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# Has S&P's impact on equity returns changed due to the financial crisis?

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**Abstract**

Since the financial crisis, rating agencies have received a lot of negative criticism, when skewed incentive systems may have led to overrated securities causing asymmetric information in the market. Despite this criticism, CRAs still play an essential role in the market place today. This thesis focuses on the impact of changes in credit rating on equity prices by employing an event study method on companies downgraded by S&P pre and post the financial crisis (07-08). We calculate cumulative abnormal returns based on the CAPM model and then make a cross-sectional analysis using an event window 5 days before to 5 days after the announcement. Data shows that pre-crisis, downgrades have a significant impact on equity returns around the announcement date at the 1% level. Surprisingly this coefficient is positive for the post sample at the 10% level. Furthermore we find that the downgrade coefficients are significantly different between the two periods of time, suggesting that S&P's impact on equity prices has decreased due to the financial crisis.

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# 1. Introduction

Credit rating agencies (CRA) play a crucial role in financial markets; they provide an independent analysis of a company's ability to meet its short and long-term obligations. Companies are dependent on CRAs in order to issue debt and communicate information to investors. Since the financial crisis, rating agencies have received a lot of negative criticism, when skewed incentive systems may have led to overrated securities causing asymmetric information in the market. Despite this criticism, CRAs still play an essential role in the market place today. Recently the downgrades of Sovereigns have caused financial turmoil, demonstrating that despite the public's decreasing confidence in CRAs, their role in assigning ratings is still very important.

This thesis focuses on the impact of changes in credit rating on equity prices. The linkage between equity prices and credit risk is less intuitive than the effect on bond yields but has still been validated in previous studies. From previous studies it has been shown that there is a negative correlation between downgrades and equity prices. This has been verified both on the announcement date but also prior to the rating change, suggesting a certain degree of market anticipation. This link has not been proved to exist between upgrades and share price returns. In particular we want to investigate if the impact of rating changes on equity prices has changed pre and post the financial crisis (07-08). A large majority of previous studies on the relationship between equity prices and credit events have been conducted pre the financial crisis. We see the financial crisis as a major event in the history of CRAs because of the involvement of CRAs in the crisis and the negative criticism that followed. Building on previous research, we provide insight on how this impact has changed over time. To our knowledge this is the first study that has investigated this question.

We find that pre-crisis downgrades have a significant impact on equity returns around the announcement date at the 1% level. Surprisingly this coefficient is positive for the post sample on the 10% level. Furthermore we find that the downgrade coefficients are significantly different between the two periods of time, suggesting that S&P's impact on equity prices has decreased due to the financial crisis.

# 2. Overview of CRAs

To better understand what criteria are important to equity holders when rating agencies assign credit ratings we examine how S&P assesses credit risk.

## 2.1 CRAs' role in the market

Credit ratings are primarily an assessment of a firm's ability to commit to its payments to debt holders and the potential loss for debt-holders should the firm fail to meet its obligations. CRAs aim to provide rigid, through-the-cycle ratings, meaning that ratings should not be influenced by cyclical volatility, but rather be affected by fundamental changes in the firm. CRAs' roles in debt capital markets are considered to be so crucial that some say that these markets would be close to non-existent without the presence of rating agencies. It is argued that investors would find it more profitable to take bank loans than communicating the same information as ratings do to investors. Especially institutional investors are dependent on credit ratings since they often are required to hold securities with a certain rating, mostly within the investment-grade sector.

## 2.2 S&P's ratings

The ratings assigned by S&P range from AAA to D, with AAA being the highest possible rating and D the lowest. All ratings entities or securities can be assigned are provided in Table 1 (note that this is for long term debt only).

**Table 1 - S&P's Long term credit rating scale**

| | |
|---|---|
| AAA | Investment Grade |
| AA+ | |
| AA | |
| AA- | |
| A+ | |
| A | |
| A- | |
| BBB+ | |
| BBB | |
| BBB- | |
| BB+ | Non Investment Grade |
| BB | |
| BB- | |
| B+ | |
| B | |
| B- | |
| CCC+ | |
| CCC | |
| CCC- | |
| CC | |
| C | |
| D | In default |

A credit rating is not equivalent to a recommendation (buy, hold or sell), often assigned to stocks. This is due to the rating's nature, which merely is a relative measure on the companies' capability of serving its debt.

Another important aspect of the assigned ratings is the outlooks, which give a more nuanced picture within each rating category. Outlooks are released by the CRAs as a view of the likely direction of the current rating of an issuer. Outlooks often have an 18-month horizon and can contribute to the degree of market anticipation once a credit event occurs.

## 2.3 S&P's Credit rating process

The credit rating process is a structured process, which may leave room for conflicts of interest or bias. The process often starts with a credit rating agency being mandated to assign a rating for an issuer. Previously, CRAs sold rating opinions to investors, but nowadays the main source of income is the fee they charge issuers. When the assigned rating team has analyzed the fundamentals of the issuer and discussed with top management, a rating recommendation is presented to a rating committee. The rating committee must, by a majority, vote for the rating recommendation to be assigned to the issuer. This is done to decrease the risk of conflicts of interests.

After a rating has been decided, the issuer can choose to publish the rating or not. This can lead to a bias in the kinds of ratings being published. Previous studies have shown that management has incentives not to disclose negative ratings (Boot et al 2005). This can decrease the amount of movement in the share price in the event of a downgrade as investors knows that rating changes are biased to positive news (or less negative news).

# 3. Literature review

Previous research has been inconclusive regarding to how much informational value CRAs actually add. Some argue that the information CRAs base their ratings on should be publicly available to all investors through financial reports. Among others Weinstein (1977), Pinches & Singleton (1978) and Kaplan & Urwitz (1979) show that rating agencies only have access to public information and add no value. However, more recent studies show that rating agencies have access to information that is not available for the public (Liu et. al 1999) and that CRAs are better at interpreting this data (Danos, Holt, & Imhoff, 1984). Other research has also shown that CRAs add informational value since they are better informed of the values of a firm's intangible assets than the public (Cornell, Landsman & Sharpio 1989).

Possible ways to explain how the information provided by CRAs is incorporated into share prices is by using the three forms of the efficient market hypothesis. The weak form of the efficient market hypothesis states that only past information is accounted for in share prices. According to this form, a change in credit rating should not be priced in and thus there should be an impact on equity returns. The semi-strong form of the EMH states that all public information should be reflected in equity prices and that share prices adjust immediately to new information. If CRAs add any informational value there should be an impact on equity returns but this should be immediately adjusted. According to the strong form of the EMH all information, public and private, is incorporated in share prices. If this hypothesis holds there should not be any impact of a change in credit rating.

The majority of studies that have been done on the relationship between rating announcements and equity returns have concluded that there is a negative correlation between downgrades and equity returns around the announcement date (i.e. Holthausen et al 1985). In their study they examine the effect of bond rating changes on common equity returns around the announcement date. They look at both upgrades and downgrades and separate their data into a contaminated and non-contaminated sample. According to their definition a credit event is contaminated if there are simultaneous news surrounding the company at the time of the credit event. Their evidence show that downgrades are associated with negative abnormal stock returns in the two-day window around the change in rating. When examining the non-contaminated sample there are increased effects on stock prices compared to the contaminated sample. This suggests that the market anticipates downgrades. They also show that this effect is bigger for companies defined as non-investment grade.

The negative impact of downgrades has also been verified on a longer term by Griffin & Sanvicente (1982). In their study they measure the stock price return eleven months before the announcement as well as the effect during the month of the announcement. In conjunction to Holthausen et al they also find that downgrades are associated with significant negative abnormal returns, both before and during the month of the announcement whereas there are no impacts of upgrades.

Furthermore studies by Chandy et al (1993), Matolscy & Lianto (1995), Boot et al (2005) and Altman & Rijken (2005) all show that downgrades are more informative to equity markets than upgrades and concludes that management has less incentives to release negative information.

These findings do not necessarily need to be entirely attributed to the rating event. A downgrade may both be an event in itself or overlapping other fundamental changes affecting a company's stock price return. Garlappi et al (2005) has shown that the effects of a change in rating is amplified for firms with large balance sheets, low R&D

costs, low book-to-market ratios and a high costs of liquidation. Industry group characteristics can also contribute to an amplified negative effect in the event of a downgrade. Gropp & Richards (2001) find that banks and other sectors that are highly regulated react more strongly to downgrades.

One hypothesis trying to explain stock price behavior around the announcement date of a credit rating is the wealth redistribution hypothesis. According to this hypothesis the wealth of the firm is redistributed between bondholders to equity holders in the event of a downgrade. This has to do with the characteristics of the equity holders' position in the company. Shares can be seen as long call options on the firm's future cash flow with a strike price equal to the value of the firm's total liabilities. Shareholders' may thus benefit from increased volatility as long as the returns do not decrease and the downgrade is motivated by firm characteristics (solvency, liquidity) and not financial performance. This is supported in a study by Ederington and Goh (1999), who show that rating updates caused by changes in a firm's financial performance are of more relevance to equity holders than changes in solidity or debt structure. Bondholders' value decreases since they implicitly have to pay for the firm's increased cost of capital while equity holders do not.

The effect of rating changes on bondholders is quite intuitive and has been examined extensively in previous research. The findings are in many ways consistent with how equity prices have been found to react to rating changes.

# 4. Data

Our data consists of a total of 195 rating changes on 183 companies rated by Standard & Poor's, meaning 12 companies are downgraded twice. As mentioned previously, studies have shown that investors rate S&P higher when it comes to credibility. That along with the fact that there might be discrepancies in ratings assigned between agencies is the reason why we have chosen to look at ratings by S&P only. The companies in our sample are listed on US stock exchanges and are traded in US dollars. The initial rationale behind the fact that we look at the US only is because it was there the presence and misconduct of CRAs was most noticeable during the financial crisis. Therefore the US market provides the best geographical area to examine.

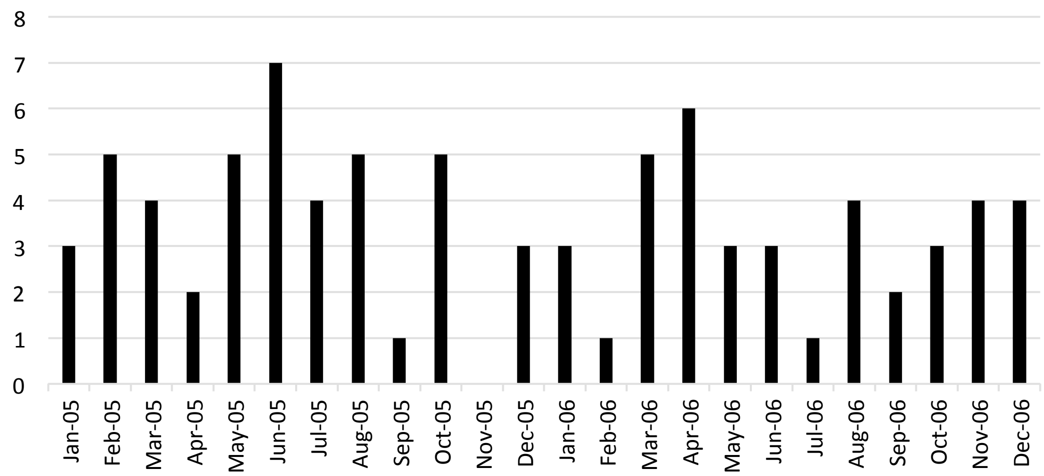
The data ranges over two distinct time periods; pre and post the financial crisis. The gap in time we consider the financial crisis is between 1st Jan 2007 to 31st Dec 2008. The pre-crisis data sample spans from 1st Jan 2005 to 31st Dec 2006 and the post-crisis data sample spans from 1st Jan 2009 to 31st Dec 2010. The date on which the rating change was announced has been obtained from Bloomberg, and a time dummy is created to divide our data into a pre and post sample, taking the value 0 for downgrades 05-06 and the value 1 for downgrades 09-10. Some companies are downgraded more than once in the respective time periods, but we only include the first downgrade in our analysis, meaning that there is only one downgrade per company in our data set. For example, if a company is downgraded 1st Jan 2005 and then again 1st Aug 2006, only the first downgrade is accounted for in our data sample.

As mentioned previously, the data does consist of 12 companies that are downgraded twice. These companies are downgraded both in the first time period pre-crisis and then again in the time period post-crisis. We separate these companies from the main sample by constructing a duplicate dummy, taking the value 1 if the company is downgraded in both time periods and the value 0 if it is not.

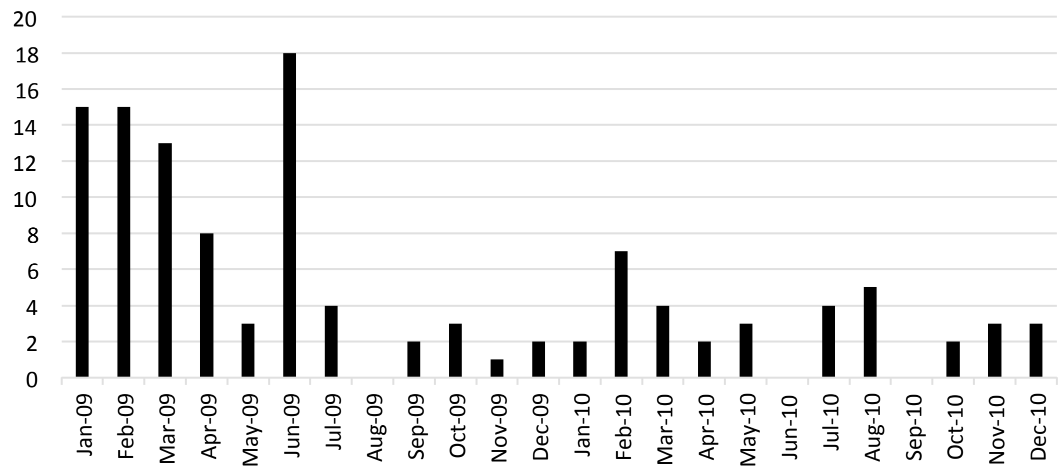
We look at downgrades only, mainly because previous research has found that upgrades don't have any significant impact on equity prices. All companies in our data set have been defined as investment grade according to Standard & Poor's, i.e. they have received a rating of BBB or above. Returns for investment grade companies are often said to be driven by flight to security and previous research has shown that non-investment grade companies react more strongly to downgrades. Non-investment grade companies are to a large extent dependent on CRAs in order to communicate with investors, which makes it hard to believe that credibility issues for CRAs should have an equally large impact within this segment. Also non-investment grade companies tend to have less analyst coverage, making it difficult to use this segment in order to investigate market anticipation. Furthermore, the data has been filtered to only display changes in rating for the issuer's local long term issued debt. This means that changes in ratings of short-term debt as well as foreign long term issued debt have been excluded. The reason for this is mainly that local issued debt will be denominated in the same currency as the share price of the companies. Debt issued in foreign currency may possibly receive different ratings and for this reason we filter our data for any such exogenous effects. Most previous research on rating changes exclusively focuses on long term issued debt. Long-term ratings may be the simplest proxy of a company's ability to meet its obligations.

The below graphs show the distribution of downgrades over time across the two samples:

*Graph 1 - Density of the 79 downgrades Pre-crisis*



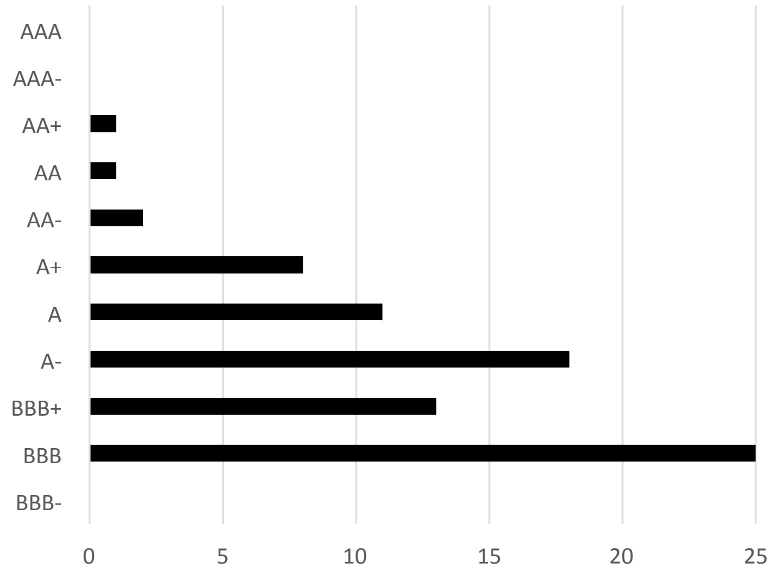

*Graph 2-Density of the 116 downgrades Post-crisis*



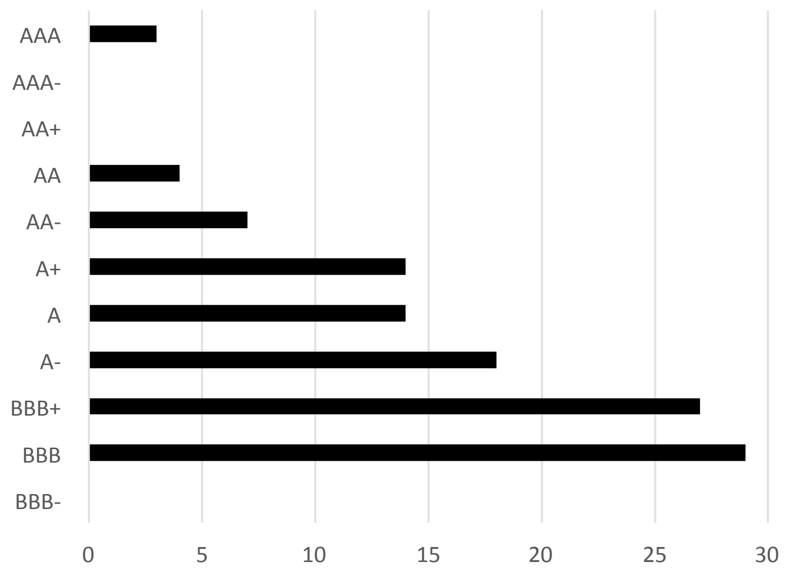
As we can see, the downgrades are evenly distributed over time for the pre sample. For the post sample the majority of downgrades occurs in the beginning of sample period. This might suggest that downgrades caused by events that occurred during the financial crisis. Moreover, 59 of the 116 companies downgraded post-crisis were also downgraded during 07-08.

The below graphs show the distribution among rating values before downgrades:

*Graph 3 - Rating distribution of the 79 companies downgraded Pre-crisis*




*Graph 4 -Rating distribution of the 116 companies downgraded Post-crisis*



As shown in the tables, the ratings distributions for the pre- and post-crisis samples are similar among the rating values within the investment grade segment for both samples. Both samples have more companies in the lower tier of the investment grade segment.

Daily share prices (business days only) for the individual companies are collected from Bloomberg, ranging back from 1st of Jun 1999 YTD. In order to obtain the abnormal return for all securities during the event period, the S&P 500 Index is used as benchmark index. Index data is also collected from Bloomberg and goes back to beginning 2000. As a proxy for the risk free rate we use the generic 3-month treasury bill. This data is collected from Datastream.

Individual company data is retrieved from Bloomberg. All companies are listed US equities, however when looking for balance sheet specific numbers, such as interest coverage ratio or debt-to-equity ratios, to be used as explanatory variables for potential abnormal returns we find large discrepancies in what is reported by individual companies. As a result we filter the data to obtain independent variables containing market data only, available for all companies to avoid any biases in our analysis. It can also be argued that figures from the balance sheet should not impact abnormal returns to such a large extent just around the announcement date, as they are normally more rigid. The independent variables used to control for cross-sectional variations are defined in the methodology section.

One potential bias with the data collected is that it is a relatively small sample, which can lead to skewed results when it comes to measuring the impact of a downgrade. The whole data sample may consist of a larger portion of companies that for some reason react more strongly to downgrades. This can be because they operate in certain industries where the credit rating is more important, or that they have an investor base that put more weight on ratings. Another bias that we potentially see is that there is no information as to why there has been a downgrade. If the downgrade is motivated by changes in financials, such as earnings etc. there should be a larger impact on share prices as those measures are more linked to the share price and investors care more about them. A downgrade due to a controlled change in capital structure on the other hand may not be of concern to equity holders, thus there might not be such a large impact on share prices.

Another potential bias with our data is that the post-crisis sample is too close to the financial crisis. As can be seen in the density graphs above, the timing of the downgrades is to a large extent skewed to the beginning of 2009 for our post-crisis sample. As investors' were so risk-averse every single negative event regarding a company might have led to amplified impacts. This may potentially lead to our post sample to be characterized by bigger movements in equity prices, both because of lagging effects from the financial crisis but also suffering from amplified effects in a risk-off environment. This can make it difficult to separate the downgrading effect.

Thirdly, one bias we believe our data might suffer from is that the two samples contain different companies. If one sample contains a larger number of companies that are more sensitive to downgrades (i.e. there's a larger portion of Financial Institutions in one sample) the results might be biased and data may show a larger impact of downgrades for this sample. Even if the two samples would contain the same portion of different industries there might still be a bias since there is no guarantee that the share price reaction of a downgrade is the same for all companies within an industry.

# 5. Methodology

## 5.1 Event study

To test the change in impact of downgrades on share price returns we conduct an event study. Over relevant event windows we examine pre and post the financial crisis, starting by calculating the abnormal equity returns. Abnormal returns (ARs) are defined as the stock prediction error that share price return deviates from a market model. We employ the CAPM to estimate the theoretical stock return. The CAPM is defined below:

$$R_{i,t} - R_f = \alpha + \beta_{i,t} * \ R_{mktp} \qquad (1)$$

The model states that the return $R_{i,t}$ above the risk free rate $(R_f)$ (i.e. the excess return) equals beta times the market premium (indicated by $\beta_{i,t} * R_{mktp}$) plus the return above the market premium $(\alpha)$, this last variable should be zero in a perfect market. We regress the actual excess returns $(R_{i,t} - R_f)$ on the monthly market premium $(R_m - R_f)$ to obtain the intercept $(\alpha)$ and the slope $(\beta_{i,t})$ for all stocks. OLS assumptions are tested to ensure the validity of the regressions and it is found that equity returns follow a normal distribution. We apply a cautious approach and use robust standard errors in the regressions[1]. In the regressions we use monthly return data 5 years back to adjust for any "extraordinary" events in the market.

In previous research, it has been more common to use daily returns to calculate betas and alphas when studying daily abnormal returns. However, employing such a method would mean that certain betas and alphas derived for our post sample would be entirely based on data from the midst of the financial crisis, a period with extreme volatile returns. Therefore this study bases betas and alphas on monthly returns. We compute the expected return for every share according to the CAPM, using betas and alphas from two calendar months prior to the announcement date.

The expected return according to the CAPM is:

$$E\left(R_{i,t} \middle| R_{mktp}\right) = \alpha + \beta_{i,t} * R_{mktp} \quad (2)$$

We subtract this from the actual returns in our whole event window (-20 to +20 business days) to obtain the abnormal returns:

$$AR_{i,t} = (R_{it} - R_{f)} - \alpha - \beta_{i,t} * R_{mktp} \qquad (3)$$

The abnormal returns are summarized over the estimation windows of interest, in order to obtain the cumulative abnormal returns (CAR).

$$CAR_{i,t} = \sum_{i}^{t} AR_{i,t} \qquad (4)$$

[1] See Econometric Data Correction section on how to test for OLS assumptions

This methodology is in line with previous research such as Holthausen & Leftwich (1992).

We look at four different estimation windows. Our main estimation window is between t=-5 and t=+5, taking into account both the time pre and post the announcement date. In addition we look at a long-term window ranging from t=-20 to t=+20 days, a post-event estimation window between t=+2 and t=+10 and finally a pre-event estimation window between t=-10 to t=-2.

The main group we look at consists of separate companies being downgraded pre- and post-crisis (excluding the duplicates in our sample). The reason why we want to do this distinction is to see whether or not being downgraded two times has any additional effects compared to companies receiving their first downgrade.

To test if CARs are significant we us a Brown-Warner test, which is defined as:

$$(\sum \frac{CAR}{N})/\sigma(\sum \left(\frac{CAR}{N}\right)^{0,5} \sim \text{t with N-2 degrees of freedom}$$

## 5.2 Cross sectional analysis

In order to explain cross-sectional variations and isolate the effects of the downgrade we do multivariate regression analysis on the results of CARs from the window spanning. As the dependent variable we use the CARs over the announcement date (t=-5 to t=+5). We formulate our multivariate regression as:

$$\begin{aligned} CAR_{i,t} = \alpha + \beta_1 * Downgrade + \ \beta_2 * Historical\ Call\ Implied\ Vol + \ \beta_3 * logmarketcap + \beta_4 \\ * Negative\ Outlook + \beta_5 * marketvolatility + \beta_6 * Financial\ Leverage + \beta_7 * drift \\ + (\beta_8 * Downgraded\ 0708) + \varepsilon_i \end{aligned}$$

### 5.2.1 Variables used in the regressions

- ***Downgrade***

  First we rank all S&P's investment grade ratings (from AAA=10 to BBB-=1), and then define the downgrade variable as the difference between the pre-downgrade value and the post-downgrade value. For example, for a company being downgraded from AAA (10) to AA (8), the downgrade variable takes the value 0 in t=-20 to t=-1, and then takes the value 2 in the period t=0 to t=20.

This is our main variable and is aimed to measure the impact of the downgrade event. The coefficient is expected to be negative and thus have a negative effect on cumulative abnormal returns.

- ***Historical Call Implied volatility***

  The historical call implied volatility measures the implied volatility for underlying securities calculated from a weighted average of the implied volatilities of the two closest call options. For all securities, the contract that is used is the closest pricing contract month that is expiring at least 20 business days out from any given date. This variable is interesting to include since it provides the future volatility implied by the options market around the downgrade event. A stronger belief in volatile share prices should be reflected in this variable.

- ***Log marketcap***

  This variable is the natural logarithm of the firm's market capitalization. This variable may contain additional information about the degree of market anticipation. Smaller firms should have a larger degree of informational asymmetry, thus perhaps increasing the impact of a downgrade.

- ***Negative outlook***

  This variable tries to capture market anticipation. The variable is a dummy variable that takes the value 1 if the company has a negative outlook assigned by S&P and the value 0 if it has a stable outlook (no company has a positive outlook in our samples). When a negative outlook is at hand we expect a higher degree of market anticipation and a lower impact of the actual announcement.

- ***Market volatility***

  This variable is intended to capture the overall volatility in the market. As a proxy for this we use the standard deviation of the 3-month generic US treasury bill. A larger deviation in this parameter should indicate a more unstable market and an impact of a rating change should be larger.

- ***Financial Leverage***

  The variable financial leverage is defined as the average total assets divided by the average of total common equity. Average is defined as the average between opening balance and closing balance. This variable should be able to capture a firm's increased cost of capital due to an increase in debt or decrease in solvency, which might have led to a downgrade.

- ***Drift***

  Drift is a complementary measure to market anticipation. It is defined as the aggregated abnormal return between t=-20 and t=-11 before the announcement date. The variable should give an indication on how much new information a downgrade provides. If there is large negative drift it shows that the market may have already priced in the fundamental change in the firm and that the actual downgrade is really just postponed information.

- ***Downgraded 07-08***

  Being downgraded once should have a different impact than being downgraded twice. This variable is only applied to the sample post the financial crisis to capture if the company was downgraded during 07-08, which we have defined as our window of the financial crisis. This is also a dummy variable with the value 1 if the company was downgraded during 07-08 and 0 if it was not.

### 5.2.2 Econometric Data Corrections

In order to ensure the validity of our cross sectional multivariate regression we must make sure that our data is adjusted for potential errors. The lack of heteroscedasticity is of large importance in order to have a valid OLS regression. This means that the variances of the error terms are not constant and varies with the dependent or some of the explanatory variables. This means that

$$E(u^2) = \sigma^2$$

We test for heteroscedasticity by running the Breusch-Pagan test. We also test for multicollinearity between our independent variables by calculating their pair-wise correlations variables and running a Variance Inflation Factor test, which measures how much the variances of the regression coefficients are inflated because of collinearity.

VIF($\beta_i$) is calculated using the following formula:

$$\text{VIF}(\beta_i)=\frac{1}{1-R^2}$$

As a rule of thumb if VIF($\beta_i$)>5 , multicollinearity is high.

The error terms in an OLS regression are assumed to be normally distributed. If this assumption is violated the significance of our model cannot be validated. A simple way to test for normality is a Jarque-Bera test. This is defined as follow[2]:

$$JB = n[\frac{S^2}{6} + \frac{(K-3)^\wedge 2}{24}]\sim\chi^\wedge 2$$

The cross sectional model will fit differently to the varying periods of time. Foremost the two sub samples, for which we run each event study, do not contain the same companies, which might be spurious bias. One sample might consist of a greater portion of firms that are more sensitive to rating changes depending on which industry they operate in. Therefore we want to test if the coefficients affected by a downgrade are significantly different between the two sub samples. By running such a test we can determine if there is a statistical difference and use our multivariate regression results to determine whether this difference has changed in a positive or negative direction. The test we run is a z-test based on the work of Clogg et al (1995), which is defined as:

$$Z = \frac{\beta_1 - \beta_1^*}{\sqrt{\sigma_{\beta_1}^2} + \sqrt{\sigma_{\beta_1^*}^2}}$$

where $\beta_1$ is the downgrade coefficient pre-crisis and $\beta_1^*$ is the downgrade coefficient post-crisis.

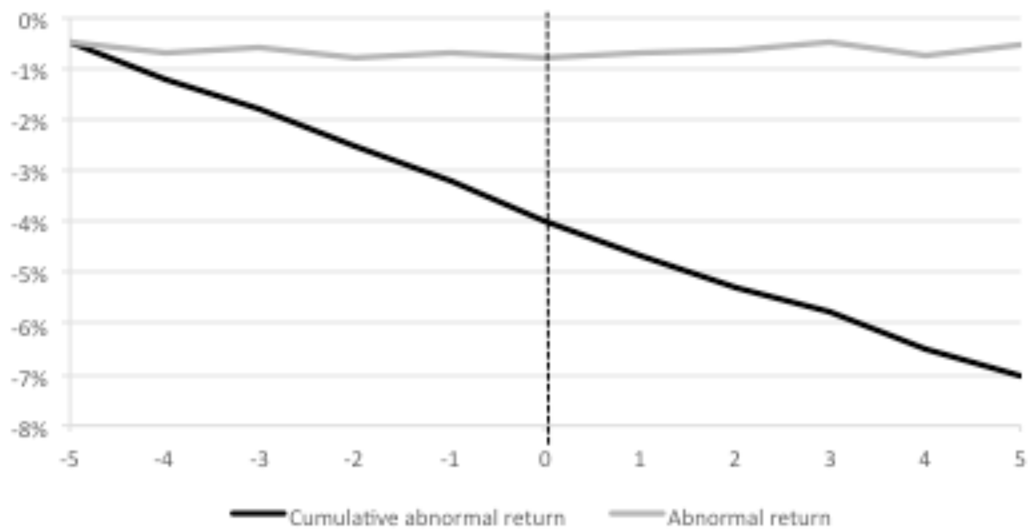
[2] This test both takes into account the skewness and kurtosis of the error terms. However, STATA does not allow us to conduct this test, so we will use a slightly modified version of the Jarque-Bera test, suitable for STATA.

# 6. Results

## 6.1 Cumulative abnormal returns

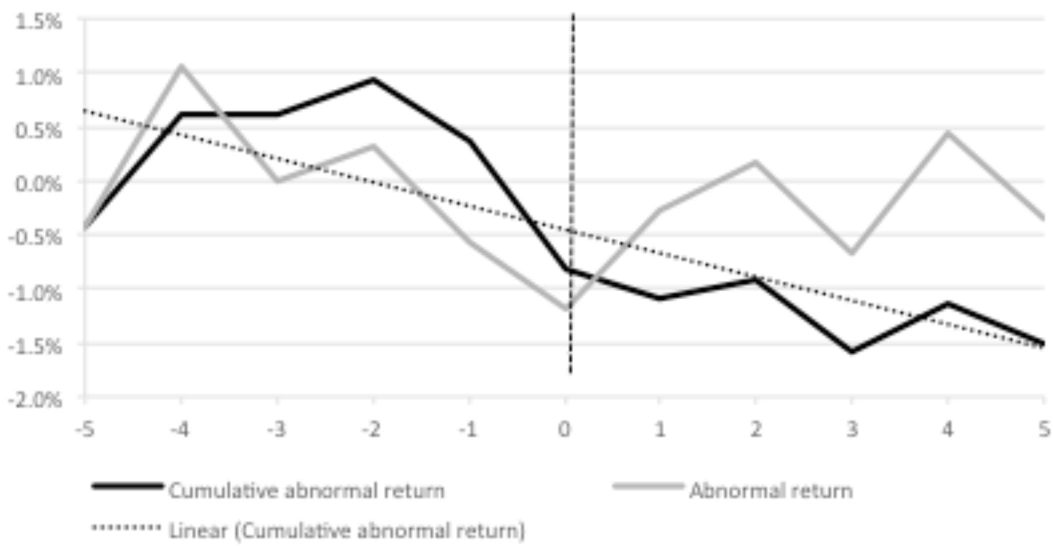
We focus on the event window from 5 days prior to the announcement to 5 days after. Many previous studies have chosen to focus on another event window, namely one day before announcement until one day after. The rationale for our choice is that we want to see the effects of not only the announcement itself, but of the actual downgrade, which often have effects both several days pre-announcement (when information regarding the downgrade might be leaked), and post-announcement (when investors seek not to dump all their shares at once, but rather rebalance their portfolios in a way that does not excessively affect the share price).

*Graph 5 - Average abnormal return and development of cumulative abnormal return Pre-crisis period (t=-5 to t=5)*




As we can see in Graph 5, the average abnormal return for the stocks in the main sample downgraded in the period 05-06 are negative throughout the event window t = -5 to t = 5, they have a negative drift. In this graph it is difficult to see any clear effect of the downgrade announcement on abnormal returns.

*Graph 6 - Average abnormal return and development of cumulative abnormal return Post-crisis period (t=-5 to t=5)*




In Graph 6 we see the average abnormal return during the event window for companies in the main sample downgraded in the period 09-10. The impact of the downgrade announcement is more evident here, with average abnormal returns falling on the announcement date and then rising again in the post-announcement period. However, the magnitude of the negative effect during the entire window is much smaller than in the pre-crisis event study.

The same trends with companies on a negative drift pre-crisis and more volatile abnormal returns post-crisis are seen for this event window in the duplicates sample (see Graph 18 and Graph 19).

## 6.2 Significance of cumulative abnormal returns

The significance of the cumulative abnormal returns differ greatly between the two event studies. Pre-crisis we find that the CAR are strongly negative and highly significant for all event windows, which is consistent with the findings in Graph 5 that these companies have a negative drift. Post-crisis figures are rather ambiguous and are only negative in two of the event windows, with relatively low significance levels.

*Table 2 - Mean and t-value for cumulative abnormal returns*

| ***Pre-crisis*** | | | | |
|---|---|---|---|---|
| **Day** | **(-5 : 5)** | **(-20 : 20)** | **(-10 : 0)** | **(0 : 10)** |
| Mean | -0.0386 | -0.1206 | -0.0344 | -0.0375 |
| t-value | -12.23 | -25.33 | -11.22 | -12.06 |
| | | | | |
| ***Post-crisis*** | | | | |
| **Day** | **(-5 : 5)** | **(-20 : 20)** | **(-10 : 0)** | **(0 : 10)** |
| Mean | -0.0045 | 0.0283 | 0.0094 | -0.0096 |
| t-value | -1.12 | 6.35 | 2.67 | -2.47 |

The findings are similar in the duplicates sample, with negative and highly significant cumulative abnormal returns in all event windows pre-crisis, and inconclusive results post-crisis (see Table 17).

## 6.3 Cross sectional analysis

Before running any regressions we need to make sure the OLS assumptions are applicable to the data set.  As demonstrated in Table 2, the data does not show important signs of multi-collinearity between the explanatory variables, meaning the effects caused by them are not amplified or skewed due to high correlation with other explanatory variables. We also find that the distribution of the residuals of the linear regression model resembles very much to a normal distribution, which is required within the OLS framework. Furthermore, the data shows significant signs of heteroscedasticity (see Table 20), but this effect is compensated by using robust standard errors in our regressions.

*Table 3 - Cross sectional regression on event window Pre-crisis (t=-5 to t=5)*

| ***Pre-crisis*** **Robust** | No. of obs = 638 | | R-squared = 0.5144 | |
|---|---|---|---|---|
| **Cum. ab. return (-5 : 5)** | **Coefficient** | **Std. Err.** | **t** | **P>\|t\|** |
| Downgrade | -0.0231537 | 0.0038463 | -6.02 | 0.000 |
| Historical call implied | -0.0019802 | 0.0004105 | -4.82 | 0.000 |
| Log marketcap | 0.0009729 | 0.0024742 | 0.39 | 0.694 |
| Negative outlook | 0.0093712 | 0.0057337 | 1.63 | 0.103 |
| Market volatility | 0.012023 | 0.0031002 | 4.20 | 0.000 |
| Financial leverage | 0.0021987 | 0.0007552 | 4.24 | 0.000 |
| Drift | 0.5946866 | 0.0349072 | 17.04 | 0.000 |
| Constant | 0.02341 | 0.0250626 | 0.93 | 0.351 |

*Table 4 - Cross sectional regression on event window Post-crisis (t=-5 to t=5)*

| ***Post-crisis*** **Robust** | No. of obs = 1,067 | | R-squared=0.2167 | |
|---|---|---|---|---|
| **Cum. ab. return (-5 : 5)** | **Coefficient** | **Std. Err.** | **t** | **P>\|t\|** |
| Downgrade | 0.0119748 | 0.0061977 | 1.93 | 0.054 |
| Historical call implied | -0.0007133 | 0.0001518 | -4.70 | 0.000 |
| Log marketcap | 0.0082179 | 0.0033317 | 2.47 | 0.014 |
| Negative outlook | 0.0322553 | 0.0077983 | 4.14 | 0.000 |
| Market volatility | 0.0019181 | 0.0072677 | 0.26 | 0.792 |
| Financial leverage | 0.0014149 | 0.000408 | 3.47 | 0.001 |
| Drift | 0.4707189 | 0.0285598 | 16.48 | 0.000 |
| Downgraded 07-08 | 0.0021269 | 0.009643 | 0.22 | 0.824 |
| Constant | -0.060921 | 0.0326208 | -1.87 | 0.062 |

As presented in Table 3 and Table 4 above, the cumulative abnormal returns during the chosen event window (t=-5 to t=5) are largely explained by the drift of the company, i.e. the abnormal returns realized by the company prior to the event window. Furthermore, we see that the historical call implied volatility, which is a proxy for future volatility, has a significant negative impact in both periods and financial leverage seems to affect cumulative abnormal returns positively in both time periods and the same goes for the variable negative outlook.

What is more striking is that the downgrade variable has different effects pre- and post the crisis; pre-crisis the downgrade coefficient is negative at a high significance level; post-crisis the effect is reversed but with a lower significance. In the duplicate sample, the pre-crisis downgrade coefficient is relatively significant and negative, whereas the post-crisis regression show insignificant results (see Table 18 and 19).

### 6.4 Hypothesis test

The calculations from our hypothesis test, testing if the difference between the downgrade coefficients pre- and post-crisis is distinct from 0 are shown below:

$$N\left( Z = \frac{\beta_1 - \beta_1^*}{\sqrt{\sigma_{\beta_1}^2} + \sqrt{\sigma_{\beta_1^*}^2}} \right) = 0.000235$$

As we can see, there does seem to be a significant change in the correlation between equity returns and S&P downgrades at the 1% level.

## 7. Analysis and discussion

In this article we study the change in impact that credit rating downgrades by S&P have on equity prices pre and post the financial crisis in 2007-2008. Consistent with previous research we find significant evidence for negative abnormal returns around the announcement date of a downgrade. Pre-crisis we find that the coefficient associated with the change in credit rating is negative and significant at the 1%. Looking at the coefficient associated with the change in rating post the financial crisis; we find that it is positive and significant at the 10%. This supports our conjecture that there might be a greater impact of downgrades pre-crisis compared to post-crisis. In order to adjust for the fact that the pre and post samples do not consist of the same firms we run a hypothesis test to see if the downgrade coefficients are significantly different from zero. This test shows that the null hypothesis can be rejected at the 1% level. This suggests that the impact of downgrades has decreased due to the financial crisis.

The effect of being put on credit watch list is significant at the 1% for the post-crisis sample (indicated by the Negative outlook variable). The positive coefficient suggests that the variable negative outlook affects the degree of market anticipation, resulting in less negative abnormal returns around the announcement date for companies with negative outlook. This suggests that there may be less informational asymmetry after the financial crisis, and that the informational value that CRAs add has decreased.

Pre-crisis the explanatory value of the model is relatively high ($R^2_{Pre} = 0.5144$). Post-crisis the explanatory value of the model decreases ($R^2_{Post} = 0.2167$). This is also an indication that abnormal returns around the announcement date of a downgrade are dependent on other factors post the financial crisis.

Possible explanations of why there is a difference in impact on equity returns around a downgrade event pre and post the financial crisis can be:

(1) ***The negative effect of downgrades has already been priced in.***
(2) ***Changes in rating are more frequent post-crisis, thus decreasing the market reaction of a downgrade.***
(3) ***Investors perceive CRAs as unreliable in the aftermath of the financial crisis, thus putting less emphasis on rating announcements.***

The negative outlook coefficient increases in magnitude and significance post-crisis, while the downgrade coefficient clearly decreases between the post and pre sample. This supports our first theory that markets have become more efficient post-crisis, since the effect of the downgrade already has been priced in before the actual announcement. The drift variable also supports this fact during both time periods but might not be the best indicator since it is composed of the cumulative abnormal returns up to 11 days before the announcement date, which might be too close to the announcement date to give a fair result. Another source of market anticipation can be market capitalization. Smaller firms tend to have more informational asymmetry and fewer analysts following, suggesting a larger impact of a credit event. In our results we find that the coefficient associated with a firm's size has a positive impact, significant at the 1% post the financial crisis. This is not the case pre the financial crisis. There is a possibility however that this is not entirely attributed to an increased anticipation in financial markets, but rather that our post sample on average contains more companies with a larger market capitalization.

Another reason for the decreasing impact of rating changes is that downgrades are more frequent post the financial crisis. This might be because of S&P applying a more cautious approach, trying to regain its reputation, which was harmed during the financial crisis. Pre-crisis, S&P might have downgraded companies with seriously deteriorating credit quality, suggested by the negative drift of the downgraded companies. Post-crisis, S&P may have applied a looser rating policy, downgrading companies showing less signs of deteriorating credit quality. It also might be because the economy still was in recession and that downgrades were motivated in many cases. Either way, market participants might place less emphasis on rating changes, as there might exist a "cry wolf" mentality among investors.

CRAs played a big role in the last financial crisis when skewed incentive systems may have led to overrated securities. CRAs suffered severely from this negative attention and this might offer one explanation why the impact of downgrades has decreased. As the credibility for S&P might have decreased, investors seek information from other sources. There have been studies verifying that damaged reputation leads to a decreased impact of downgrades. Reputational changes and the change in impact on bond yields, have been examined in previous studies. Allen & Dudney (2006) studied the impact of rating agency reputation on local government bond yields. They found that Moody's influence on bond yields decreased after an investigation in 1995, regarding market misconduct, by the Department of Justice.

# 8. Conclusion & Future research

The findings in this thesis show that S&P's impact on equity returns has decreased post the financial crisis. We study the abnormal equity returns around the announcement date of a downgrade for two separate samples, one before the financial crisis and one after the financial crisis. In line with previous research we find that downgrades are associated with negative abnormal returns around the announcement date. We regress cumulative abnormal returns over the announcement date (t=-5 to t=5) on a set of explanatory variables and find that the impact of the actual downgrade has decreased post the financial crisis. We also find that being given a negative outlook prior to the actual downgrade event has a positive impact on CARs over the announcement date for our post-crisis sample. This suggests that markets have become more efficient after the financial crisis and that downgrades are anticipated to a larger extent. The other possible explanations we offer is that downgrades have become more frequent post-crisis, which could lead to investors putting less emphasis on credit ratings. The third explanation we discuss to this finding is that investors perceive S&P as unreliable in the aftermath of the financial crisis, leading investors to seek information from other sources.

Suggested future research on the topic could be to conduct a similar study on bond returns instead of equity returns. As we have established the decreasing impact of downgrades on equity returns the impact on bond returns should be similar and would provide more evidence for S&P's decreasing influence. One could also expand this analysis to cover non-investment grade companies and other geographical areas. In this thesis we focus on S&P only, but further studies could be done comparing CRAs and see if a particular CRA experiences a larger decreasing impact. This analysis could also be expanded to include split-rated issuances compared to dual-rated issuances.

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## *Databases*

**Bloomberg data base**. (2013)

**Datastream.** (2013)

# Appendix

*Table 5 - Correlation matrix of estimated regression coefficients Pre-crisis*

| | Downgrade | Hist. call imp. | Log mktcap | Neg. outl. | Market vol. | Fin. lev. | Drift | Constant |
|---|---|---|---|---|---|---|---|---|
| **Downgrade** | 1.0000 | | | | | | | |
| **Historical call implied** | 0.0609 | 1.0000 | | | | | | |
| **Log marketcap** | -0.1041 | 0.2067 | 1.0000 | | | | | |
| **Negative outlook** | 0.5674 | 0.0354 | -0.0326 | 1.0000 | | | | |
| **Market volatility** | -0.1470 | -0.0553 | 0.0481 | -0.1543 | 1.0000 | | | |
| **Financial leverage** | 0.1793 | 0.1219 | -0.2831 | 0.1220 | 0.1164 | 1.0000 | | |
| **Drift** | 0.0838 | 0.1301 | -0.1521 | 0.0538 | 0.0487 | 0.1115 | 1.0000 | |
| **Constant** | -0.0744 | -0.5598 | -0.8860 | -0.0960 | -0.1638 | 0.0566 | 0.0956 | 1.0000 |

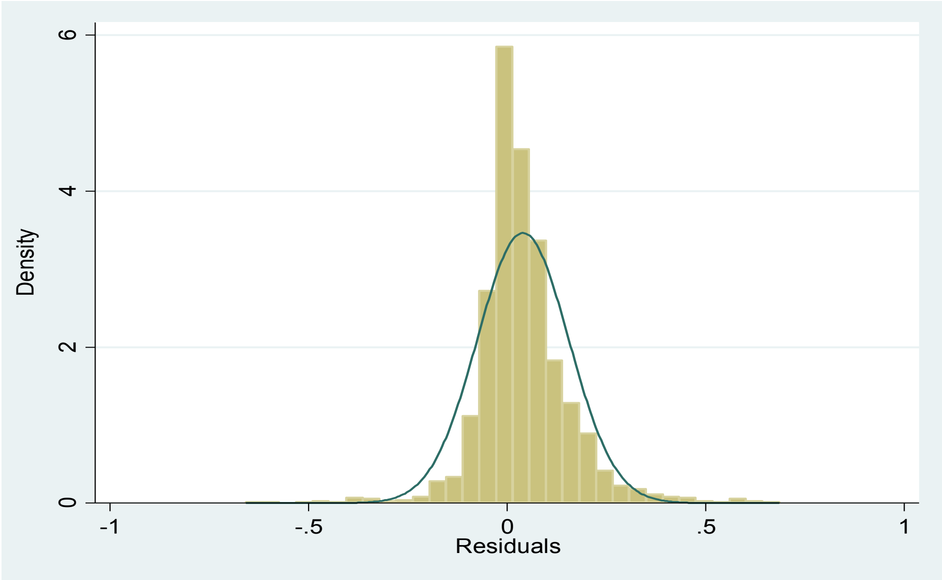
This table presents the pair wise correlation between the independent regression factors pre-crisis; the numbers of notches downgraded (Downgrade), the future implied volatility (Hist Call Imp), the size of the company (Log mkt cap), the dummy variable indicating a negative outlook (Neg Outl), the volatility of the market (Market vol.), the level of financial debt (Fin lev), the aggregated abnormal return before the announcement date (Drift).

*Table 6 - Correlation matrix of estimated regression coefficients Post-crisis*

| | Downgrade | Hist. call imp. | Log mktcap | Neg. outl. | Market vol. | Fin. lev. | Drift | Dwgr. 07-08 | Constant |
|---|---|---|---|---|---|---|---|---|---|
| **Downgrade** | 1.0000 | | | | | | | | |
| **Historical call implied** | -0.0890 | 1.0000 | | | | | | | |
| **Log marketcap** | -0.1023 | 0.1804 | 1.0000 | | | | | | |
| **Negative outlook** | 0.4851 | 0.0048 | -0.0896 | 1.0000 | | | | | |
| **Market volatility** | -0.0043 | -0.3750 | 0.0125 | -0.0557 | 1.0000 | | | | |
| **Financial leverage** | 0.0340 | -0.4216 | 0.1228 | -0.0350 | -0.1156 | 1.0000 | | | |
| **Drift** | -0.0463 | 0.0576 | 0.1846 | -0.0222 | 0.0296 | 0.0071 | 1.0000 | | |
| **Downgraded 07-08** | -0.0090 | -0.1556 | -0.0160 | 0.0223 | -0.0757 | 0.1495 | -0.0759 | 1.0000 | |
| **Constant** | -0.0825 | -0.2493 | -0.9390 | -0.0627 | -0.1285 | -0.1389 | -0.1910 | -0.0292 | 1.0000 |

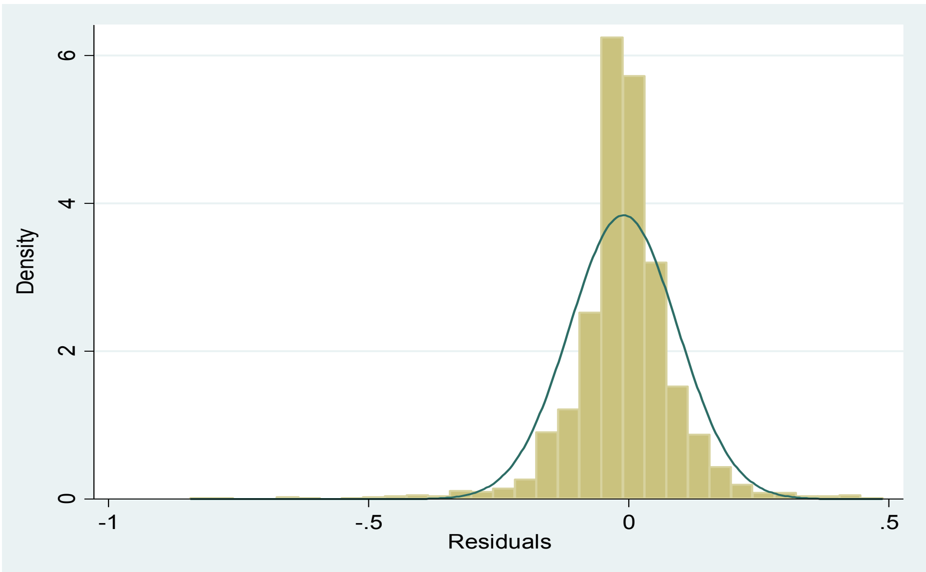
This table presents the pair wise correlation between the independent regression factors post-crisis; the numbers of notches downgraded (Downgrade), the future implied volatility (Hist Call Imp), the size of the company (Log mkt cap), the dummy variable indicating a negative outlook (Neg Outl), the volatility of the market (Market vol.), the level of financial debt (Fin lev), the aggregated abnormal return before the announcement date (Drift), the dummy variable indicating if the company has been downgraded during the financial crisis (Dowgr 07-08)

*Graph 7 – Regression residuals pre-crisis (t=-5 to t=5)*



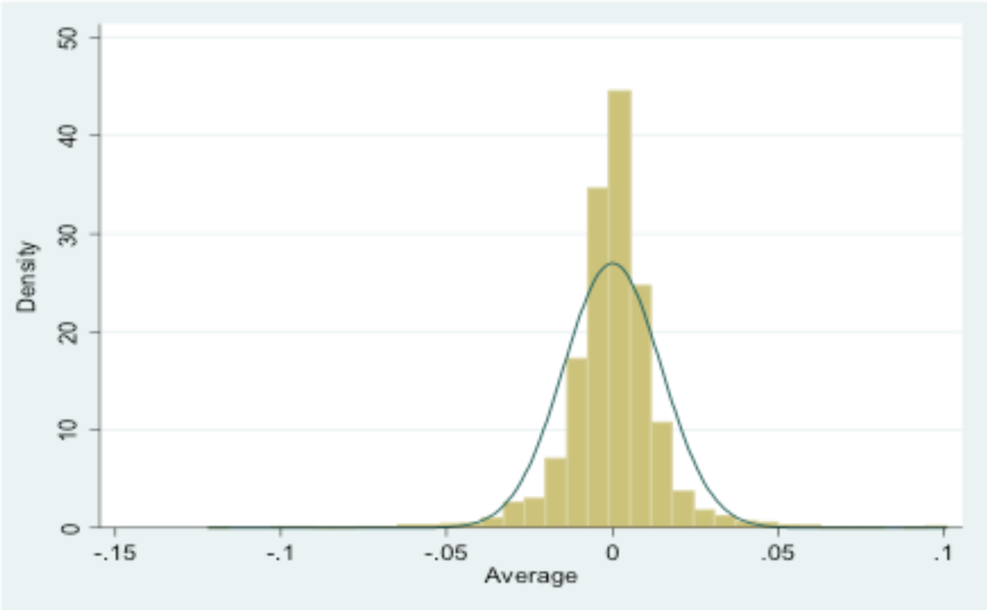

Graph showing the residuals of the multivariate regression pre-crisis. The residuals seem to follow a normal distribution with minor tails.

*Graph 8 – Regression residuals post-crisis (t=-5 to t=5)*




Graph showing the residuals of the multivariate regression post-crisis. The residuals seem to follow a normal distribution with minor tails.

*Graph 9 - Residuals of equity returns*




Graph showing the distribution of the average equity returns for both samples. The returns seem to follow a normal distribution.

*Table 7 - VIF table Pre-crisis*

| ***VIF Pre-crisis*** | | |
|---|---|---|
| **Independent variable** | **VIF** | **1/VIF** |
| Downgrade | 1.53 | 0.654 |
| Historical call implied | 1.13 | 0.885 |
| Log marketcap | 1.22 | 0.820 |
| Negative outlook | 1.49 | 0.671 |
| Market volatility | 1.07 | 0.935 |
| Financial leverage | 1.19 | 0.840 |
| Drift | 1.06 | 0.943 |

VIF table Pre-crisis for the main sample. As a rule of thumb, a VIF value of more than 5 suggests that data suffers from high collinearity. The collinearity in this sample is thus low.

*Table 8 - VIF table Post-crisis*

| ***VIF Post-crisis*** | | |
|---|---|---|
| **Independent variable** | **VIF** | **1/VIF** |
| Downgrade | 1.33 | 0.752 |
| Historical call implied | 1.77 | 0.565 |
| Log marketcap | 1.16 | 0.862 |
| Negative outlook | 1.32 | 0.758 |
| Market volatility | 1.37 | 0.730 |
| Financial leverage | 1.47 | 0.680 |
| Downgraded 07-08 | 1.06 | 0.943 |
| Drift | 1.04 | 0.962 |

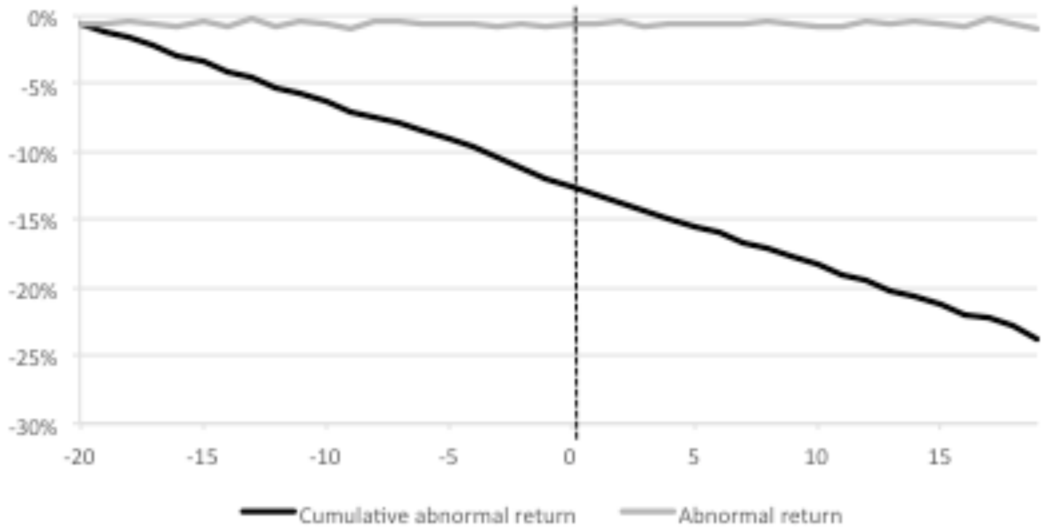
VIF table Post-crisis for the main sample. As a rule of thumb, a VIF value of more than 5 suggests that data suffers from high collinearity. The collinearity in this sample is thus low.

*Table 9 - Sktest statistics for pre and post regressions*

| **Regression** | **Pr(skewness)** | **Pr(kurtosis)** | **Pr(>chi2)** |
|---|---|---|---|
| Residuals pre-crisis (-5:5) | 0.000 | 0.000 | 0.000 |
| Residuals post-crisis (-5:5) | 0.000 | 0.000 | 0.000 |

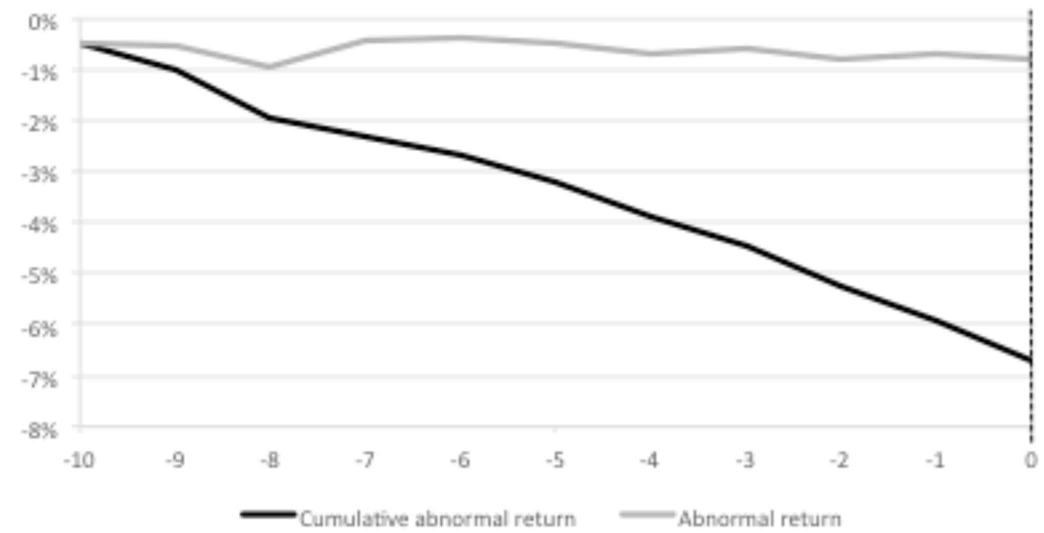
Probabilities that the residuals in the respective regressions are skewed (above a certain threshold), show kurtosis (above a certain threshold), and lastly are both skewed and show kurtosis (above a certain threshold). The residuals in these samples seem to be normally distributed..

*Graph 10 - Average abnormal return and development of cumulative abnormal return Pre-crisis (t=-20 to t=20)*



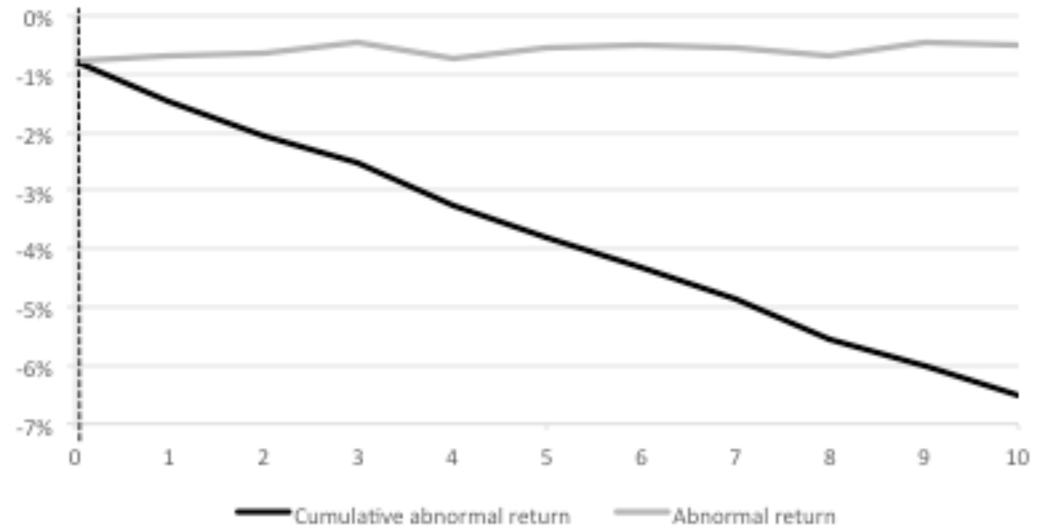

Development of abnormal and cumulative abnormal returns over the whole event window (t=-20 to t=20) for the pre sample. Abnormal returns seem to have a negative drift for the pre sample.

*Graph 11 - Average abnormal return and development of cumulative abnormal return Pre-crisis (t==-10 to t=0)*



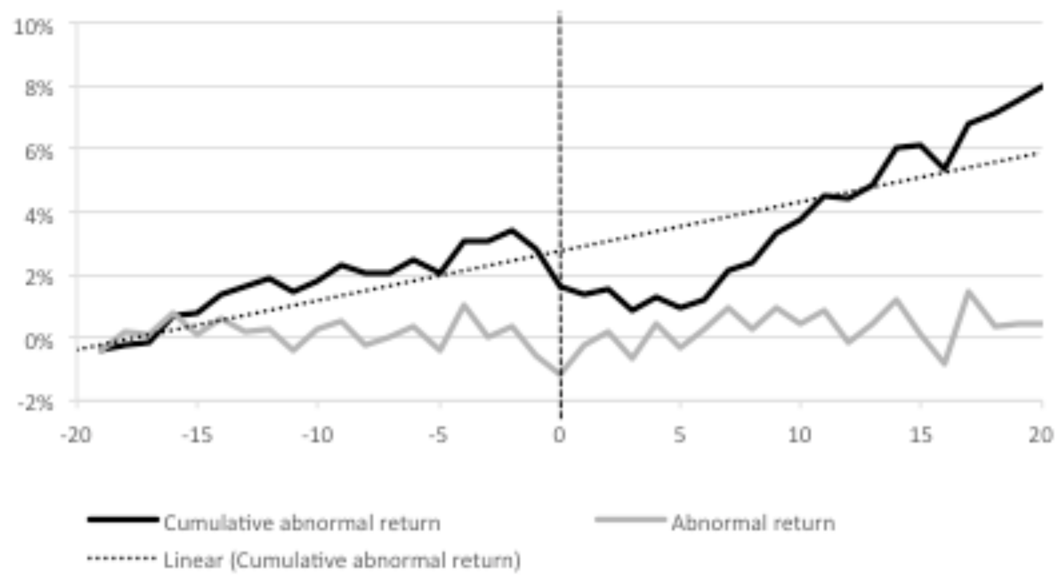

Development of abnormal and cumulative abnormal returns over the pre event window (t=-10 to t=0) for the pre sample. Abnormal returns seem to have a negative drift before the announcement date of the downgrade.

*Graph 12 - Average abnormal return and development of cumulative abnormal return Pre-crisis (t=0 to t=+10)*



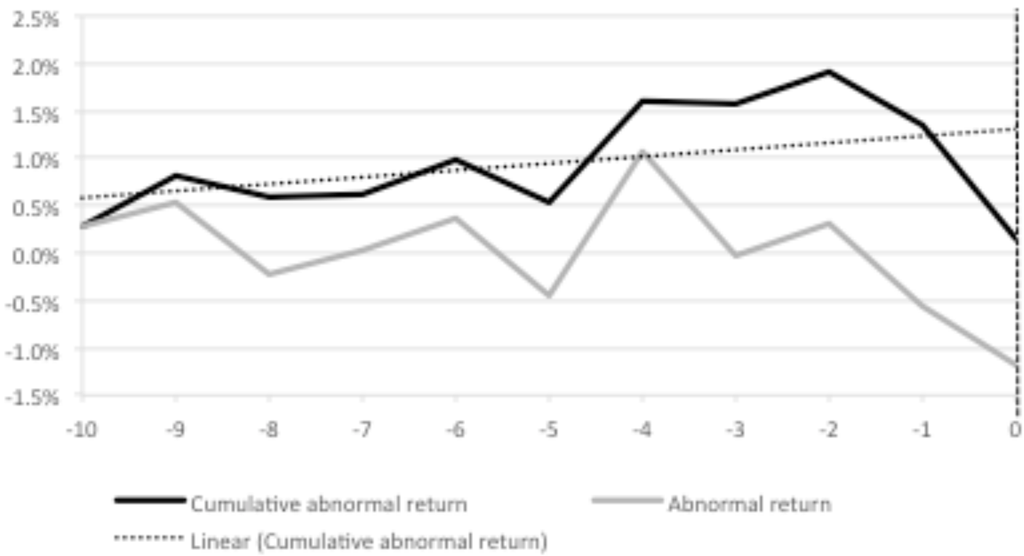

Development of abnormal and cumulative abnormal returns over the post event window (t=-0 to t=10) for the pre sample. The negative drift for abnormal returns continues after the announcement date of the downgrade.

*Graph 13 - Average abnormal return and development of cumulative abnormal return Post-crisis (t=-20 to t=20)*



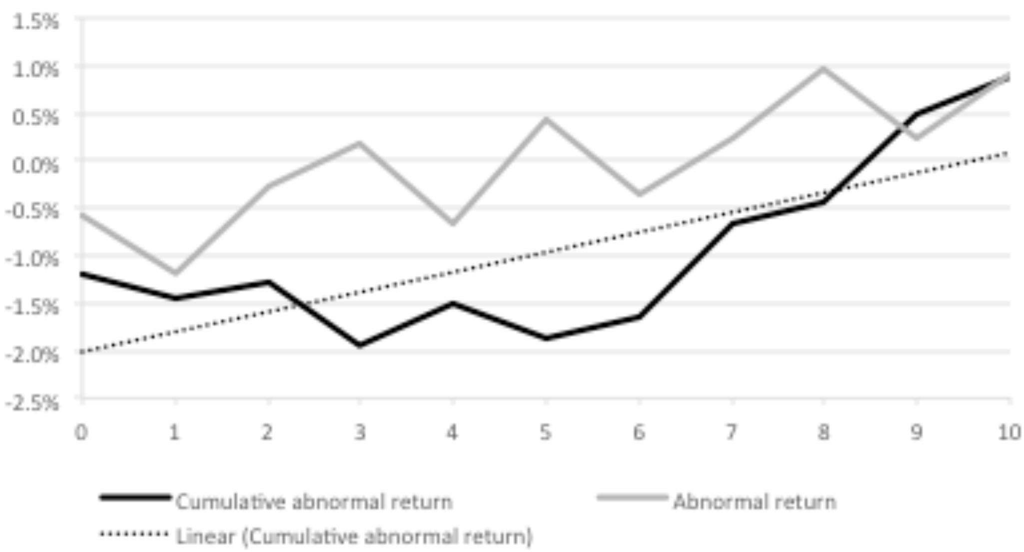

Development of abnormal and cumulative abnormal returns over the whole event window (t=-20 to t=20) for the post sample. Abnormal returns see a small decrease just before the announcement date and recover after the announcement.

*Graph 14 - Average abnormal return and development of cumulative abnormal return Post-crisis (t=-10 to t=0)*




Development of abnormal and cumulative abnormal returns over the pre event window (t=-10 to t=0) for the post sample. Abnormal returns see a small decrease from t=-4 to t=0. It does not seem that the downgrades are anticipated 10 days before the announcement date of the downgrade.

*Graph 15 - Average abnormal return and development of cumulative abnormal return Post-crisis (t=0 to t=10)*




Development of abnormal and cumulative abnormal returns over the post event window (t=0 to t=10) for the post sample. Abnormal returns seem to recover after the announcement date of the downgrade.

*Table 10 - Companies in the Pre-crisis sample*

| Companies Pre-crisis | |
|---|---|
| Acuity Brands Inc | Kaman Corp |
| American Axle & Manufacturing Holdings Inc | KeyCorp |
| American International Group Inc | Kohl's Corp |
| Anadarko Petroleum Corp | Kroger Co |
| Archer-Daniels-Midland Co | Macy's Inc |
| AutoNation Inc | Mattel Inc |
| **Beam Inc** | McClatchy Co |
| Belo Corp | MDU Resources Group Inc |
| Boston Scientific Corp | Middlesex Water Co |
| Brinker International Inc | Mohawk Industries Inc |
| Bunge Ltd | **Molson Coors Brewing Co** |
| Cameron International Corp | Murphy Oil Corp |
| **CBS Corp** | National Western Life Insurance Co |
| CenturyLink Inc | New York Times Co |
| Computer Sciences Corp | News Corp |
| Cooper Tire & Rubber Co | Noble Energy Inc |
| CVS Caremark Corp | Northeast Utilities |
| **Cytec Industries Inc** | NuStar Energy LP |
| Deluxe Corp | ONEOK Inc |
| Dominion Resources Inc | ONEOK Partners LP |
| Dover Corp | Pepco Holdings Inc |
| Edison International | PHH Corp |
| EI du Pont de Nemours & Co | Pinnacle West Capital Corp |
| Empire District Electric Co | RadioShack Corp |
| **Energen Corp** | RPM International Inc |
| EQT Corp | **RR Donnelley & Sons Co** |
| Exelon Corp | Safeway Inc |
| **Fifth Third Bancorp** | SEACOR Holdings Inc |
| Furniture Brands International Inc | Sherwin-Williams Co |
| Gannett Co Inc | Snap-on Inc |
| GTE Southwest Inc | Sonoco Products Co |
| HCP Inc | Southwestern Energy Co |
| Health Management Associates Inc | Sprint Nextel Corp |
| Hill-Rom Holdings Inc | Telephone & Data Systems Inc |
| **Hillshire Brands Co** | Tyson Foods Inc |
| HJ Heinz Co | United Fire Group Inc |
| HJ Heinz Co | United States Cellular Corp |
| Home Depot Inc | Universal Corp |
| **Huntington Bancshares Inc** | Weingarten Realty Investors |
| Janus Capital Group Inc | **Verizon Communications Inc** |
| **Johnson Controls Inc** | **Whirlpool Corp** |
| Jones Group Inc | |

Companies in **bold** are included in both pre and post samples, and are treated separately in the duplicates sub-sample.

*Table 11 - Companies in the Post-crisis sample*

| Companies Post-crisis | | |
|---|---|---|
| Avon Products Inc | Hubbell Inc | Regency Centers Corp |
| Bank of America Corp | Humana Inc | Regions Financial Corp |
| BB&T Corp | **Huntington Bancshares Inc** | **RR Donnelley & Sons Co** |
| **Beam Inc** | Hyatt Hotels Corp | SCANA Corp |
| Bemis Co Inc | Illinois Tool Works Inc | Selective Insurance Group Inc |
| Berkshire Hathaway Inc | Integrys Energy Group Inc | Southwest Airlines Co |
| BlackRock Inc | Jefferies Group LLC | State Auto Financial Corp |
| Boeing Co/The | **Johnson Controls Inc** | State Street Corp |
| BorgWarner Inc | Kemper Corp | SunTrust Banks Inc |
| Camden Property Trust | KeyCorp | Susquehanna Bancshares Inc |
| Capital One Financial Corp | Leggett & Platt Inc | Synovus Financial Corp |
| Carnival Corp | Lexmark International Inc | TCF Financial Corp |
| **CBS Corp** | Lincoln National Corp | Textron Inc |
| Cigna Corp | Lowe's Cos Inc | US Bancorp |
| Cincinnati Financial Corp | Marriott International Inc | Walgreen Co |
| Cintas Corp | Matson Inc | Washington Post Co |
| CIT Group Inc | Mercury General Corp | Webster Financial Corp |
| City National Corp/CA | MetLife Inc | Wells Fargo & Co |
| Comerica Inc | MF Global Holdings Ltd | **Verizon Communications Inc** |
| Commercial Metals Co | **Molson Coors Brewing Co** | Weyerhaeuser Co |
| ConAgra Foods Inc | Mondelez International Inc | **Whirlpool Corp** |
| **Cytec Industries Inc** | National Fuel Gas Co | White Mountains Insurance Group Ltd |
| Duke Realty Corp | Nelnet Inc | Vulcan Materials Co |
| Eli Lilly & Co | Newell Rubbermaid Inc | Xerox Corp |
| **Energen Corp** | NextEra Energy Inc | Zions Bancorporation |
| FBL Financial Group Inc | Nordstrom Inc | |
| Fidelity National Financial Inc | Northwest Natural Gas Co | |
| **Fifth Third Bancorp** | Nucor Corp | |
| First Horizon National Corp | NYSE Euronext | |
| First Midwest Bancorp Inc | Omnicom Group Inc | |
| FirstEnergy Corp | OneBeacon Insurance Group Ltd | |
| Fiserv Inc | PACCAR Inc | |
| GATX Corp | PepsiCo Inc | |
| General Electric Co | Pfizer Inc | |
| Genworth Financial Inc | Pitney Bowes Inc | |
| GTE Southwest Inc | PNC Financial Services Group Inc | |
| Harley-Davidson Inc | Portland General Electric Co | |
| Hartford Financial Services Group Inc | Post Properties Inc | |
| Hawaiian Electric Industries Inc | PPG Industries Inc | |
| Herman Miller Inc | Principal Financial Group Inc | |
| **Hillshire Brands Co** | Protective Life Corp | |
| Hospitality Properties Trust | Prudential Financial Inc | |

Companies in **bold** are included in both pre and post samples, and are treated separately in the duplicates sub-sample.

*Table 12 - Correlation matrix of estimated regression coefficients Pre-crisis (duplicate sample)*

| | Downgrade | Hist. call imp. | Log mktcap | Neg. outl. | Market vol. | Fin. lev. | Drift | Constant |
|---|---|---|---|---|---|---|---|---|
| **Downgrade** | 1.0000 | | | | | | | |
| **Historical call implied** | -0.0825 | 1.0000 | | | | | | |
| **Log marketcap** | -0.1882 | -0.0123 | 1.0000 | | | | | |
| **Negative outlook** | 0.5035 | -0.1956 | -0.2784 | 1.0000 | | | | |
| **Market volatility** | -0.1430 | 0.0476 | -0.1135 | -0.0094 | 1.0000 | | | |
| **Financial leverage** | -0.1024 | 0.2103 | 0.1857 | -0.0831 | 0.3509 | 1.0000 | | |
| **Drift** | 0.2526 | 0.3346 | -0.6938 | 0.3416 | -0.2157 | -0.379 | 1.0000 | |
| **Constant** | 0.1562 | -0.3711 | -0.8874 | 0.2887 | -0.1138 | -0.4279 | 0.5959 | 1.0000 |

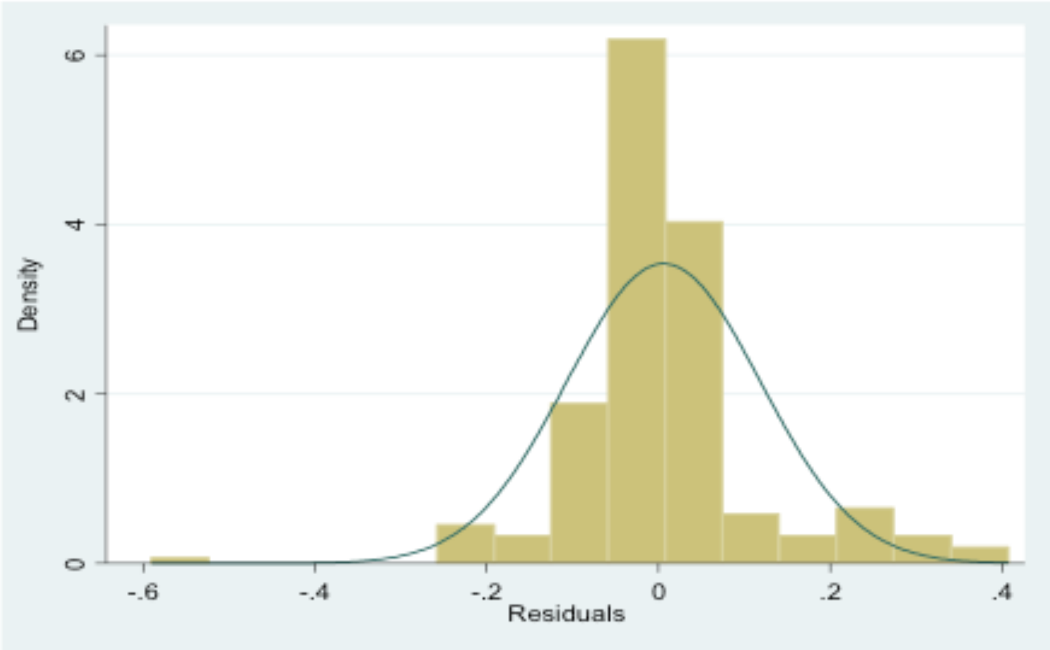
This table presents the pair wise correlation between the independent regression factors pre-crisis for the duplicate sample; the numbers of notches downgraded (Downgrade), the future implied volatility (Hist Call Imp), the size of the company (Log mkt cap), the dummy variable indicating a negative outlook (Neg Outl), the volatility of the market (Market vol.), the level of financial debt (Fin lev), the aggregated abnormal return before the announcement date (Drift).

*Table 13 - Correlation matrix of estimated regression coefficients Post-crisis (duplicate sample)*

| | Downgrade | Hist. call imp. | Log mktcap | Neg. outl. | Market vol. | Fin. lev. | Drift | Dwgr. 07-08 | Constant |
|---|---|---|---|---|---|---|---|---|---|
| **Downgrade** | 1.0000 | | | | | | | | |
| **Historical call implied** | -0.3346 | 1.0000 | | | | | | | |
| **Log marketcap** | -0.4247 | 0.8809 | 1.0000 | | | | | | |
| **Negative outlook** | 0.8301 | -0.3367 | -0.4661 | 1.0000 | | | | | |
| **Market volatility** | -0.2596 | -0.1378 | 0.1135 | -0.3811 | 1.0000 | | | | |
| **Financial leverage** | 0.3524 | -0.8353 | -0.7757 | 0.3810 | 0.0634 | 1.0000 | | | |
| **Drift** | 0.1607 | 0.2846 | 0.3186 | 0.1287 | -0.0466 | -0.4441 | 1.0000 | | |
| **Downgraded 07-08** | -0.5029 | 0.7407 | 0.7253 | -0.5256 | 0.0857 | -0.9236 | 0.3203 | 1.0000 | |
| **Constant** | 0.3094 | -0.8711 | -0.9769 | 0.3642 | -0.1761 | 0.6953 | -0.3019 | -0.6395 | 1.0000 |

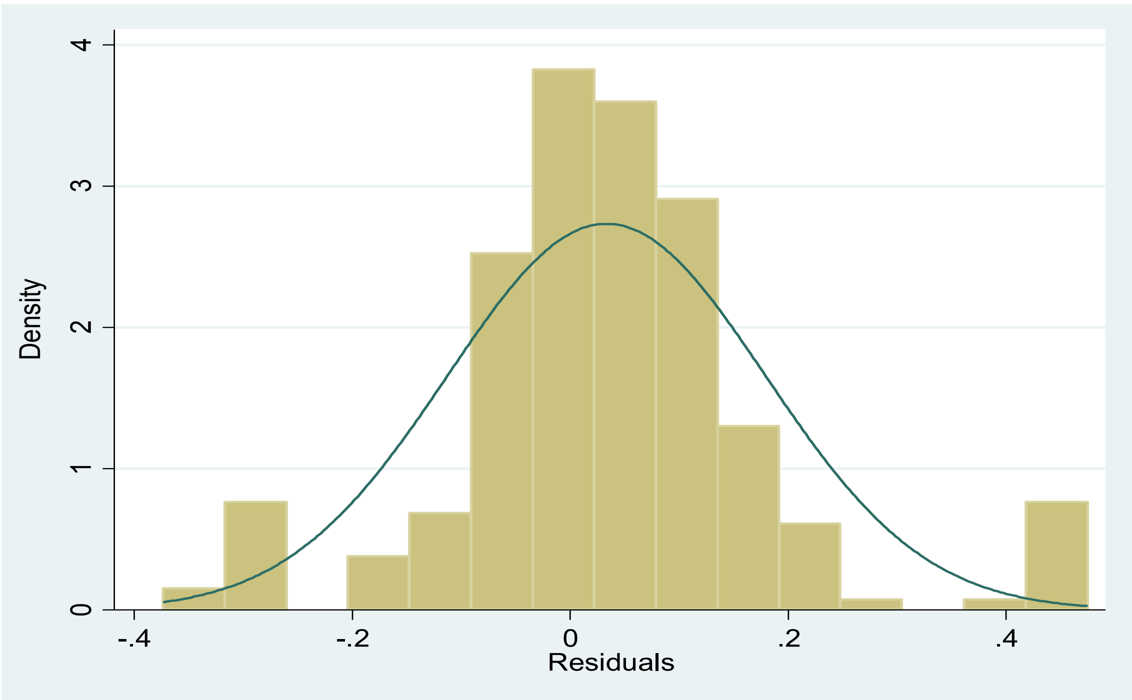
This table presents the pair wise correlation between the independent regression factors post-crisis for the duplicate sample; the numbers of notches downgraded (Downgrade), the future implied volatility (Hist Call Imp), the size of the company (Log mkt cap), the dummy variable indicating a negative outlook (Neg Outl), the volatility of the market (Market vol.), the level of financial debt (Fin lev), the aggregated abnormal return before the announcement date (Drift).

*Graph 16 – Regression residuals Pre-crisis for duplicate sample (t=-5 to t=5)*




Graph showing the residuals of the multivariate regression pre-crisis for the duplicate sample. The residuals seem to follow a normal distribution with minor tails.

*Graph 17 – Regression residuals Post-crisis for duplicate sample (t=-5 to t=5)*




Graph showing the residuals of the multivariate regression post-crisis for the duplicate sample. The residuals seem to follow a normal distribution but with heavy tails.

*Table 14- VIF table Pre-crisis (duplicate sample)*

| ***VIF Pre-crisis*** | | |
|---|---|---|
| **Independent variable** | **VIF** | **1/VIF** |
| Downgrade | 1.38 | 0.725 |
| Historical call implied | 2.01 | 0.498 |
| Log marketcap | 2.86 | 0.350 |
| Negative outlook | 1.73 | 0.578 |
| Market volatility | 1.42 | 0.704 |
| Financial leverage | 1.61 | 0.621 |
| Drift | 4.72 | 0.212 |

VIF table Pre-crisis for the duplicate sample. As a rule of thumb, a VIF value of more than 5 suggests that data suffers from high collinearity. The collinearity in this sample is thus moderate.

*Table 15 - VIF table Post-crisis (duplicate sample)*

| ***VIF Post-crisis*** | | |
|---|---|---|
| **Independent variable** | **VIF** | **1/VIF** |
| Downgrade | 3.51 | 0.285 |
| Historical call implied | 8.31 | 0.120 |
| Log marketcap | 6.63 | 0.151 |
| Negative outlook | 3.96 | 0.253 |
| Market volatility | 1.62 | 0.617 |
| Financial leverage | 14.48 | 0.069 |
| Downgraded 07-08 | 10.36 | 0.097 |
| Drift | 1.65 | 0.606 |

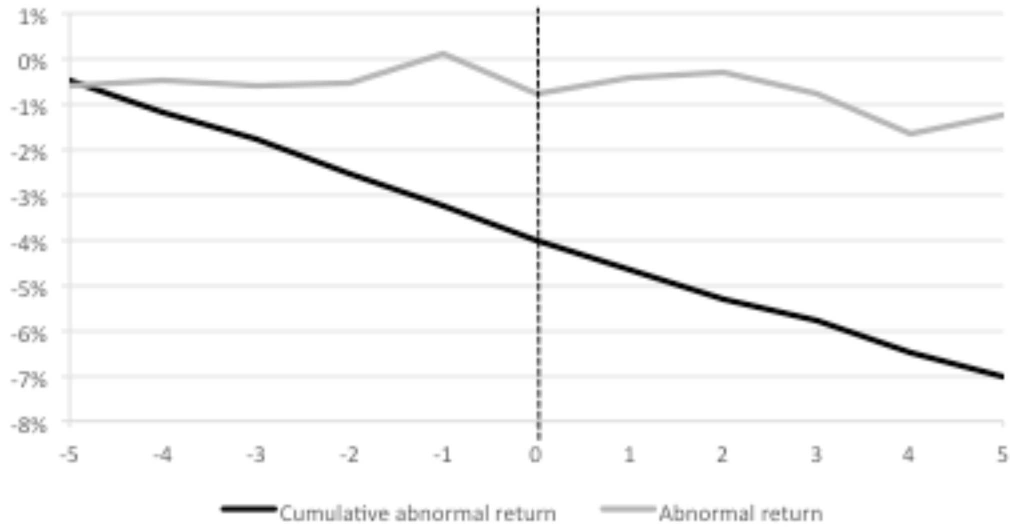
VIF table Post-crisis for the duplicate sample. As a rule of thumb, a VIF value of more than 5 suggests that data suffers from high collinearity. The collinearity in this sample is thus severe.

*Table 16 - Sktest statistics for Pre- and Post-crisis regressions (duplicate sample)*

| **Regression** | **Pr(skewness)** | **Pr(kurtosis)** | **Pr(>chi2)** |
|---|---|---|---|
| Residuals pre-crisis (-5:5) | 0.0773 | 0.0000 | 0.0000 |
| Residuals post-crisis (-5:5) | 0.0126 | 0.0001 | 0.0002 |

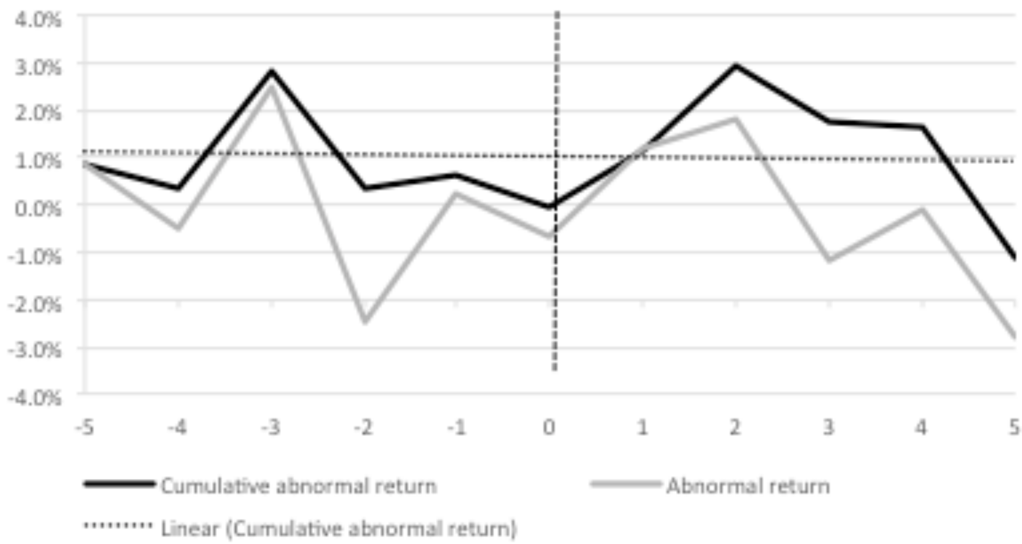
Probabilities that the residuals in the respective regressions are skewed (above a certain threshold), show kurtosis (above a certain threshold), and lastly are both skewed and show kurtosis (above a certain threshold). The residuals in these samples seem to be skewed, but with no or little kurtosis.

*Graph 18 - Average abnormal return and development of cumulative abnormal return Pre-crisis (t=-5 to t=5)*




Development of abnormal and cumulative abnormal returns for the duplicate sample pre-crisis over the announcement date (t=-5 to t=5). The data does not seem to behave any differently from the main sample.

*Graph 19 - Average abnormal return and development of cumulative abnormal return Post-crisis (t=-5 to t=5)*




Development of abnormal and cumulative abnormal returns for the duplicate sample post-crisis over the announcement date (t=-5 to t=5). The data behaves in many ways the same as the main sample, however, these findings have low significance.

*Table 17 - Significance of cumulative abnormal returns for duplicate sample*

| ***Pre-crisis*** | | | | |
|---|---|---|---|---|
| **Day** | **(-5 : 5)** | **(-20 : 20)** | **(-10 : 0)** | **(0 : 10)** |
| Mean | -0.0319 | -0.1504 | -0.0453 | -0.0449 |
| t-value | -5.13 | -15.00 | -7.65 | -7.20 |
| | | | | |
| ***Post-crisis*** | | | | |
| **Day** | **(-5 : 5)** | **(-20 : 20)** | **(-10 : 0)** | **(0 : 10)** |
| Mean | 0.0103 | -0.0180 | -0.0041 | -0.0140 |
| t-value | 0.94 | -1.32 | -0.29 | -1.24 |

*Table 18 - Regression table for duplicates Pre-crisis*

| ***Duplicates Pre-crisis*** **Robust** | No. of obs = 110 | | R-squared = 0.7568 | |
|---|---|---|---|---|
| **Cum. ab. return (-5 : 5)** | **Coefficient** | **Std. Err.** | **T** | **P>\|t\|** |
| Downgrade | -0.0105419 | 0.0064589 | -1.63 | 0.106 |
| Historical call implied | -0.0008941 | 0.0010388 | -0.86 | 0.391 |
| Log marketcap | -0.0158517 | 0.0033649 | -4.71 | 0.000 |
| Negative outlook | 0.0672671 | 0.0103323 | 6.51 | 0.000 |
| Market volatility | -0.0037801 | 0.0039205 | -0.96 | 0.337 |
| Financial leverage | -0.0006454 | 0.006959 | -0.93 | 0.356 |
| Drift | 0.8434913 | 0.0664486 | 12.69 | 0.000 |
| Constant | 0.1974406 | 0.0393585 | 5.02 | 0.000 |

Regression table for the duplicate sample pre-crisis. The downgrade coefficient is negative but not significant on the 5% level. The results are considered to be weak as there are few observations.

*Table 19 - Regression table for duplicates Post-crisis*

| ***Duplicates Post-crisis* Robust** | No. of obs = 121 | | R-squared = 0.5670 | |
|---|---|---|---|---|
| **Cum. ab. return (-5 : 5)** | **Coefficient** | **Std. Err.** | **t** | **P>\|t\|** |
| Downgrade | -0.0115139 | 0.0269423 | -0.43 | 0.670 |
| Historical call implied | 0.0023176 | 0.0007485 | 3.10 | 0.002 |
| Log marketcap | 0.0670958 | 0.0174896 | 3.84 | 0.000 |
| Negative outlook | -0.0258243 | 0.0366572 | -0.70 | 0.483 |
| Market volatility | -0.0754554 | 0.0279665 | -2.70 | 0.008 |
| Financial leverage | -0.0384899 | 0.0103365 | -3.72 | 0.000 |
| Drift | 0.1410415 | 0.0830787 | 1.70 | 0.092 |
| Downgraded 07-08 | 0.6328745 | 0.1191982 | 5.31 | 0.000 |
| Constant | -0.4886102 | 0.1438231 | -3.40 | 0.001 |

Regression table for the duplicate sample post-crisis. The sample suffers from severe collinearity and no conclusions can be drawn from this regression.

*Table 20 – Test for heteroscedasticity (main sample)*

| **Regression** | **Chi2(1)** | **Pr(>chi2)** |
|---|---|---|
| Pre-crisis (-5:5) | 45.4 | 0.0000 |
| Post-crisis (-5:5) | 135.2 | 0.0000 |

A high Chi2(1) level indicates a high level of heteroscedasticity