) are robust to this finding. Using the approach explained in the methodology chapter I find that the predicted ratings are, on average, two notches lower (better) than the actual ratings. This shows that a company is now rated with an 8 (BBB+), if the same standards were applicable, would be rated 6 (A).

To contextualize the analysis, I present in Table 9 the average monthly returns of the momentum strategy across the dataset used to perform this analysis as the dataset is substantially smaller both in terms of timeframe used and the companies that have data available. The period used is 1995 to 2021 as the period before that was used to estimate the parameters of the regression used to predict the credit ratings ahead. The companies used are a subset of the ones used before as here I had the limitation of financial data availability. The momentum strategy for this time frame and with this set of companies yields a lower return compared to the base case where I could find monthly returns above 1% and in this case none of scenarios have returns higher than 1%. For consistency purposes, for the following analysis both the formation period and holding period used are 6 months.

Table 9

For each month t , all NYSE, AMEX and NASDAQ stocks extracted from CRSP which are rated by S&P are ranked according to their past 6-month cumulative return ($t - 6$ to $t - 1$). Stocks which are priced below \$5 or are smaller than the smallest NYSE size decile are excluded. Portfolios are formed based on what decile the stocks fall and the returns of each portfolio correspond to the equal weighted average of the returns of the stocks inside that portfolio. The momentum strategy corresponds to buying the winner and selling the loser portfolio. Positions are then held for 6 months but there is a lag of 1 month which means that the portfolios are held in the period of $t + 1$ to $t + 6$. Table shows the average monthly returns of the momentum returns as well as the winner portfolio returns, and loser portfolio returns for different formation ($J \in \{3,6,9,12\}$) and holding ($K \in \{3,6,9,12\}$) periods. Below the returns I show the p-value which demonstrates the statistical significance of the results.

The “***”, “**”, “*” denote significance at the 1%, 5% and 10% level, respectively.

Returns of Momentum Strategy in Rated Firms					
J=	K=	3	6	9	12
3	P10-P1	0.73%**	0.70%**	0.61%**	0.44%*
		0.041	0.027	0.034	0.073
	P1	0.35%	0.30%	0.33%	0.42%
		0.533	0.587	0.547	0.425
	P10	1.08%**	1.00%**	0.94%**	0.86%**
		0.012	0.021	0.030	0.049
6	P10-P1	0.78%*	0.67%*	0.53%	0.42%*
		0.064	0.085	0.127	0.059
	P1	0.20%	0.25%	0.34%	0.41%
		0.739	0.667	0.545	0.451
	P10	0.97%**	0.91%**	0.87%**	0.83%**
		0.024	0.038	0.046	0.059
9	P10-P1	0.55%	0.53%	0.43%	0.36%
		0.172	0.165	0.223	0.260
	P1	0.25%	0.28%	0.39%	0.44%
		0.670	0.624	0.492	0.426
	P10	0.80%**	0.81%**	0.81%**	0.80%**
		0.069	0.065	0.063	0.069
12	P10-P1	0.55%	0.49%	0.41%	0.38%
		0.185	0.209	0.262	0.263
	P1	0.25%	0.30%	0.38%	0.41%
		0.676	0.611	0.508	0.459
	P10	0.79%**	0.79%**	0.79%**	0.79%**
		0.063	0.071	0.069	0.067

In Table 10 I show the average credit rating over the formation period using the predicted credit ratings and the actual credit ratings. The average predicted ratings of the portfolios over the formation period are lower, as expected, given the overall lower credit ratings. They continue to form a U-shape across the portfolios being the portfolios in the extremes (both the winner and the loser) the ones with the highest average credit rating. This is true across the entire all the formation periods used. The trend that as I increase the formation period the average credit rating increases for the loser portfolio and decreases for the winner still holds using the predicted ratings.

In Table 11 I show the results of the analysis where I drop the observations which have a credit rating higher (worse) than a value sequentially starting from the worst rated stocks. In this case, even with all the firm's momentum results are not significantly different from 0 at a 5% significance level. However, a big drop happens when I exclude companies rated worse than 12 (BB) with returns coming from 0.56% immediately before to 0.43%. Here, the percentage of market capitalization inside the dataset is 98.01% but with only 85.38% of the companies. Comparing to the case where I use the actual ratings (Table 8) the returns were non-significant at a 5% level also when I dropped the observations with a credit rating worse than 12 (BB). This is quite intriguing as the predicted credit ratings are tilted towards the left (better rated stocks) comparing with the actual ratings but the point at which the returns see a big drop is the same.

Table 10

For each month t , stocks which are rated by Standard & Poor's that had residual returns available for the months $t - J$ and $t - 1$ are ranked into 10 portfolios based on past J months cumulative returns. Filtering is done as above, stocks that are priced below \$5 or are smaller than the smallest NYSE decile are excluded. The table shows the average credit rating during formation period J ($J \in \{3,6,9,12\}$). The sample period is from January 1981 to December 2021. Predicted ratings are the ones which are the result of the regression (2) using the data from 1981 to 1995 to compute the parameters of the regression. Thus, the timeframe used for this analysis is January 1996 to December 2021. Panel A presents the average credit rating over formation period using the predicted ratings whereas Panel B represents the average credit rating over formation period using the actual ratings with the exact same observations to make the results comparable.

Panel A: Credit Rating Profile over Formation Period using Predicted Ratings				
	J=3	J=6	J=9	J=12
P1	9.74 (<i>BBB-</i>)	9.91 (<i>BBB-</i>)	9.93 (<i>BBB-</i>)	9.93 (<i>BBB-</i>)
P2	8.90 (<i>BBB</i>)	8.93 (<i>BBB</i>)	8.91 (<i>BBB</i>)	9.01 (<i>BBB-</i>)
P3	8.50 (<i>BBB</i>)	8.55 (<i>BBB</i>)	8.59 (<i>BBB</i>)	8.53 (<i>BBB</i>)
P4	8.47 (<i>BBB</i>)	8.37 (<i>BBB</i>)	8.38 (<i>BBB</i>)	8.33 (<i>BBB</i>)
P5	8.33 (<i>BBB</i>)	8.21 (<i>BBB</i>)	8.23 (<i>BBB</i>)	8.14 (<i>BBB</i>)
P6	8.33 (<i>BBB</i>)	8.24 (<i>BBB</i>)	8.16 (<i>BBB</i>)	8.13 (<i>BBB</i>)
P7	8.27 (<i>BBB</i>)	8.27 (<i>BBB</i>)	8.19 (<i>BBB</i>)	8.14 (<i>BBB</i>)
P8	8.39 (<i>BBB</i>)	8.34 (<i>BBB</i>)	8.25 (<i>BBB</i>)	8.27 (<i>BBB</i>)
P9	8.57 (<i>BBB</i>)	8.48 (<i>BBB</i>)	8.44 (<i>BBB</i>)	8.46 (<i>BBB</i>)
P10	9.25 (<i>BBB-</i>)	9.11 (<i>BBB-</i>)	8.96 (<i>BBB</i>)	8.82 (<i>BBB</i>)
Panel B: Credit Rating Profile over Formation Period using Actual Ratings				
	J=3	J=6	J=9	J=12
P1	12.71 (<i>BB-</i>)	12.92 (<i>BB-</i>)	13.04 (<i>B+</i>)	13.19 (<i>B+</i>)
P2	10.61 (<i>BB+</i>)	10.74 (<i>BB+</i>)	10.85 (<i>BB+</i>)	10.92 (<i>BB+</i>)
P3	9.81 (<i>BBB-</i>)	9.89 (<i>BBB-</i>)	9.93 (<i>BBB-</i>)	9.82 (<i>BBB-</i>)
P4	9.52 (<i>BBB-</i>)	9.46 (<i>BBB-</i>)	9.48 (<i>BBB-</i>)	9.47 (<i>BBB-</i>)
P5	9.30 (<i>BBB-</i>)	9.22 (<i>BBB-</i>)	9.20 (<i>BBB-</i>)	9.17 (<i>BBB-</i>)
P6	9.22 (<i>BBB-</i>)	9.13 (<i>BBB-</i>)	9.11 (<i>BBB-</i>)	9.08 (<i>BBB-</i>)
P7	9.36 (<i>BBB-</i>)	9.24 (<i>BBB-</i>)	9.13 (<i>BBB-</i>)	9.11 (<i>BBB-</i>)
P8	9.51 (<i>BBB-</i>)	9.45 (<i>BBB-</i>)	9.35 (<i>BBB-</i>)	9.23 (<i>BBB-</i>)
P9	10.13 (<i>BB+</i>)	9.96 (<i>BBB-</i>)	9.81 (<i>BBB-</i>)	9.73 (<i>BBB-</i>)
P10	11.75 (<i>BB</i>)	11.53 (<i>BB</i>)	11.21 (<i>BB</i>)	11.04 (<i>BB</i>)

Table 11

For each month t , all NYSE, AMEX and NASDAQ stocks rated by S&P available on the dataset provided and with available data on CRSP with returns for months $t - 6$ to $t - 1$ are ranked into decile portfolios based on their return during that period. Stocks that are priced below \$5 dollars or are smaller than the smallest NYSE decile are excluded. Portfolio returns are computed monthly by assigning equal weights to the firms in that decile ranking. The momentum strategy corresponds to buying the winner and selling the losing portfolio and holding the position for J months, in this case 6 months. The first row represents monthly returns computed as the equal-weighted average return for the momentum strategy across the time period used (1985 to 2021). The subsequent rows represent the returns for a decreasing sample of stocks obtained by excluding firms with the worst credit ratings. First, column shows the raw average monthly profits for the momentum strategy for each subsample of companies, below the returns there are the t-stats. The second column shows the percentage of the overall sample of rated firms used in this study. The third and fourth column provide the number of firms in each sample and the corresponding percentage to the total number of firms, respectively. Predicted ratings are the ones which are the result of the regression (2) using the data from 1981 to 1995 to compute the parameters of the regression. Thus, the timeframe used for this analysis is January 1996 to December 2021. Panel A shows the results using predicted ratings whereas Panel B shows the results using the actual ratings with the exact same observations to make the results comparable. The “****”, “***”, “**” denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Unconditional Momentum over Different Rating Subsamples using Predicted Ratings				
Stock Sample	Momentum Profits	Percent of Total Market Cap	Number of Firms	Percentage of firms
All Firms	0.67%* 0.08	100.00%	2 059	100.00%
AAA - D	0.66%* 0.08	99.92%	2 056	99.85%
AAA - C	0.68%** 0.05	99.92%	2 055	99.81%
AAA - CC	0.65%* 0.09	99.90%	2 054	99.76%
AAA - CCC-	0.66%* 0.09	99.89%	2 052	99.66%
AAA - CCC	0.64%* 0.10	99.87%	2 050	99.56%
AAA - CCC+	0.59% 0.12	99.85%	2 039	99.03%
AAA - B-	0.61% 0.11	99.77%	2 031	98.64%
AAA - B	0.59% 0.12	99.54%	2 007	97.47%
AAA - B+	0.57% 0.14	99.26%	1 957	95.05%
AAA - BB-	0.56% 0.15	98.78%	1 886	91.60%
AAA - BB	0.43% 0.27	98.01%	1 758	85.38%
AAA - BB+	0.40% 0.31	95.82%	1 584	76.93%
AAA - BBB-	0.43% 0.31	92.09%	1 326	64.40%
AAA - BBB	0.30% 0.46	85.46%	1 052	51.09%
AAA - BBB+	0.26% 0.54	75.56%	750	36.43%
AAA - A-	-0.04% 0.93	62.45%	489	23.75%
AAA - A	-0.04% 0.94	47.80%	289	14.04%
AAA - A+	-0.15% 0.78	31.05%	181	8.79%

Panel B: Unconditional Momentum over Different Rating Subsamples using Predicted Ratings				
Stock Sample	Momentum Profits	Percent of Total Market Cap	Number of Firms	Percentage of firms
All Firms	0.67%* 0.08	100.00%	2 059	100.00%
AAA - D	0.68%* 0.08	99.99%	2 059	100.00%
AAA - C	0.68%* 0.08	99.99%	2 059	100.00%
AAA - CC	0.69%* 0.07	99.99%	2 058	99.95%
AAA - CCC-	0.70%* 0.07	99.99%	2 057	99.90%
AAA - CCC	0.70%* 0.07	99.98%	2 055	99.81%
AAA - CCC+	0.66%* 0.08	99.91%	2 044	99.27%
AAA - B-	0.59% 0.12	99.57%	2 013	97.77%
AAA - B	0.52% 0.16	98.89%	1 924	93.44%
AAA - B+	0.48% 0.18	97.57%	1 719	83.49%
AAA - BB-	0.45% 0.20	95.50%	1 444	70.13%
AAA - BB	0.40% 0.24	92.75%	1 210	58.77%
AAA - BB+	0.26% 0.45	89.41%	1 039	50.46%
AAA - BBB-	0.36% 0.29	83.70%	871	42.30%
AAA - BBB	0.31% 0.35	72.66%	656	31.86%
AAA - BBB+	0.26% 0.46	60.40%	479	23.26%
AAA - A-	0.13% 0.71	50.52%	343	16.66%
AAA - A	0.32% 0.43	34.15%	181	8.79%
AAA - A+	0.30% 0.52	25.70%	92	4.47%

There are some limitations to this work, namely the fact that there might be missing variables in the analysis of the conservatism of credit rating agencies. On the same topic, the R^2 of the regression I use is lower than the one found by Baghai, Servaes and Tamayo (2014). Lastly, when doing further analysis, I must drop many observations which decrease the size of the dataset both in terms of timeframe and companies used which can lead to bias in the results.

To extend this research, it is possible to further understand the financial characteristics of the companies in the extreme portfolios (winner and loser) as well the companies that are driving the momentum returns. Further, it is feasible to understand the impact of the fact that credit rating agencies tend to lag updating the credit rating of a company, as suggested by White (2013), which can impact the results found in this thesis. It is also achievable to

analyse firms globally, instead of only focusing on the ones situated in the United States of America since there could be different relationships.

Conclusion

This thesis dives into understanding further the relationship between momentum and credit rating namely on a timeframe that has not been used before but also into answering a set of questions that are yet to be researched by the literature namely the impact of the conservatism of the credit rating agencies on the finding of Avramov (2007) and the relationship between residual momentum and credit ratings.

My empirical evidence is based on a sample of 3 008 rated companies listed on the New York (NYSE), American (AMEX), and Nasdaq stock markets over the timeframe of January 1985 to December 2021. My selected sample is representative as rated and non-rated stocks exhibit similar descriptive statistics and momentum returns.

I find that the relationship between momentum and credit ratings holds when expanding the dataset used until 2021 as it is suggested by Avramov (2007) using data until 2006. I find that over the formation period the extreme winner and loser portfolio are comprised of high (worst) rated stocks. When I exclude the worst rated stocks (comprising 4% of the market capitalization) the momentum returns are statistically not significant. The relationship between residual momentum and credit ratings is similar to the one seen in momentum however the concentration of the worst rated stocks in the extreme portfolios is less significant.

I show that the relationship between credit ratings and momentum shown above holds after controlling for the changing standards of credit rating agencies as the worst rated stocks remain concentrated in the extreme portfolios over the formation period. The momentum strategy returns are also driven in this case by 2% of the total market capitalization of the rated stocks.

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Appendix

Table 12

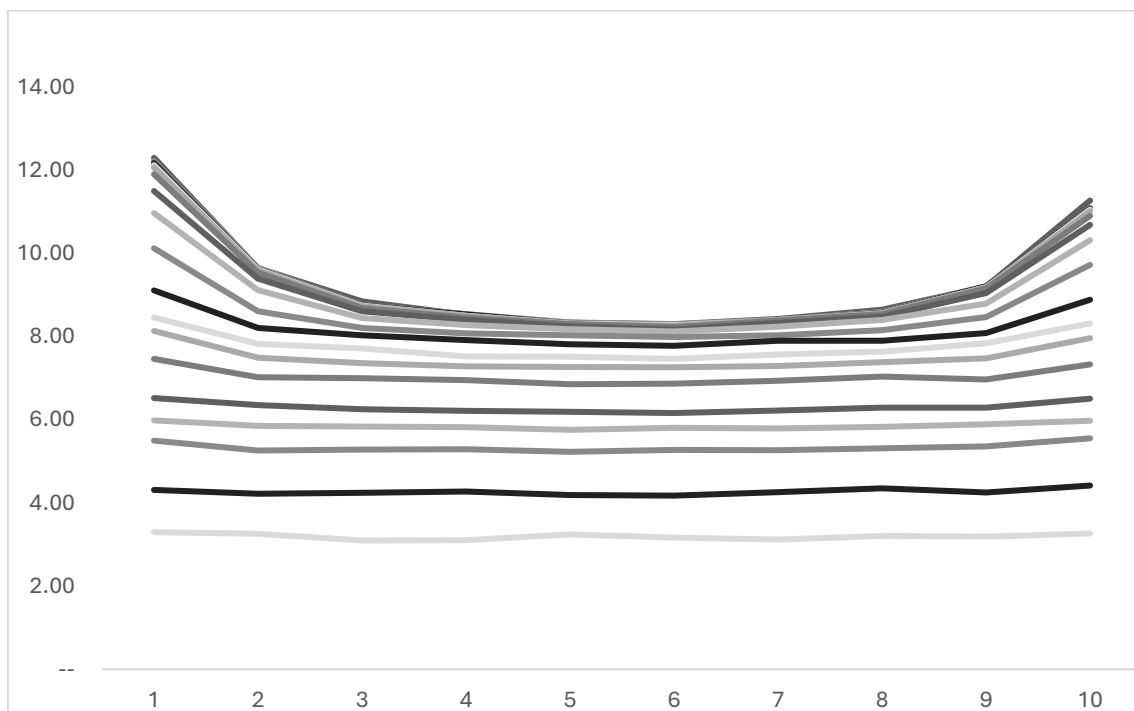
For each month t , stocks that have available past 36 month returns on CRSP, I take their residual return by regressing past 36 month returns on the three Fama and French factors and subtracting its actual return with the predicted value. After that, stocks which are rated by Standard & Poor's that had residual returns available for the months $t - J$ and $t - 1$ are ranked into 10 portfolios based on past J months cumulative residual returns. Filtering is done as above, stocks that are priced below \$5 or are smaller than the smallest NYSE decile are excluded. The momentum strategy corresponds to buying the winner and selling the loser portfolio. Positions are then held for 6 months but there is a lag of 1 month which means that the portfolios are held in the period of $t + 1$ to $t + 6$. The table shows the average monthly returns of the momentum returns as well as the winner portfolio returns, and loser portfolio returns for different formation ($J \in \{3,6,9,12\}$) and holding ($K \in \{3,6,9,12\}$) periods. Below the returns I show the p-value which demonstrates the statistical significance of the results. Panel A shows the returns of residual momentum and Panel B shows the returns of normal momentum using the exact same observations. The “***”, “**”, “*” denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Returns of residual momentum strategy in rated firms					
J=	K=	3	6	9	12
3	P10-P1	0.40%***	0.16%	0.11%	-0.05%
		0.008	0.163	0.250	0.639
	P1	0.90%***	0.97%***	0.98%***	1.01%***
		0.007	0.003	0.003	0.002
	P10	1.30%***	1.13%***	1.09%***	0.97%***
		0.000	0.004	0.001	0.002
	P10-P1	0.06%	0.11%	0.08%	0.08%
		0.708	0.422	0.530	0.491
6	P1	0.82%**	0.85%**	0.91%***	0.91%***
		0.016	0.013	0.007	0.007
	P10	0.89%***	0.96%***	1.00%***	0.99%***
		0.007	0.003	0.002	0.003
	P10-P1	0.17%	0.21%	0.18%	0.17%
		0.361	0.210	0.253	0.238
	P1	0.80%**	0.83%**	0.87%***	0.84%**
		0.023	0.016	0.010	0.012
9	P10	0.97%***	1.04%***	1.05%***	1.01%***
		0.003	0.002	0.001	0.002
	P10-P1	0.12%	0.19%	0.21%	0.15%
		0.550	0.289	0.217	0.338
	P1	0.89%**	0.81%**	0.83%**	0.83%**
		0.012	0.017	0.014	0.014
	P10	1.01%***	1.00%***	1.04%***	0.98%***
		0.003	0.003	0.002	0.003

Panel B: Returns of momentum strategy in rated firms					
J=	K=	3	6	9	12
3	P10-P1	-0.02%	0.15%	0.23%	0.19%
		0.941	0.421	0.144	0.185
	P1	1.12%***	0.10%***	0.97%***	0.97%***
		0.004	0.006	0.007	0.006
	P10	1.10%***	0.12%***	1.20%***	1.16%***
		0.001	0.001	0.000	0.001
6	P10-P1	0.15%	0.07%	0.17%	0.11%
		0.529	0.733	0.354	0.504
	P1	1.06%***	1.06%***	1.00%***	1.02%***
		0.007	0.005	0.007	0.005
	P10	1.21%***	1.13%***	1.17%***	1.13%***
		0.000	0.001	0.000	0.001
9	P10-P1	0.13%	0.16%	0.19%	0.10%
		0.596	0.485	0.333	0.593
	P1	1.01%***	1.00%***	0.97%***	1.01%***
		0.009	0.008	0.009	0.006
	P10	1.15%***	1.16%***	1.17%***	1.11%***
		0.001	0.001	0.001	0.001
12	P10-P1	0.19%	0.18%	0.17%	0.06%
		0.461	0.439	0.417	0.744
	P1	0.96%***	0.98%***	0.99%***	1.02%***
		0.015	0.010	0.008	0.006
	P10	1.15%***	1.16%***	1.16%***	1.08%***
		0.001	0.001	0.000	0.001

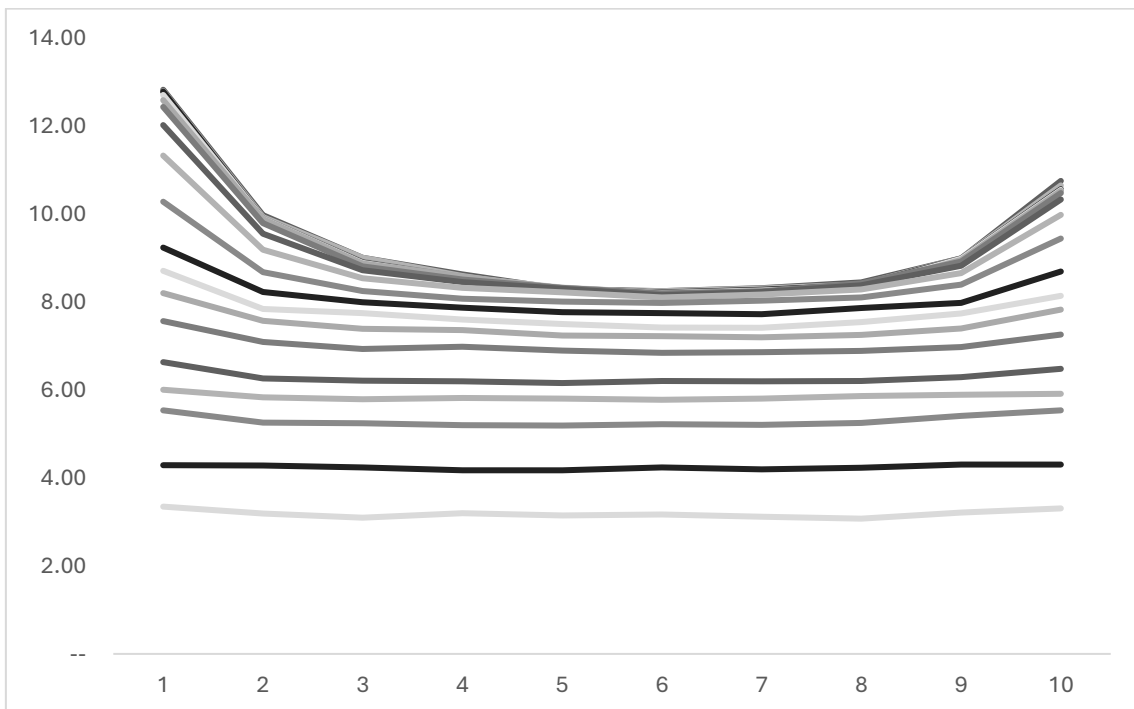
Graph 3

For each month t , stocks which are rated by Standard & Poor's that had returns available for the months $t - 6$ and $t - 1$ are ranked into 10 portfolios based on past 3 months cumulative returns. Filtering is done as above, stocks that are priced below \$5 or are smaller than the smallest NYSE decile are excluded. Sequentially, for each month t , I drop the companies that have a credit rating worse than x ($x \in \{4, \dots, 22\}$ and starts at 22 going until 4). The graph below shows, on the vertical axis, the average credit rating over the formation period for every iteration of companies dropped. The first line corresponds to the results using all the companies, the second line corresponds to the dataset with companies with a credit rating worst than 22 (D) dropped and so on until the last line which corresponds to the dataset with companies with a credit rating worse than 4 (A+) dropped. The horizontal axis corresponds to the portfolios which are formed (1 is the loser portfolio and 10 corresponds to the winner portfolio).



Graph 4

For each month t , stocks which are rated by Standard & Poor's that had returns available for the months $t - 6$ and $t - 1$ are ranked into 10 portfolios based on past 9 months cumulative returns. Filtering is done as above, stocks that are priced below \$5 or are smaller than the smallest NYSE decile are excluded. Sequentially, for each month t , I drop the companies that have a credit rating worse than x ($x \in \{4, \dots, 22\}$ and starts at 22 going until 4). The graph below shows, on the vertical axis, the average credit rating over the formation period for every iteration of companies dropped. The first line corresponds to the results using all the companies, the second line corresponds to the dataset with companies with a credit rating worst than 22 (D) dropped and so on until the last line which corresponds to the dataset with companies with a credit rating worse than 4 (A+) dropped. The horizontal axis corresponds to the portfolios which are formed (1 is the loser portfolio and 10 corresponds to the winner portfolio).



Graph 5

For each month t , stocks which are rated by Standard & Poor's that had returns available for the months $t - 6$ and $t - 1$ are ranked into 10 portfolios based on past 12 months cumulative returns. Filtering is done as above, stocks that are priced below \$5 or are smaller than the smallest NYSE decile are excluded. Sequentially, for each month t , I drop the companies that have a credit rating worse than x ($x \in \{4, \dots, 22\}$ and starts at 22 going until 4). The graph below shows, on the vertical axis, the average credit rating over the formation period for every iteration of companies dropped. The first line corresponds to the results using all the companies, the second line corresponds to the dataset with companies with a credit rating worst than 22 (D) dropped and so on until the last line which corresponds to the dataset with companies with a credit rating worse than 4 (A+) dropped. The horizontal axis corresponds to the portfolios which are formed (1 is the loser portfolio and 10 corresponds to the winner portfolio).

