The Informational Value of Credit Rating Events

The European Case of the Stock Market Reaction to Credit Rating Agencies' Announcements

Abstract

The paper applies the event study methodology to investigate the impact of credit rating events including outlook, watch, and rating change announcements (rating events) on share prices in Europe. In general, statistically significant, however, weak market reaction to negative rating events is found. The results before and after European rating agencies were first regulated at the end of 2009 are compared to examine if the stock market reacts differently to rating events, amid presumably increased quality of information contained in credit rating actions, in the post-regulation era. Nevertheless, there is no significant indication that the market reacts uniquely to rating events before or after the regulation. There is neither any compelling evidence that outlook, watch, and rating change announcements bear different information for investment and non-investment grade rating classes. Moreover, the paper concludes that rating migrations preceded by watch or outlook are neither more nor less informative than direct rating changes.

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INTRODUCTION

Year 2008, New York. Imagine a mass of unqualified bankers granting mortgage loans without any prior credit checks, originators securitising these mortgages, and rating companies giving them the highest rating of AAA with virtually no credit risk. We all know the end of the story. We all know the consequences. We also know that inflated ratings were part of the problem and one of the reasons for the global financial crisis of 2008-2009. In line with this statement, Alan Greenspan – the former Chairman of the Federal Reserve – testified on Capitol Hill at the end of October 2008:

> *The [consequent] surge in global demand for U.S. subprime securities by banks, hedge and pension funds supported by unrealistically positive rating designations by credit agencies was, in my judgment, the core of the problem.* (Retuers, 2008)

What followed was regulation, regulation and more regulation. Credit rating agencies (CRAs) were one of the subjects of this legislative drive. As a result, the rating industry altered not only in the US but also in Europe. Our study analyses the relation between credit rating announcements – such as outlook, watch, and rating changes (also referred to as rating events) – and shares prices of European companies. One of the aims of the paper is to investigate if the more stringent regulatory environment has had any effect on this relationship.

Credit rating events and their impact on the market have been extensively examined in the past. Since the 1970s, scholars have been investigating the effect of rating announcements on equity prices and bond yields. From the 2000s, the research has advanced to include an increasing number of studies on the reaction of credit default swaps (CDS) spreads to credit rating announcements. The basic premise of these studies is that CRAs possess private knowledge about issuers and thus the rating announcements may bring new information to the market. Given that the market is semi-strong-form-efficient[1], asset prices should respond to the introduction of a new piece of information. In general, the research finds this response to be asymmetric, i.e. more pronounced for negative than positive events (Holthausen & Leftwich, 1986; Goh & Ederington, 1999; Dichev & Piotroski, 2001; Norden & Weber, 2004; Jorion, Liu, & Shi, 2005; Bannier & Hirsch, 2010). Nevertheless, the limitation present in these studies was

[1] Concept introduced by Fama 1970, all public information is reflected in security prices (White Gerald I, Sondhi Aswinpaul C, Fried Dov Ph.D., 2003)

a small sample size of the positive announcements which could have contributed to the asymmetric response.

Despite the prominence of the research that investigated the effect of credit rating events on the stock market, there are still a few gaps in the literature that could be addressed. First, with an exception of Jorion et al. (2005) and Kiesel (2016), the research investigating the change in regulatory environment has been scarce. Secondly, some papers used monthly or weekly data leaving opportunities to replicate their studies with more frequent observations (Griffin & Sanvicente, 1982; Pinches & Singleton, 1978). Third, most studies concentrated strictly on US market, leaving Europe widely under-investigated (Griffin & Sanvicente, 1982; Holthausen & Leftwich, 1986; Hand, Holthausen & Leftwich,1992; Goh & Ederington, 1993; Hite & Warga, 1997; Goh & Ederington, 1999; Kliger & Sarig, 2000; Dichev & Piotroski, 2001; Jorion et al., 2005; Bannier & Hirsch, 2010). Finally, the vast majority of studies neglected outlook and investigated only rating, watch or both.

We employ the event study methodology proposed by MacKinlay (1997) to address the gaps in the aforementioned European research. This paper examines the reaction of share prices to credit rating announcements including outlook, watch, and rating changes. Further, we distinguish between various groups, including but not limited to the announcement type (outlook, watch, and rating), its timing (pre- or post-regulation era), and the investment grade class of the issuer rating (investment grade [IG] or non-investment grade [NIG]). Finally, we focus solely on further investigation of rating migrations and look at factors such as direct anticipation by a precedent watch or outlook, geographical location of the firm, and number of notches by which the rating changed.

The rest of the paper is structured as follows. Section I provides the background of the study, including description of credit ratings and agencies, and presents a brief literature review. Additionally, the section discusses the theoretical framework and derivation of the hypotheses. We address information content hypothesis, the concept of equity viewed as a call option on company's assets (Merton, 1974), and the regulation of CRAs in Europe. The paper then proceeds to the presentation of data and method (section II), the results and analysis (section III), and the main conclusions (section IV).

1 SECTION I – THE BACKGROUND OF THE STUDY

1.1 BACKGROUND ON CREDIT RATING AGENCIES (CRAS) AND THE RATINGS

1.1.1 Credit Rating Agencies (CRAs) and Ratings

Credit rating agencies (CRAs) are institutions that assign credit ratings for debt issuers and their issues. The main CRAs, sometimes called "the Big Three", are Standard & Poor´s, Moody´s Investor Services, and Fitch. They issue credit ratings, which are forward-looking opinions on the ability of a firm to meet its financial commitments. To reach those opinions, CRAs collect both public and private information (i.e. internal forecasts or strategies) on issuers and use it to assess their creditworthiness. Their methodologies are transparent and are comprised of quantitative models and qualitative assessment of an issuer's credit risk. As S&P (2016) describes, the qualitative part evaluates factors such as corporate governance framework, the financial and operational strategy, and even the experience of company's management. The quantitative considerations comprise various financial measures such as free cash flow, volatility, and EBITDA.

1.1.2 Different Types of Rating Actions: Rating, Watch, and Outlook

In addition to credit ratings, CRAs may place a company on outlook or credit watch (review)[2]. Below, we briefly describe and eventually link all types of rating actions addressed in the research.

Commencing from the credit rating, S&P and Fitch use the same scale with rating classes spanning from AAA, which indicates the issuer's extremely strong capacity to meet financial obligations, to D, which indicates obligor's default on one or more of its financial commitments. Similarly, Moody´s rating scale extends from Aaa to C. Additionally, within most rating classes, agencies use notches to designate if an issuer ranks in its highest or lowest range (f.eg. BBB+, BBB, BBB-; see Table 11 in appendix). In that manner, a notch is the smallest possible unit of the rating change. As shown, the rating scales differ and since we use all three rating agencies in the study, we need to equate the rating scales. For this purpose, we

[2] Moody's, S&P and Fitch use diversified nomenclature to refer to the concept of credit watch – "CreditWatch", "Rating Watch", "Rating Review", and "Watchlist" – all refer to the same event. Through the paper, we refer to the aforementioned as "watch" or "review".

employ Thomson Reuters numerical scale (see Table 11 in the appendix). Finally, rating agencies provide investors with a plethora of different rating types. Nevertheless, this research focuses solely on the long-term issuer ratings which designate firm's ability to repay senior unsecured debt.

When there is an enduring change in a company's risk profile, Moody's, S&P, or Fitch revise corporate's credit rating to a different one that more accurately reflects the ability of an entity to meet its financial commitments. Nevertheless, the ratings are meant to be stable as they measure the risk of bankruptcy over the long time horizon (Cantor, 2004). At the same time, they also need to be precise. Therefore, the rating bureaus strive to find a balance between accuracy and stability of ratings, as their reversals could be costly due to, for instance, rating portfolio governance rules that force fund managers to sell particular holdings.[3] Therefore, when circumstances regarding the creditworthiness of an entity are not sufficient to affect the rating itself, the CRA might put a company on a watch or outlook in an attempt to achieve the right mix between accuracy and stability (Richard Cantor, 2006; Chung, Ann Frost, & Kim, 2012).

The credit watch is an opinion regarding the potential direction of the current issuer rating, usually in the near term. Moody's, S&P, or Fitch may put a company on a negative, positive, or evolving watch.[4] This could be done due to various reasons. Typically, it is driven by discrete events such as mergers and acquisitions, share buybacks, or change in an entity's operating and financial developments (Bannier & Hirsch, 2010). An issuer can be put on watch because either the CRA needs more information to evaluate the current rating or the event triggering the review has to be completed, for instance, in the case of regulatory approvals or a merger. During this time, the CRA investigates the situation and collects additional information about the company. Even though CRAs do not explicitly specify in their methodologies the exact term until the watch is resolved, Moody´s Investors Service (2017) reveals that watch is typically resolved within 30 to 90 days. However, in case a watch is driven by an event that Moody's cannot control, the review could last up to 180 days or even longer. The watchlist

[3] The debt investors are often restricted by governance rules and credit limits as to the amount of a particular rating class they may hold in their books. Therefore, when debt is downgraded into a speculative-grade class, debt investors may be forced to sell-off their position (Cantor, 2006)

[4] Different rating agencies have diverging nomenclature for events, see below:

- CreditWatch of S&P falls into three categories: Positive, Negative and Developing
- Moody´s Watchlist falls into three categories: Upgrade, Downgrade or with a Direction Uncertain
- Rating Watch of Fitch falls into three categories: Positive, Negative or Evolving

usually results in a confirmation or a change of the corresponding credit rating. Chung et al. (2012) investigated the effect of credit watch announcements on the credit rating process using a sample of 4,539 credit watch and 10,790 rating change announcements by Moody's from 1992 to 2010. The research revealed that (approximately 67%) of the negative watch events were followed by rating downgrades and (approximately 69%) of the positive watch events were followed by rating upgrades. Therefore, when a company is put on watch in any direction, it is not certain that a rating transition will happen. Instead, the current rating might be confirmed.

The outlook is a potential direction of a long-term credit rating assessed by a CRA over the intermediate term.[5] Historically, rating outlooks have usually been resolved by a credit watch, a change in outlook or rating within a year. However, some outlooks remained for a much shorter or longer time. The outlook is usually announced due to changes in economic or fundamental business conditions. It could also reflect financial and other trends that have not yet reached the level to change the credit rating, yet may do so if the trends continue (Fitch, 2017). In addition to positive, negative or developing direction that watch can indicate, outlook can additionally be stable.[6] Even though outlook increases the likelihood of rating change and indicates its potential direction, similarly as credit watch, it does not necessarily have to result in a credit rating change. According to Moody´s Investors Service (2017), only one-third of outlooks are resolved within 18 months from their assignment, and around 90% of ratings are not changed during the following year.

Finally, rating definitions indicate that rating outlooks and watches are mutually exclusive (Fitch, 2017). In other words, at any point in time, a company could be placed on watch or outlook but not both.[7] Moreover, it does not mean that a company must be placed on watch or outlook. It is possible that it just holds a stand-alone rating. However, a company could

[5] Which is usually from 6 months to 2 years for S&P, from 1 to 2 years for Fitch and around 18 months for Moody´s

[6] Different rating agencies have diverging nomenclature for events, see below:

- S&P's outlook falls into three categories: positive, negative, stable, developing, or not meaningful
- Moody´s outlook falls into four categories: positive, negative, stable, or developing
- Fitch's outlook falls into four categories: positive, negative, stable, or evolving

[7] Even though Moody´s Investors Service (2017) does not explicitly state that credit watch and outlook are mutually exclusive, "the Big Three" CRAs have similar approach and closely follow each other. Furthermore, Finnerty et al. (2013) that study the impact of credit rating announcements on CDS spreads using S&P data, claim that at any point in time credit ratings might be put either on watch or outlook but not both.

not be put on watch or outlook if it does not possess a rating. Moreover, a company could be rated by either one or two or even all “the Big Three” rating agencies.

1.2 BRIEF LITERATURE REVIEW

The informational value of credit rating announcements seems to be of high interest to academia. Katz (1974) and Pinches and Singleton (1978) were one of the first to investigate the effect of bond credit rating migrations on bond and stock prices respectively. The primary purpose of the research was to investigate stock and bond market efficiency. However, the following research was more concerned with the informational value of credit ratings rather than market efficiency hypothesis (Goh & Ederington, 1993; Kliger & Sarig, 2000; Norden & Weber, 2004; Jorion et al., 2005; Abad-Romero & Robles-Fernandez, 2006). The research claimed that CRAs possess private information and credit rating announcements could indirectly disclose this inside information to the market. Consequently, CRAs decrease the information asymmetry by their rating announcements.

Despite different presumptions of the market and across different time period, most studies, regardless whether they examined bond, stock or CDS market, found similar results. Most studies found only minor (0.5% to 2.0%) stock market reaction to rating change announcements (Goh & Ederington, 1993; Kliger & Sarig, 2000; Norden & Weber, 2004) and strong anticipation of credit rating events (Pinches & Singleton, 1978; Holthausen & Leftwich, 1986; Glascock et al., 1987; Goh & Ederington, 1993; Goh & Ederington, 1999; Norden & Weber, 2004; Finnerty, Miller, & Chen, 2013; Kiesel, 2016). Furthermore, the research found that the market reacts much stronger to negative than positive rating events (Holthausen & Leftwich, 1986; Goh & Ederington, 1999; Dichev & Piotroski, 2001; Norden & Weber, 2004; Jorion et al., 2005; Bannier & Hirsch, 2010). This could be explained by “good news travel fast” (Holthausen & Leftwich, 1986) and “clustering of bad news” (Galil & Soffer, 2011) phenomena, which will be addressed in the section 3.3. Furthermore, the research that distinguished between investment and non-investment (speculative) grade observations, found that market reaction to rating change within a speculative grade was substantially larger than to rating migrations that occurred within the investment grade (Hand et al., 1992; Hite & Warga, 1997; Dichev & Piotroski, 2001). Moreover, most studies made a clear distinction between rating events that occurred simultaneously with other company-specific events (contaminated observations) and rating events that did not interfere with other events (non-contaminated observations) (Pinches & Singleton, 1978; Holthausen & Leftwich, 1986; Hand et al., 1992;

Goh & Ederington, 1993; Followill & Martell, 1997). Research that compared the results from contaminated and non-contaminated samples found a substantially stronger market reaction to rating migrations in the contaminated sample (Holthausen & Leftwich, 1986; Galil & Soffer, 2011). This is intuitive as the market reacts to other company-specific events rather than credit rating changes in isolation.

To conclude, even though watch and outlook announcements are less-investigated than rating migrations, studies that analysed them, found similar results. First, watch had a significant effect on the event day (Griffin & Sanvicente, 1982; Holthausen & Leftwich, 1986; Hand et al., 1992; Followill & Martell, 1997; Steiner & Heinke, 2001; J. Hull, Predescu, & White, 2004; Galil & Soffer, 2011; Chung et al., 2012). Second, watch and outlook preceded ratings had a smaller effect on the market than direct rating changes (Holthausen & Leftwich, 1986; Norden & Weber, 2004). And finally, credit watch announcements had a more pronounced effect on the market than outlook announcements (J. Hull et al., 2004; Finnerty et al., 2013).

Several other findings were not uniform across studies. First of all, there was no consensus with regard to informational value of positive rating events. While most studies did not find any significant effect of positive rating announcements, a few studies found statistically significant positive effect of upgrades for CDS or stock market (Jorion et al., 2005; Finnerty et al., 2013; Kiesel, 2016). Furthermore, a few research papers even found a statistically significant positive reaction after downgrades. It was explained by "wealth redistribution hypothesis", which argues that downgrade of the credit risk should affect the bondholders negatively, whereas shareholders as residual claimants benefit from the credit downgrade (Goh & Ederington, 1993; Clare, & Thomas, 1997; Barron, Kliger & Sarig, 2000; Abad-Romero & Robles-Fernandez, 2006). Wealth redistribution hypothesis claims that the rating downgrade negatively affect the value of debt, however, as the value of assets is not changed, the value of equity increases on the day of the announcement. The wealth is transferred from debt holders to equity holders. Nevertheless, as the hypothesis was not supported by a sound theoretical explanation, the paper will not elaborate on it in the following sections. Moreover, studies found different results with regard to stock market behaviour after the credit event announcements. Some either did not investigate the issue or did not find any reliable evidence (Goh & Ederington, 1999; Jorion et al., 2005; Bannier & Hirsch, 2010; Kiesel, 2016), others observed negative post-announcement drift (Holthausen & Leftwich, 1986; Goh & Ederington, 1993; Dichev & Piotroski, 2001), and a few even found post-announcement reversal (Pinches & Singleton, 1978; Glascock et al., 1987).

1.3 EUROPEAN STUDIES

Apart from the study by Kiesel (2016), the research that analysed the impact of rating actions on the European market is limited. Barron, Clare and Thomas (1997) studied the effect of credit rating changes on UK stock market. They found abnormal returns after rating downgrades and positive watch announcements. The research also suggested that rating changes, as well as new long-term debt ratings, have no significant impact on UK share prices. Steiner and Heinke (2001) investigated German Eurobond market and its reaction to both rating and watch migrations. They found statistically significant negative abnormal returns after a downgrade or inclusion to a negative watchlist and no significant market reaction to upgrades or positive watch. Finally, Abad-Romero and Robles-Fernandez (2006) analysed the reaction of the Spanish stock market to corporate bond rating change. Remarkably, the study revealed that Spanish stock market reacts negatively to rating upgrades and there were no statistically significant abnormal returns following downgrades.

1.4 INFORMATION CONTENT HYPOTHESIS AND DEVELOPMENT OF THE FIRST HYPOTHESIS

In 1968, Ball and Brown pioneered a new field of study aimed at measuring the "information content" of accounting data represented by the market's reaction to the announcements (White, 2003). As illustrated above, this field has developed to include outlook, watch, and rating change announcements. Our study contributes to this field as it aims to measure the information content of these credit rating events. Therefore, it is essential to examine if there is any reason to believe that the European rating agencies bring new information to the market.

CRAs might bring new information to the market through issuer rating actions. While some ratings may be based solely on publicly available information, in most instances the agencies may become insiders on a particular company. Recent documents that cover rating methodologies and processes of Moody's, S&P and Fitch specify that analysts may possess material non-public information about the customer. As described by the S&P credit rating process, the CRA opines on the creditworthiness of an entity, only if it has information of satisfactory quality. Therefore, meetings with management are commonly undertaken as part of the credit rating process, where analysts may gain material non-public information. Glascock et al. (1987) called this phenomenon "a potential agency problem", where the managers do not reveal inside information to the public, which they do often provide to rating agencies. Despite the fact that rating agencies might receive inside information such as an issuer's acquisition plans, new products, expansion and debt issuance plans, they are not allowed to reveal this information to the public (Goh & Ederington, 1993). The question raised by Kliger and Sarig (2000) was why companies would pay for ratings if credit rating agencies reflected in their ratings only publicly available information. The study claimed that companies are interested in better credit ratings, and therefore, they might benefit from communicating some inside information to CRAs without revealing sensitive details to the public, and competitors in particular. For instance, if a certain company is unexpectedly put on positive watch, it could indicate to the market some promising future plans of the issuer that only CRAs are aware of.

Moreover, even though it is difficult to estimate how much inside information CRAs possess, credit rating announcements could also bring new information to the market though CRAs performance of superior analysis, the so-called Briloff effect[8]. Although some information used by CRAs is publicly available, there could be economies of scale in its collection and evaluation (Goh & Ederington, 1993). Consequently, regardless if it is based on publicly available information, CRAs' announcements may still move the market.

Based on insights from previous studies and CRAs credit rating methodologies, we expect CRAs to possess private information, provide superior analysis, and reduce the informational asymmetry by bringing new information to the market through rating, watch, and outlook announcements. Therefore, our first hypothesis is as follows:

Hypothesis 1: Credit rating announcements bring new information to the market. Therefore, European stock markets should react to watch, outlook, and rating change announcements.

1.5 EQUITY AS A CALL OPTION ON THE COMPANY'S ASSETS

1.5.1 The Model

In this section we illustrate the association between probability of failure and equity value. In 1974, Robert Merton developed a model, where the company's equity can be viewed as an option on the company's assets. The intuition behind the model is straightforward.

[8] In the 1970s, Professor Adam Brioff has scrutinised financial reporting policies applied by certain firms. He based his analysis entirely on publically available sources. After publishing his critique in a periodical, the share prices of the studied companies plunged, meaning that the Briloff shared superior analysis and the market did not reflect all available public information (White et al., 2003)

Consider a company, where the assets are financed solely by equity and one zero-coupon bond with face value X and maturity at time T. The components of the model are defined as:

A_0: *current value of assets*

E_0: *current value of equity*

A_T: *value of company's assets at time T*

E_T: *value of company's equity at time T*

D_T: *value of company's debt at time T*

X: *the face value of debt to be repaid at time T*

σ_A: *constant volatility of assets*

Deriving from a fundamental accounting theory that assets equal the sum of equity and debt ($A = E + D$), we recognise that if the value of debt exceeds the value of assets at time T, default occurs. Moreover, the covenants on the bonds grant debt-holders priority on the company's assets in case of default, making the equity holders the residual claimants. Assuming that new debt cannot be issued to refinance the existing zero-coupon bonds and shares cannot be repurchased, then, in the event of a firm's default, equity holders receive the value of assets that remains after the debt holders are fully paid. If the value of debt exceeds the value of assets, equity holders are left with nothing (see Figure 1). Consequently, the payoff on company's equity is identical to the payoff on a European call option on a non-dividend-paying stock, where the strike price corresponds to the face value of debt X and stock price corresponds to the value of assets (A_T):

$$European\ call\ option\ on\ Assets = E_T = max(A_T - X; 0) \quad \textit{(Equation 1)}$$

Since the payoff on the company's equity (see Equation 1) is identical to a payoff on a call option, we can use the Black-Scholes call option formula to calculate the value of equity (J. Hull, 2012; Merton, 1974):

$$E_0 = A_0 N(d_1) - X e^{-rT} N(d_2), \text{ where}$$

$$d_1 = \frac{\log\left(\frac{A_0}{X}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}$$

$$d_2 = d_1 - \sigma_A\sqrt{T}$$

The model allows one to calculate the risk-neutral probability of default, which equals to $N(-d_2)$ (Hull, 2012). This is based on the probability that the value of option is out of money. Finally, with some reverse engineering, the model could be modified in a way that the probability of default is one of the inputs and the current value of equity is the output. In section 1.7 we further discuss the empirical implications of the model.

1.5.2 Criticism of the Model

One of the main drawbacks of Merton's model are over-simplistic assumptions[9] such as that the default could only occur at a debt's maturity date (see Figure 2) and that the company's capital structure consists of one zero coupon bond and equity. According to Hull (2012), the original model has been extended in many ways to, for instance, allow for payments to investors at more than one time, adjust for default at more than one time, and even transform risk-neutral into the real-world probability of default. Nevertheless, the model in its original form outlines the link between equity and probability of default.

Figure 1 illustrates payoff on equity designated as a call option on the company's assets, with the strike price corresponding to the face value of debt X. If at time T, $A_T > X$, the company can repay the debt and the value of the company's equity is $A_T - X$. If $A_T < X$, then the company is bankrupt and value of equity is zero. Figure 2 illustrates that in Merton's model the value of equity could at any time fall behind X, yet default could occur only at time T when the bonds mature.

Figure 1 - Payoff on Equity

$$E_T = max(A_T - X; 0)$$

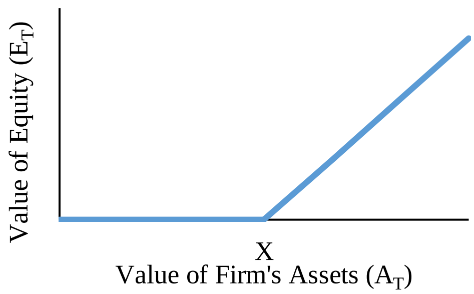
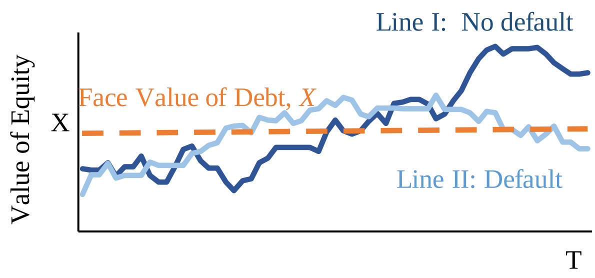


Figure 2 – Time to Default



[9] Some other assumptions in Merton model include: perfect market, continuous trading, value of the firm does not depend on capital structure, flat term structure, value of the firm follows a stochastic process, no payment of dividends, no new issuance of debt, borrowing and lending rates are equal, constant volatility of stock prices, and debt of a company represented by a single zero-coupon bond (Merton, 1974)

1.6 REGULATION OF CRA IN EUROPE AND ITS IMPLICATIONS

1.6.1 A Brief History of CRA Regulation in Europe

In contrast to the US, traditionally the European credit rating agencies (CRAs) have not been regulated. In the aftermath of the Enron scandal in 2001, the European Commission investigated CRAs and decided that no statute governing the agencies was needed. Instead, they relied on other measures, and consequently, in 2004 International Organisation of Securities Commission (IOSCO) published a non-binding Code of Conduct to assure accountability of CRAs. It was administered by the "comply or explain" principle, where CRAs could either adopt IOSCO's Code of Conduct or explain any deviations from it (Coffee, 2011). It was not until 2009, when in response to the global financial crisis, the European Commission adopted the first piece of legislation governing CRAs in Europe. The primary objective of this project was to restore market confidence and increase investor protection (the EU Commission, 2014). The legislature also introduced a mandatory registration of CRAs with a supervisory authority. Nevertheless, it remained unclear who the authority would be until 2011, when the European Commission granted supervisory power to the European Securities and Markets Authority (ESMA) (Coffee, 2011; the EU Commission, 2014). Since the initial version of the law, the regulation has been amended in 2011 and 2013 and updated with several supplements. Nevertheless, the fundamental precepts – including decrease of over-reliance on external rating sources, enhancement of investor protection, mitigation of conflicts of interest and better quality ratings for sovereign debt of EU countries – have been retained and further strengthened (the EU Commission, 2014).

1.6.2 Potential Implications of the Regulation and Second Hypothesis

Taking into account the increased supervisory environment of CRAs in Europe, we expect the effect of credit rating events on stock prices to increase in the post-regulation era (after the regulation came into effect in 2009). According to Coffee (2011), during the subprime crisis, structured financial products were the primary area of CRA's misconduct. Similar problems did not characterise the corporate bond rating business. Nevertheless, we conclude that a more stringent regulatory environment is likely to affect the quality of all available ratings and investors´ perception of them.

We commence the analysis by pointing out some contrasts between the regulation and our study and clarifying potentially confusing areas. First of all, the law focuses on instruments that could possess credit ratings (i.e. debt or structured finance products), yet our study focuses solely on equity, which does not possess such ratings. Second, the law primarily concerns fixed-income investors, authorities and financial institutions, while the investor group in our study comprises solely equity investors. For this reason, many of the restrictions the regulation imposes are not directly applicable to the equity market. Nevertheless, the overall effect on the European credit rating industry could be of high concern to the study. The following section addresses a few points taken up by the law.

On the one hand, one of the reasons for the European Commission to adopt the regulation was to decrease the over-reliance on credit ratings (the EU Commission, 2014). Investors and financial institutions are now required to carry out their own assessment of the credit risk attributed to an entity or financial instrument and are restricted from relying on credit rating unconditionally. This could be achieved by application of internal credit ratings, for instance. On the other hand, the quality of credit ratings has increased as the regulation increased transparency, governance, and reliability of credit rating activities. Furthermore, the responsibility of CRAs has increased as investors, who suffer damages from an incorrect credit rating (outlook or watch) announced either intentionally or through gross negligence, could sue for compensation (the EU Commission, 2014). While the fixed income investors are affected by both sides of this reasoning, the equity investors should only consider the fact that the ratings have become more accurate and reliable. The equity investors are unlikely to be governed by rules that force them to sell-off their holdings in case a company's credit rating decreases below a certain threshold. In contrast, the debt investors are often restricted by governance rules and credit limits as to the amount of particular rating class they may hold in their books. Therefore, when debt is downgraded into speculative-grade class, they may be forced to sell-off their position (Cantor, 2006). Nevertheless, the equity investors may benefit from more reliable ratings in a way that they use the informative power of a rating change. Since, as we previously mentioned, the rating agencies are likely to possess confidential information and conduct superior analysis, the informational value of a rating change may be significant to the market. This informational effect can be especially present after the EU Commission has regulated the CRA industry and made the agencies liable to provide a reliable rating of high quality.

Moreover, the regulation aims to mitigate the conflict of interests between issuers and CRAs (the EU Commission, 2014), which could also contribute to improvement in precision of credit ratings, watches, and outlooks. While the conflict of interest could take on different forms, we would like to address the payment model in the industry. CRAs receive compensation from issuers for rating them and their debt, which in particular circumstances causes a conflict of interest (Coffee, 2011). Issuers strive for the highest credit ratings as it decreases their cost of capital. Therefore, they could apply to different CRAs and "buy" the best rating. Meanwhile, CRAs are interested in a long-term co-operation with issuers, and therefore, could be inclined to inflate credit ratings. With the new regulation governing the market, the problem of "rating shopping" is mitigated.

In summary, given the enhanced regulatory environment for CRAs in Europe and the incentive for them to provide more precise risk indicators rather than engaging in "rating shopping", it is likely that the quality of credit ratings, watches or outlooks and potential new information they bring into the market has improved. With this in mind, we propose the second hypothesis:

Hypothesis 2: The rating actions are more informative in the post-regulation era, i.e. the effect of rating events (watch, outlook, and rating) on stock prices is larger during the post-regulation than pre-regulation period.

1.7 DIFFERENCE IN REACTION TO RATING CHANGES FOR INVESTMENT AND SPECULATIVE GRADES AND DEVELOPMENT OF THE THIRD HYPOTHESIS

Corporate default rates tables published by S&P, Moody's and Fitch provide a useful proxy for default risk corresponding to a given credit rating. They reveal that, in general, the lower the rating, the higher the default rate. S&P's Global Corporate Average Cumulative Default Rates Table 2015 ("the S&P Table") shows that an AAA rating corresponds to essentially 0.00% average default risk within one year, BBB to 0.36% and B to 8.74%. With this in mind, we are interested in investigating whether the equity value of a non-investment grade company drops (rises) by a larger amount after a downgrade (upgrade) than the equity value of an investment grade company. Let us study this question with a two stage model (Berk Jonathan, 2011).[10]

Consider a company with current equity value V_0 and cumulative probability of default $p_{fail,t}$ until time t. Assuming that there are no intermediate cash flows between now and time

[10] In section 1.5.1 we present the Merton's model (1974) and link the value of equity with the probability of default. We initially develop similar analysis using that framework with the intention to compare the market reaction to rating changes for IG and NIG companies. We modify the original form of the model in a way that change in the probability of default corresponding to the change in rating is one of the inputs and change of the value in equity is the output. Another required input is directly unobservable volatility of assets. As Hull (2012) suggests, one of the possible ways to estimate the volatility of assets is to use historical data (listed equity + liabilities). Therefore, we retrieve the data from Thompson Reuters Eikon and calculate the required inputs for the volatility of assets. Nevertheless, as leverage of NIG companies in the tested sample is highly diverse, it is difficult to find a reasonable estimate for the volatility of assets. Therefore, in our case, it seems to be inaccurate to perform the analysis using the Merton model.

t and the recovery rate in case of default is zero, the company's equity is worthless in case of default, $V_{default} = 0$. If the company survives until t and there are no intermediate cash flows, the present value of the equity equals $V_{survival}$. Hence, we can derive the current equity value V_0 as follows:

$$V_0 = (1 - p_{fail,t}) \times V_{survival} + p_{fail,t} \times V_{default} = (1 - p_{fail,t}) \times V_{survival}$$

The above equation suggests that (keeping all other constant) when the probability of default increases, the value of equity V_0 falls. We empirically examine the abovementioned relation taking $p_{fail,t}$ from the S&P Table for two arbitrary rating migrations from A+ to A (IG class) and BB- to B+ (NIG class). To estimate expected time to the default t we take a sample weighted average maturity of bonds outstanding for respective rating classes.[11] The results show that the average debt maturity for the IG-rated companies is approximately 7 years and 4 years for the NIG-rated companies. The computed average maturities are used to identify (in the S&P Table) the appropriate cumulative probability of default $p_{fail,t}$ for a given rating.

The S&P Table reveals that the 7-year cumulative probability of default for an A+ rated issuers is 0.75 % and 0.97% for an A rated one. According to the model, the equity value for A+ rating $V_{0,A+}$ and A rating $V_{0,A}$ are respectively equal to:

$$V_{0,A+} = (1 - 0.0075)V_{survival}$$
$$V_{0,A} = (1 - 0.0097)V_{survival}$$

The difference between them suggests that when the company is downgraded from A+ to A, the value of equity decreases by 0.22%, ceteris paribus.

$$V_{0,A} - V_{0,A+} = (1 - 0.0097)V_{survival} - (1 - 0.0075)V_{survival} = -0.0022V_{survival}$$

We repeat the procedure for NIG companies. Based on the S&P Table, 4-year cumulated probability of default for BB- rated issuers is 8.50 % and 13.76% for B+. Consistent with the model, the equity value for the BB- rating $V_{0,BB-}$ and $V_{0,B+}$ are then equal to:

$$V_{0,BB-} = (1 - 0.0850)V_{survival}$$
$$V_{0,B+} = (1 - 0.1376)V_{survival}$$

[11] We arbitrary choose 5 companies each within BB and A rating classes, calculate the weighted average maturity of their debt outstanding for each company, and then the average of the maturities for the respective class. The data is obtained from Thompson Reuters Eikon.

Hence, for the speculative grade the downgrade from BB- to B+ decreases the value of equity by 5.26%.

$$V_{0,B+} - V_{0,BB-} = (1 - 0.1376)V_{survival} - (1 - 0.0850)V_{survival}$$
$$= -0.0526V_{survival}$$

Based on these findings, we expect share prices of the NIG companies to react stronger to the rating announcements than the share prices of the IG firms. Hence, we propose the hypothesis below.

Hypothesis 3: The market reaction is larger to credit rating events such as rating, watch, and outlook announcements for companies within the speculative than investment grade.

2 SECTION II – DATA AND METHOD

2.1 COLLECTION AND PREPARATION OF DATA

Most of the data was obtained from Thompson Reuters Eikon and complemented with dividend announcement dates from Compustat. An equity screening of all active and inactive companies with a primary country of risk[12] based in Europe was performed in order to determine a list of companies used for the analysis. In order to be eligible for this study, firms had to be listed on a European stock exchange. Overall, 14,020 companies satisfied this inclusion criteria. Furthermore, state-owned enterprises were excluded from this study as they are likely to receive state-support in case of financial difficulties. Moreover, companies were examined for the issuer rating by Moody's, S&P, or Fitch and 613 companies with a rating were identified. Thus, 613 companies fulfilled the overall inclusion criteria for this study. The issuer rating was chosen as it the most appropriately reflects the creditworthiness of a company, rather than a particular issue, which could have a different rating due to covenants or characteristics of the product itself. Hence, international issuer rating, watch, and outlook by Moody's, S&P or Fitch are of prime interest in this study. For simplicity, they are referred to collectively as rating actions, announcements or events. All available effective dates of rating actions for the 613 companies were obtained from the Thomson Reuters Eikon platform. The total sample up to that point consisted of 14,554 observations spread across rating (4,385), watch (1,453), and outlook (8,716).

Data preparation was divided into three steps. First, all observations which did not meet the definition of an event were eliminated. In that manner, from the above sample we excluded affirmations of rating, watch and outlook as well as changes from preliminary to actual rating as no actual shift in rating essentially occurs and thus the possibility that the action carries any market-driving information is minimal. Following the same logic, changes of outlook from "no outlook" to "outlook stable" were excluded. As the result of this procedure, we eliminated almost 6,000 observations, where the majority was attributable to events concerning outlook. Having completed all of these procedures, we were left with 8,567 events across rating (4,231), watch (1,335) and outlook (3,001).

[12] Thompson Reuters uses an algorithm to calculate the "primary country of risk" that takes into account factors such as the domicile of a firm, its headquarters location, countries in which it generates revenue, the countries in which its securities trade, and the base currency used in its financial reports.

Second, we dropped first-time ratings (when the issuer was rated for the first time, around 990 observations) and withdrawals as it is unclear if the information carried by the action is positive or negative. We also dropped instances of default (around 300 including withdrawals), as they are likely to be CRAs reaction to other events. We were finally left with 7,283 event dates. However, we needed to exclude events that took place when a company was not listed or events that did not yield enough stock price values to estimate the market model.

Third, to increase the robustness of the analysis, we excluded a few outliers and observations that do not explicitly fall into pre- or post- regulation era. These points will be addressed separately in sections 2.3 and 2.2.3. The final dataset contains 5,512 observations (contaminated and non-contaminated) across outlook (2,445), rating (2,526), and watch (541) (see Table 2).

2.2 DEFINITION OF VARIABLES

2.2.1 Direction of the Outcome

An event was defined as "positive" or "negative" based on the company´s creditworthiness and its expected future development. While for some events the answer is more intuitive – upgrade, positive watch, and outlook represent positive outcomes as well as downgrade, negative watch, or outlook represent negative outcomes – the analysis becomes slightly more complicated when it comes to designations such as “stable outlook“ or “evolving watch”. It is important to note, that the watch and outlook changes were treated as events only in case the rating remained unchanged. As previously described, watch and outlook might take a value of “evolving” and could eventually result in either an upgrade or downgrade of the issuer’s rating. This resulted in the elimination of roughly 60 such observations. For the rest of the events, Table 1 provides a summary of how and when they are treated as negative or positive. For instance, when the rating remains unchanged, yet outlook becomes positive or changes from negative to stable, we treat both as a positive developments.

Table 1 provides definitions of the direction of credit rating actions. Rating upgrades and downgrades indicate positive and negative events respectively. Watch and outlook changes are defined conditioned on an unchanged rating. When the rating remains the same and a watch changes to positive or negative, then it is treated as positive or negative event respectively. Finally, when an outlook changes to positive or from negative to stable, then it is treated as a positive event. Correspondingly, when outlook changes to negative or from positive to stable, then it is treated as a negative event.

Outcome	Previous state	Outcome	Direction of the Outcome
Rating	N/A	Upgrade	Positive / Up
		Downgrade	Negative / Down
Watch (within the same rating)	No watch / Negative / Evolving	Positive	Positive / Up
	No watch / Positive / Evolving	Negative	Negative / Down
Outlook	No outlook / Stable / Negative / Evolving	Positive	Positive / Up
	No outlook / Stable / Positive / Evolving	Negative	Negative / Down
	Negative	Stable	Positive / Up
	Positive	Stable	Negative / Down

2.2.2 Definition of Contaminated and Non-contaminated Observations

An event was defined as contaminated if there were other events such as earnings releases, annual shareholder meetings or dividend announcements within a seven-day window before or after the rating action [-7,+7]. Additionally, possible contamination with other rating events was also taken into account. In case there were more than one rating announcements within a seven-day window [-7,+7], all rating events that happened on the first day of the sequence were deemed as non-contaminated, and succeeding events were deemed as contaminated. For instance, if S&P upgrades company X on day 1, followed by Fitch on day 2 and Moody’s on day 3, then (given that there are no other events) the rating event on day 1 was defined as non-contaminated and the events on day 2 and 3 as contaminated. This ensures that events that could have the most significant effect on the results are indeed included in the sample (see section 3.6). Table 2 exhibits the final data broken-down by contaminated and non-contaminated events. All in all, the sample is comprised of 1,620 contaminated and 3,892 non-contaminated observations.

2.2.3 Definition of Pre- and Post-Regulation Eras

Since one of the aims of the study is to compare results before and after the European CRA industry has become regulated (pre- and post-regulation eras), the time span for these periods had to be defined. Therefore, the pre-regulation era was determined as the time from the earliest data point in the sample up to one month before the law was published in the Official Journal of European Union. Similarly, the post-regulation era was defined as the time after the regulation officially entered into force. Consequently, the pre-regulation era spans from 1989 until 16th of October 2009, and post-regulation era from 7th of December 2009 until October 2017. For unambiguity, around 20 events were removed as they took place between mid-October and December 2009 and did not fall into any of the above-defined eras.

2.3 EXTREME VALUES

After thorough examination of the data, outliers were discovered in the sample, which as defined by Newbold and Carlson (2010) are data points that deviate substantially in value from the rest of observations. Most outliers did not result from recording errors but rather were extreme values. Nevertheless, regardless of their nature, outliers could have a significant influence on the results. There are several methods to tackle outliers. As Newbold and Carlson (2010) suggested, outliers could either be retained if they are a part of the process being studied or be excluded otherwise. The majority of previous studies, with an exception of Norden and Weber (2004) that eliminated the extreme values, did not explicitly discuss how they treated the outliers. In-depth analysis of the data identified many of these extreme values as stock price moves of Greek companies. Consequently, data points from Greek companies were eliminated. Nevertheless, other categories could not be controlled for as there were no visible trends regarding other countries, years or sectors. Therefore, an in-depth examination of individual values was required. Cumulative abnormal returns were constructed (CAR, see the definition in the section 2.5.1) over the 60 day period for observations that exhibited most extreme values of abnormal returns (AR, see section 2.5.12.5.1) (+/-50%) and CAR (+/-100%) to decide if the extreme values were a result of a one-off event or a steady trend. Next, if an extreme value was indeed a result of a one off price drop or increase, the observation was eliminated (all 60 days; around 10 ids). Exclusion of individual observations partially solved the problem of extreme values. However, elimination of all extreme values would lead to a removal of a large number of observations from the analysis[13]. Therefore, another approach was required and the remaining data was winsorised for abnormal returns at 1% and 99%[14]. Consequently, any data value above the 99th percentile of the sample data was replaced by the 99th percentile, and correspondingly, any value below the 1st percentile was replaced by the 1st percentile.

[13] Elimination of contaminated observations has already decreased the sample size by nearly 30%. Further exclusion of AR > 10% and AR < -10% would additionally decrease the sample size by around 23%.

[14] The results with exclusion of outliers and no further winsorising yielded similar results.

2.4 Data Description

The data is comprised of companies based and listed in Europe that hold at least one international credit rating by Moody's, S&P, or Fitch. The final data set consists of 3,892 non-contaminated observations between 1989 and 2017, distributed across rating, watch, and outlook. Table 2 suggests that out of 5,512 observations, only 3,892 are non-contaminated and are hence used for further analysis. The time distribution of contaminated events reveals that over 44% of events fall into the pre-regulation period and 56% into the post-regulation one. The distribution is also similar for non-contaminated events. The numbers reveal that the sample is dominated by negative events, which is in line with previous research. Nevertheless, the number of positive events (with an exception for the watch) is sufficient to perform analysis on the positive rating events as well. Concerning the distribution by type, the sample is dominated by outlook changes (1,844), with 1,084 negative and 760 positive outcomes. Next, there are 1,694 rating migrations, with 1,111 downgrades and 583 upgrades. Watch exhibits the lowest number of observations, i.e. 354 distributed by 302 negative and 52 positive outcomes. Investment grade credits also dominate the data. As Table 3 suggests, almost 78% events in the sample are rated BBB- or above. Moreover, companies with rating class of A and BBB are the most abundant in the data and comprise over 65% of the total number of observations. Furthermore, the breakdown by the agency reveals that the majority of non-contaminated observations (approximately 63%) are attributable to S&P, followed by Fitch, (approximately 28%), and Moody's (approximately 9%) (see Table 12 in the appendix). Table 4 indicates that the non-contaminated sample is dominated by financial companies. While we acknowledge that financial companies might differ from other sectors in terms of capital structure, this does not affect the analysis, which is aimed at investigating equity investors' reaction to watch, outlook, and rating announcements. Finally, the sample consists of companies from various European countries (see Table 13 in the appendix). Even though the sample is dominated by more financially developed countries with well-established stock exchanges such as by France, UK, Germany, and Italy that together comprise more than 56% of the total number of observations, the data also includes emerging Europe with less advanced and liquid financial markets such as Romania, Hungary, Croatia, and Bulgaria.

Table 2 exhibits distribution of all events (after elimination of outliers and Greece) during pre- and post-regulation period and the breakdown by contamination, the direction of the outcome and type (outlook, rating and watch). Pre-regulation era covers the period from 1989 to mid-October 2009 and the post-regulation period covers the time from mid-December 2009 to October 2017. 1 denotes contaminated data points, i.e. that there were other events such as earnings releases, dividend announcements, annual shareholders meetings, or another rating action within seven days preceding and succeeding the event. Likewise, 0 denotes non-contaminated events. "Down" represents negative events and "Up" represents positive events. In total, there are 5,512 observations, and about 70% of them comprise non-contaminated events.

Time and Type of the Event	Contamination and Direction of the Outcome								
	0			1			Total		
	Down	Up	Total	Down	Up	Total	Down	Up	Total
pre-regulation era									
Outlook	474	251	725	214	105	319	688	356	1,044
Rating	542	245	787	285	99	384	827	344	1,171
Watch	122	19	141	77	15	92	199	34	233
Total	1,138	515	1,653	576	219	795	1,714	734	2,448
post-regulation era									
Outlook	610	509	1,119	223	140	363	833	649	1,482
Rating	569	338	907	255	112	367	824	450	1,274
Watch	180	33	213	88	7	95	268	40	308
Total	1,359	880	2,239	566	259	825	1,925	1,139	3,064

Table 3 presents the distribution of all non-contaminated events across rating classes for the whole investigation period, between 1989 and the end of 2017. A rating class includes all issuer ratings distinguished by notches within the same category, for instance, rating class AA includes AA-, AA and AA+. Table 4 presents distribution of non-contaminated observations by GICS sector.

Table 3

Initial Rating Class	Freq.	Percent	Cum.
AAA	14	0.36	0.36
AA	432	11.10	11.46
A	1,305	33.53	44.99
BBB	1,273	32.71	77.70
BB	525	13.49	91.19
B	287	7.37	98.56
CCC	55	1.41	99.97
CC	1	0.03	100.00
Total	3,892	100.00	

Table 4

GICS Sector	Freq.	Percent	Cum.
Financials	1,360	34.94	34.94
Industrials	497	12.77	47.71
Consumer Discretionary	494	12.69	60.41
Materials	373	9.58	69.99
Utilities	241	6.19	76.18
Consumer Staples	228	5.86	82.04
Telecommunication Service	215	5.52	87.56
Energy	189	4.86	92.42
Information Technology	125	3.21	95.63
Health Care	106	2.72	98.36
Real Estate	64	1.64	100.00
Total	3,892	100	

2.5 METHOD

2.5.1 The Market Model

The event study methodology proposed by MacKinlay (1997) was utilised in the design of this study. The cumulative abnormal returns (CAR) were defined as a sum of abnormal returns estimated by the market model (Equations 2 and 3). In the model α_i and β_i are OLS regression estimation parameters for a company i, and $\varepsilon_{i,t}$ is the zero mean disturbance term. $R_{i,t}$ is the log-return of the share price at time t for the company i. $R_{m,t}$ is the log-return on the underlying market m at time t.

$$R_{i,t} = \alpha_i + \beta_i \times R_{m,t} + \varepsilon_{i,t} \;\; , \;\; E(\varepsilon_{i,t} = 0) \;\; , \;\; var(\varepsilon_{i,t}) = \delta^2_{\varepsilon_i} \quad \textit{(Equation 2)}$$

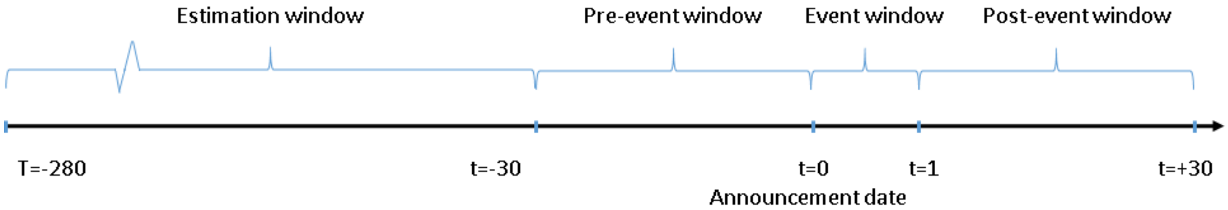
$$CAR_i(t_1, t_n) = \sum_{t=t_1}^{t_n} AR_{i,t} = \sum_{t=t_1}^{t_n} (R_{i,t} - \alpha_i - \beta_i \times R_{m,t}) \quad \textit{(Equation 3)}$$

The Stoxx600 index was chosen as a proxy for the European market because of two main reasons. First, it constitutes 600 listed companies across various sectors and provides a broad regional coverage. Second, its performance can be tracked back to January 1987 which enables the use of the same proxy for the market over the entire investigation period.

In order to estimate the market model and normal returns, an estimation window of 250 days prior to the event window was established. If the observation number was insufficient for the whole period, the event was eliminated (see Figure 3).

An event day was defined as the actual day the event occurred and the following business day after outlook, rating or watch change was announced [0,+1]. An event was defined as an actual change (i.e. affirmations are excluded) in either issuer rating, watch or outlook. In order to investigate potential short-term pre- and post-announcement drifts, pre- and post-event window were set from 30 days before until the event window [-30,-1] and from day 2 until 30 day after the event date [+2,+30].

Figure 3 provides a timeline illustration of the chosen periods for estimation window [-280,-31], pre-event window [-30,-1], event window [0,+1], and post-event window [+2,+30].



3 Section III – Results and Analysis

3.1 Introduction

The results and the analysis of the market reaction to credit rating events are presented below. Cumulative abnormal returns (CAR) were investigated during up to 30 days before and after a credit rating event such as rating, watch, or outlook change. The graphs show the market reaction during the whole pre- and post-event period [-30,+30], and the tables exhibit results for up to 7 days around the event window. Market reaction to positive and negative events, divided by type (rating, watch, and outlook), and investment grade class was examined. Analysis of rating change announcements distinguished by geography, the magnitude of change (expressed in a number of notches), firm's size, and direct anticipation conditional on pre-existence of watch or outlook was also conducted. Even though stronger results in the contaminated sample were found, this section presents results only for the non-contaminated sample to illustrate the market reaction attributable strictly to the rating announcements. Nevertheless, the contaminated sample is addressed in section 3.7. In general, we expect positive reaction (+) on the day of positive events including – upgrades, positive watch and outlook announcements. Correspondingly, we anticipate negative signs (-) on the day of negative events including – downgrades, negative watch and outlook announcements.

In line with previous research, negative events yield stronger results. However, significant positive market reaction on the event day for some positive events is also observed. Overall, the analysis indicates stronger results in the post-regulation era and within the non-investment grade class.

Figure 4 shows cumulative abnormal returns for the period 30 day before to 30 days after a credit rating event, where the event day is marked by 0. The graph on the left covers non-contaminated events including outlook, watch, and rating changes. The sample consists of 2,497 negative and 1,395 positive events spanning from 1989 to 2017. CAR after positive events reach the peak on day 0. CAR after negative events hit trough on day 1. Figure 5 and Figure 6 additionally split the positive and negative events into investment grade (IG) and non-investment grade (NIG) rating classes respectively. On Figure 5, the IG sample comprises 1,925 negative and 981 positive events. On Figure 6, the NIG sample is smaller and comprises 447 negative and 349 positive events across all types. Figures 5 and 6 do not include events that resulted in crossing the IG line.

Figure 4

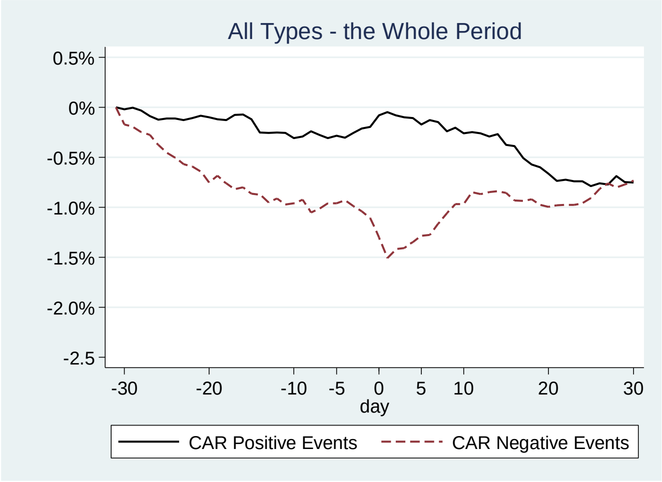


Figure 5

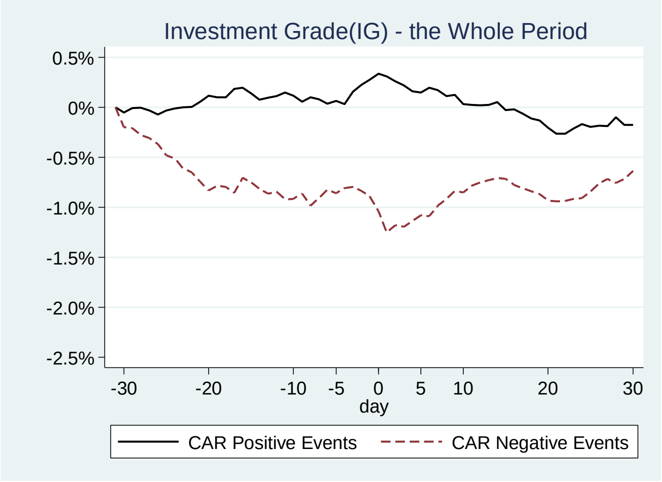
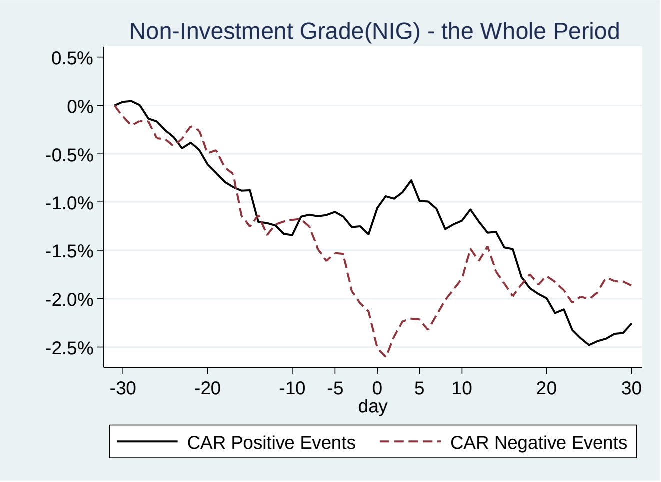


Figure 6



3.2 PART ONE: GENERIC RESULTS

3.2.1 Medium-Term Trends

Figure 4 shows overarching trends in market reaction to positive and negative events for the whole period from 1989 to 2017. Hereinafter, the sample with positive events will be referred to as "positive sub-sample" and with negative events as "negative sub-sample". The reversals and negative mean CAR for the positive sample seem to be quite peculiar and not in line with expectations.

In the negative sub-sample the mean cumulative abnormal returns (CAR) start declining 30 days before the event day, hit the trough on day 1 and continue with a slight reversal afterwards. Even though the trend seems to be more pronounced for the negative events, a slight reversal in the positive sub-sample is also observed. Having investigated whether individual events could drive the results, it can be concluded that this is not the case. On the contrary, many observations exhibit negative returns after a positive event and vice versa. The analysis shows that 164 observations out of total 1,395 positive events exhibit CAR<-10% within 7 days after the event. Similarly, 441 out of 2,497 observations that have CAR>10% on the 7th day after the event are negative rating events.

Further analysis of the difference between IG and NIG (Figure 5 and 6) reveals that NIG companies seem to push the trend observed in Figure 4. The mean CAR for the positive NIG events seem to drive the overall results for the positive sub-sample and push the returns below zero. Similarly, the uptrend after a negative event can partially be explained by the performance of NIG companies. Even though small positive returns for the IG companies after the event window could be seen, the uptrend for the NIG names is more pronounced and drives the results for up to 14 days after the event (see Figure 6).

Moreover, the reversal after negative events is quite a puzzling result. This could, of course, be due to other events happening at the same time that were not excluded by the previously described procedure. However, the sample has a sufficiently large number of observations for these effects to offset each other. It should be noted that several previous studies also observed the positive market reversal after negative events. Pinches and Singleton (1978) and Glascock et al. (1987) found a positive share price reversal following bond rating changes. Glascock et al. (1987) proposed that the trend could be potentially explained by the price pressure phenomenon. In brief, they suggested that if only some investors believe that the downgrades have an impact on the share price – while the rest of the market does not have the same opinion – then, some *metaorders* could drive the market in a way that there would be an anticipation before the event, a small decline on the event day, and a positive post-announcement drift.

Moreover, Steiner (2001) found the positive reversal in bond returns after downgrades and placement on the negative watch and Hill and Faff (2007) in stock returns after a negative watch at the sovereign level. They claimed that the reversal occurred due to the overreaction of a market to negative events and the failure of market participants to adequately gauge the change in the risk profile.

Nevertheless, further analysis reveals that there may be another potential explanation for the reversal. The positive reversal can be a reaction to some hedge fund activity in the most distressed companies. After the elimination of new ratings below BB, the positive reversal disappears. This finding suggests that only the most troubled names, rated at the lowest end of NIG spectrum, show positive share returns after negative events.[15] According to Jiang et al. (2012), hedge funds (or vulture funds) are the most active investors in the distressed-debt market, which could suggest that they also hold some of the lowest rated junk debt of companies in our sample. The authors further proposed that the presence of vulture funds as a creditor enhances the probability of a successful company re-organisation in case of bankruptcy and is favourable for the shareholders. Their results showed that after a firm has filed the Chapter 11 petition, companies with hedge funds among unsecured investors experienced a stock price increase. Since, our data shows that the reversal after negative events is the most pronounced for the lowest rated issuers, some adverse events that even further diminish creditworthiness and put it closer to bankruptcy, could trigger an analogous reaction for the share prices in the data. This is an interesting finding, however it requires more research.

3.2.2 Anticipation of Credit Rating Events

Another trend observed in Figure 4 is market anticipation of negative announcements up to 30 days before the event. Previous research also found that the market anticipates credit rating actions, especially rating downgrades and negative watch announcements (Pinches & Singleton, 1978; Holthausen & Leftwich; 1986, Glascock et al., 1987; Goh & Ederington, 1993; Goh & Ederington, 1999; Norden & Weber, 2004; Finnerty et al., 2013; Kiesel, 2016).

[15] The NIG sub-sample for new ratings consists of around 500 names with 190 new firms rated at BB- or below. This suggests that the disappearance of the reversal should not be a result of removal of a few individual observations.

Additionally, Holthausen and Leftwich (1986) found that the market anticipates upgrades from 300 days before the event. There is less evidence of anticipation of outlook.

Since the sample is controlled for specific events up to seven days before and after the event, the results could suggest that there were other company-specific news before that period. Then, the anticipation could merely represent the lag between a deterioration (improvement) of a company and CRAs response (Pinches & Singleton, 1978). The explanation of the negative drift could be that CRAs simply react to the deterioration of the company by various rating actions. Nevertheless, Finnerty et al. (2013) proposed that CRAs may have strengthened their corporate credit rating process since 2003 so that they respond more quickly to a credit rating change before it is reflected in market prices.

The anticipation could also be explained by leakage of rating information before the actual change of credit rating, watch or outlook. This argument can be strengthened by the observed decline in stock price a few days before a rating action.

Finally, as with reversals, the anticipation of negative credit rating is commonly observed for the non-investment grade (see Figure 6). Goh and Ederington (1999) also found evidence that the stock market is anticipating credit rating downgrades within the NIG more prominently than within the IG.

3.2.3 Before and After the Regulation

Even though the graphs provide valuable insights about the trends in the sample, in order to make a conclusion about the hypotheses, mean CAR were analysed and z-tests were performed to check if the reaction was statistically significant and different than zero. Table 5 summarises the results of positive and negative events for the whole period as well as for pre- and post-regulation eras. In general, statistically significant market anticipation of the events is not seen during the week preceding the announcement. Furthermore, for the negative sub-sample, with an exception for the post-regulation period, statistically significant post-announcement drift or reversal with the magnitude approximately offsetting the reaction on the event day could be seen. On the event day, negative rating events exhibit statistically significant negative market reaction before and after the regulation. Positive events show statistically significant results on the event day after the regulation, but prove to be statistically insignificant before the regulation. Even though the conclusions should be drawn cautiously, the results might suggest that in the pre-regulation era, the investors relied on negative rating events more than on positive. After the adoption of the regulation, due to amongst others increased quality of credit ratings, investors started to trust positive rating events and adjusted the stock prices accordingly. Nevertheless, since the magnitude of the results is very small, the economic significance of positive events is questionable.

Table 5 shows mean cumulative abnormal returns recorded as the response to negative and positive credit rating events. The table covers non-contaminated events and summarises all types including rating, watch, and outlook. CAR are exhibited for the pre-event window between days -7 and -1, the event window of days 0 and 1, and the immediate post-event window comprising days 2 to 7. Additionally, the results are divided into three periods. Starting from the left, "Whole Period" represents all years used in the study, i.e. from 1989 to 2017; "Before Regulation" represents the period before the European CRAs have been regulated, i.e. 1989 to October 2009; and "After Regulation" represents the period from the mid-December 2009 to October 2017. All numbers are presented as percentages (%). Significance level is explained underneath the table.

All Types: Rating, Watch and Outlook

	Whole Period		**Before Regulation**		**After Regulation**	
	Negative	Positive	Negative	Positive	Negative	Positive
CAR[-7,-1]	-0.10	0.04	0.03	0.05	-0.22	0.04
(z-test)	*(-0.81)*	*(-0.36)*	*(-0.16)*	*(-0.23)*	*(-1.34)*	*(-0.28)*
N	2,497	1,395	1,138	515	1,359	880
CAR [0,+1]	-0.49***	0.16*	-0.55***	0.05	-0.44***	0.22**
(z-test)	*(-7.22)*	*(-2.54)*	*(-4.88)*	*(-0.44)*	*(-5.38)*	*(-3.05)*
N	2,497	1,395	1,138	515	1,359	880
CAR [+2,+7]	0.41***	-0.11	0.62***	-0.14	0.23	-0.10
(z-test)	*(-3.68)*	*(-1.23)*	*(-3.56)*	*(-0.88)*	*(-1.62)*	*(-0.87)*
N	2,497	1,395	1,138	515	1,359	880

** p<0.05, ** p<0.01, *** p<0.001*

In order to see whether market reaction to the rating announcements is different before and after the regulation, the z-test was performed. The results reveal that there is no statistically significant difference in the effect on the stock prices in pre and post regulation era. As a result, based on the data of all rating events, it cannot be claimed that rating announcements became more informative after the adoption of the regulation.

3.3 PART TWO: RESULTS BROKEN-DOWN BY TYPE

In part one there was no significant difference found in the effect of rating announcements before and after the regulation. However, to assure that the observed results were not driven by a particular rating event type, separate analysis was performed for the effect of outlook, watch, and rating change announcements. Comparing Figures 7, 8 and 9 (see page 33) it could be noted that rating and outlook plots for the negative sub-sample show much resemblance.

Figure 7 shows cumulative abnormal returns for the period from 30 days before to 30 days after an outlook change on day 0. The graph covers non-contaminated events including 1,084 negative and 760 positive events from 1989 to 2017. Figure 8 shows cumulative abnormal returns for the period 30 day before to 30 days after a credit rating change, where the event day is marked as 0. The graph covers non-contaminated events including 1,111 downgrades and 583 upgrades from 1989 to 2017. Figure 9 shows cumulative abnormal returns for the period 30 day before to 30 days after a watch announcement on day 0. The graph covers non-contaminated events including 302 negative and 52 positive reviews from 1989 to 2017. Please note, that Figure 9 has a different scale than Figure 7 and 8.

Figure 7

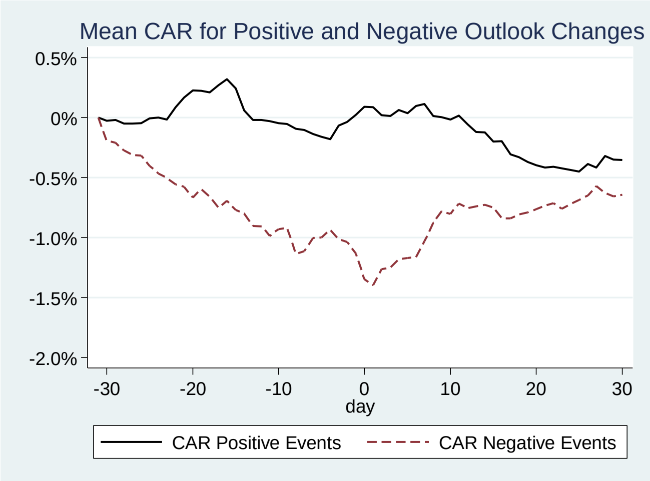


Figure 8

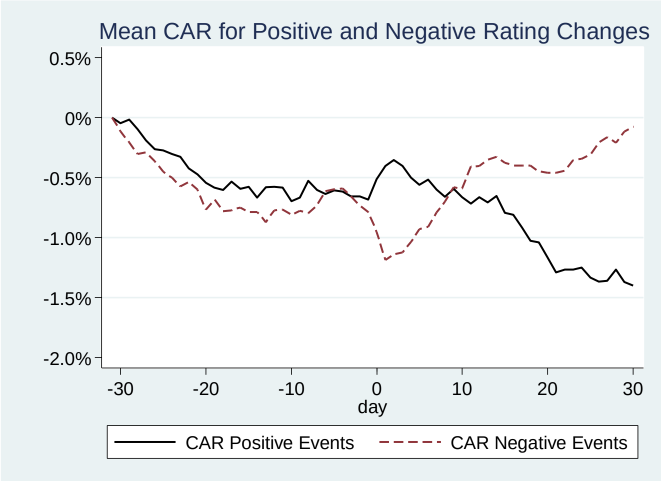
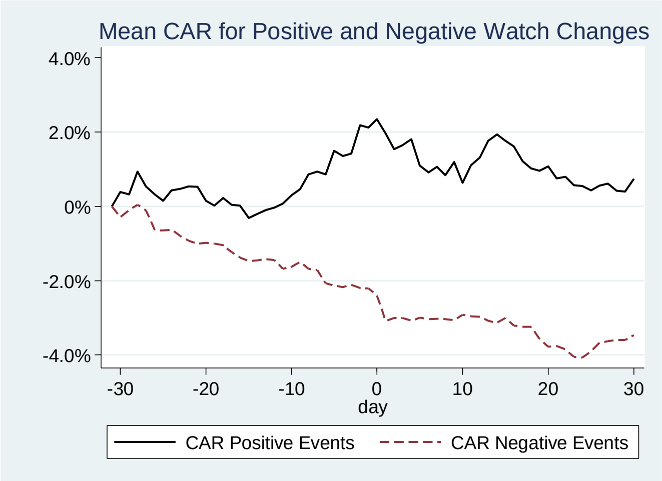


Figure 9



Negative mean CAR after the positive rating events observed in Figure 4 seem to be mostly influenced by rating change, whereas the post-announcement reversal is driven by rating and outlook. However, the plot of the market reaction to negative credit watch, contrary to plots of rating and outlook, exhibit an apparent negative post-announcement drift. This finding is consistent with several previous studies that found a negative short-term (Goh & Ederington, 1993) and long-term (Dichev & Pietroski, 2001) share price reaction to both rating downgrades and placement on negative watch (Holthausen & Leftwich, 1986).

The authors explained this phenomenon mainly with the initial under-reaction to negative rating events. However, this could have simply been caused by the subsequent adverse events that previous research did not control for. Concerning our study, even though major events during the 14 days event window were controlled for, there could be other events that happened in any other period. This explanation is consistent with the nature of watch, which suggests that there are some pending issues with the issuers that await resolution.

Therefore, we further investigate only the event window, which is not contaminated by other significant events [-7,+7] and analyse the significance of rating informational effect before and after the regulation by dividing the results by outlook, watch, and rating change announcements into pre and post-regulation era.

Table 6 shows that, in general, negative outlook, watch, and rating change announcements show stronger results both in the context of statistical significance and magnitude. This is consistent with previous research (Hand et al., 1992; Goh & Ederington, 1999; Dichev & Piotroski, 2001; Norden & Weber, 2004; Bannier & Hirsch, 2010; Kiesel, 2016). The stronger reaction to negative events could be explained by a higher number of negative observations or the “good news travel fast phenomenon”. According to Holthausen and Leftwich (1985) on average, “good news” accounting earnings reports are early, whereas “bad news” earnings reports are late. Managers are inclined to announce good news about a company immediately, but withhold the bad ones until it is necessary to make them public. Moreover, Galil and Soffer (2011) proposed that rating agencies and other information providers focus on adverse news and hence cause them to cluster. Meanwhile, positive news are less frequent and tend to cluster less. Consequently, the overall market response to bad news is stronger.

Table 6 exhibits mean CAR during the period immediately before the event window (days -7 to -1), the event window (days 0 to 1) and the immediate period after the event window (days +2 to +7). The results are broken down by type (rating, watch, and outlook), outcome (positive and negative), and time period – the whole period from 1989 to October 2017, pre-regulation era covering 1989 to mid-October 2009, and post-regulation era covering mid-December 2009 to October 2017. The significance level is denoted by stars and described below the table. All numbers are presented in percentages

All Types Separately- Rating, Watch, and Outlook

Broken-down by pre- and post-regulation era

		Whole Period		Before Regulation		After Regulation	
		Negative	Positive	Negative	Positive	Negative	Positive
RATING							
	CAR[-7,-1]	0.01	-0.11	0.27	0.02	-0.24	-0.21
	(z-test)	*(-0.05)*	*(-0.67)*	*(-0.89)*	*(-0.08)*	*(-0.92)*	*(-1.04)*
	N	1,111	583	542	245	569	338
	CAR [0,+1]	-0.50***	0.29**	-0.46**	0.08	-0.54***	0.45***
	(z-test)	*(-4.65)*	*(-2.86)*	*(-2.69)*	*(-0.45)*	*(-4.07)*	*(-3.68)*
	N	1,111	583	542	245	569	338
	CAR [+2,+7]	0.42*	-0.24	0.48	-0.25	0.36	-0.23
	(z-test)	*(-2.46)*	*(-1.71)*	*(-1.90)*	*(-1.11)*	*(-1.57)*	*(-1.30)*
	N	1,111	583	542	245	569	338
WATCH							
	CAR[-7,-1]	-0.63	1.36	-0.90	1.79	-0.44	1.11
	(z-test)	*(-1.82)*	*(-1.63)*	*(-1.80)*	*(-1.24)*	*(-0.94)*	*(-1.08)*
	N	302	52	122	19	180	33
	CAR [0,+1]	-0.92***	0.02	-0.68	0.57	-1.08***	-0.30
	(z-test)	*(-4.60)*	*(-0.04)*	*(-1.89)*	*(-0.66)*	*(-4.70)*	*(-0.96)*
	N	302	52	122	19	180	33
	CAR [+2,+7]	0.01	-0.85	0.11	-1.55	-0.05	-0.45
	(z-test)	*(-0.03)*	*(-1.66)*	*(-0.21)*	*(-1.49)*	*(-0.14)*	*(-0.82)*
	N	302	52	122	19	180	33
OUTLOOK							
	CAR[-7,-1]	-0.07	0.06	0.00	-0.06	-0.13	0.13
	(z-test)	*(-0.39)*	*(-0.44)*	*(-0.01)*	*(-0.23)*	*(-0.57)*	*(-0.76)*
	N	1,084	760	474	251	610	509
	CAR [0,+1]	-0.37***	0.06	-0.62***	-0.02	-0.17	0.10
	(z-test)	*(-3.76)*	*(-0.78)*	*(-3.80)*	*(-0.13)*	*(-1.45)*	*(-1.08)*
	N	1,084	760	474	251	610	509
	CAR [+2,+7]	0.50**	0.03	0.90***	0.07	0.20	0.02
	(z-test)	*(-3.09)*	*(-0.28)*	*(-3.35)*	*(-0.32)*	*(-0.97)*	*(-0.11)*
	N	1,084	760	474	251	610	509

* p<0.05, ** p<0.01, *** p<0.001

The comparison of the separate rating event types before and after the regulation (see Table 6), provides ambiguous results. In general, all significant reactions have expected signs, i.e. plus on the day of positive events and minus of the negative. Further, rating changes are the only type of announcements that show a significant market response to positive news. At the same time, despite the number of observations, positive results are statistically significant in the post- but not in the pre-regulation era. This could suggest that information quality of the positive ratings has improved after the adoption of the regulation. Nevertheless, in both pre- and post-regulation eras, downgrades trigger abnormal returns with the magnitude of around -0.5%. Negative watch announcements exhibit statistically significant reaction only after the enforcement of the regulation, suggesting that revisions for downgrade could have indeed become more informative than in the pre-regulation era. Compared to the rest of the results, negative watch triggers a relatively high excess return of over -1.1% during the event window. On the other hand, positive credit watch does not show any statistically significant results at all. This is most likely due to a small positive watch sample size. The results of outlook are significant only for the negative events and only before the regulation. After the regulation, the outlook does not seem to bring any information to the market.

Even though the results after the regulation in general seem to be slightly stronger than before the regulation, z-tests for separate rating event types were performed to check if coefficients of pre- and post-regulation eras are statistically different. The results show that there is no significant difference between the mean of coefficients and hence the null hypothesis that the mean CAR before and after the regulation are equal for either watch, rating, or the whole sample cannot be rejected. Therefore, even though some evidence suggesting positive effects of the regulation was found, we are not able to accept the Hypothesis 2 that the regulation increased the informational value of credit events after 2010.

Nevertheless, confound variables that could have influenced our results were not profoundly examined. Other factors that had a considerable influence on the European market, such as European debt crisis, quantitative easing and other regulations, could have precluded from an objective assessment of change in credit rating quality and its effect on the stock market.

3.4 PART THREE: RESULTS BROKEN-DOWN BY INVESTMENT GRADE CLASSES

Based on the reasoning provided in section 1.7 we expect larger share price reaction to outlook, watch, and rating changes for non-investment grade than investment grade rated companies.

As it could be seen in Table 7, a slightly larger negative market reaction to adverse announcements is observed in the non-investment grade group (-0.72%) than for the observations that are within the investment grade (-0.42%). Moreover, positive rating events are not significant in the IG class, however, they are statistically significant in the NIG class.

Consistent with previous procedure, z-test was performed to see whether this difference is statistically significant. The results of z-test revealed that there is no statistically significant difference between the mean CAR of IG and NIG companies. Therefore, the Hypothesis 3 could not be accepted for the data that comprises all event types. However, as suggested before, one rating event type – for example, rating change - might be driving the results. Therefore, following the same procedure as in the section 3.2.3, the sample was divided into different rating event types to analyse the results of each rating event type separately.

Table 7 exhibits the cumulative abnormal returns for the investment grade and non-investment grade companies separately. The analysis covers all observations since 1989 and includes all event types (rating, watch, and outlook). All numbers are presented in percentage. The significance level is denoted by starts and presented underneath the table.

Investment and Non-Investment Grade

	IG		NIG	
	Negative	**Positive**	**Negative**	**Positive**
CAR[-7,-1]	0.09	0.18	-1.15**	-0.25
(z-test)	*(-0.66)*	*(-1.57)*	*(-3.12)*	*(-0.94)*
N	1,925	981	447	349
CAR [0,+1]	-0.42***	0.06	-0.72***	0.36*
(z-test)	*(-5.80)*	*(-0.96)*	*(-3.79)*	*(-2.3)*
N	1,925	981	447	349
CAR [+2,+7]	0.26*	-0.14	0.71*	-0.17
(z-test)	*(-2.23)*	*(-1.44)*	*(-2.24)*	*(-0.73)*
N	1,925	981	447	349

** p<0.05, ** p<0.01, *** p<0.001*

As no significant results for positive rating events were observed, Table 8 presents only the negative sub-sample, broken-down by outlook, watch, and rating changes. It indicates little consistency with the expectations other than the results of the rating change. As expected, the reaction for the non-investment grade downgrades is larger than for the investment grade. However, the difference in magnitude of the coefficients is not statistically different from zero.

Relatively strong reversal is also observed after rating downgrades for the NIG companies. This reversal, even though statistically significant only at 10% level, is also well observed for the post-announcement period after NIG watch events. As mentioned before, the observed surge in the stock price could be a result of hedge fund involvement (Jiang et al., 2012).

Nevertheless, based on the results, we conclude that there is no statistically significant difference for the rating changes within the NIG and IG rating classes. Nevertheless, it should be noted that the sample is dominated by IG credits. It would be interesting to perform the test with larger sample of NIG ratings and see whether the results are consistent.

Finally, we investigated the market reaction to rating change that crossed the investment grade line (upgrade to, or downgrade from BBB- equivalent rating). Unfortunately, due to a small number of observations, no significant results were found. It would be interesting to repeat the analysis with a larger sample size.

Table 8 shows CAR after an adverse credit rating event for the whole time period form 1989 till 2017 and all types including rating, outlook, and watch. The types are further broken-down by the investment grade class of the rating to investment grade (IG) and non-investment grade (NIG). In order to be classified as either IG or NIG, both the initial and the new ratings need to be in the same category. All numbers are presented as percentages (%). The significance level is denoted by starts and presented underneath the table.

IG and NIG Reaction to Negative Events by Type

	Rating		Outlook		Watch	
	IG	NIG	IG	NIG	IG	NIG
CAR[-7,-1]	0.24	-1.04	0.11	-1.19*	-0.47	-1.40
(z-test)	*(-1.17)*	*(-1.79)*	*(-0.53)*	*(-2.32)*	*(-1.31)*	*(-1.07)*
N	839	197	826	219	260	35
CAR [0,+1]	-0.35**	-0.94**	-0.36***	-0.46	-0.86***	-0.85
(z-test)	*(-3.06)*	*(-2.98)*	*(-3.43)*	*(-1.84)*	*(-4.1)*	*(-1.23)*
N	839	197	826	219	260	35
CAR [+2,+7]	0.24	1.08*	0.46**	0.41	-0.33	1.87
(z-test)	*(-1.34)*	*(-2.01)*	*(-2.68)*	*(-0.92)*	*(-1.03)*	*(-1.76)*
N	839	197	826	219	260	35

** p<0.05, ** p<0.01, *** p<0.001*

3.5 PART FIVE: FURTHER ANALYSIS OF THE RATING MIGRATION

Based on the previous results, further analysis concentrates on the equity market reaction to rating changes. Since the sample is well diversified, it is possible to differentiate between various groups based on characteristics of the companies such as geography, size, and the nature of the rating change itself, i.e. magnitude of change (in number of notches) and anticipation of the rating change by pre-existence of watch or outlook.[16] Table 9 presents the results and demonstrates that, as expected, the Emerging Europe and countries that were most

[16] We also distinguished between other groups, such as parent vs subsidiary, financial vs non-financial companies, and financial crisis vs non-financial crisis period. Due to small coefficients, we did not find any significant difference between any of the groups. We presented the summary of these results in Table 15 in the appendix.

affected by the sovereign debt crisis in 2010s[17] indeed reacted stronger to adverse events on the event day. The other country group[18], which consists of more financially developed and stable economies, did not exhibit any significant reaction on the event day. The results could suggest that the informational value of ratings depends on the characteristics of the underlying country-specific market such as efficiency and liquidity. Nevertheless, since the difference in coefficients is not proven to be different by the z-test, based on the results, it is not possible to conclude that there is a significant difference between the country groups.

Furthermore, we distinguished between groups with one notch and more than one notch rating changes. The magnitude of CAR on the event window was expected to be higher for changes by more than one notch. The reasoning behind this is intuitive – the higher the change in notches, the higher the relative change in default risk and therefore the stock price reaction should be larger. Previous research highlighted the importance of the magnitude, represented in the number of notches, and claimed that the measure is indeed significantly related to the excess returns (Holthausen & Leftwich, 1986; Hand et al., 1992; Norden & Weber, 2004). Table 9 illustrates that in the sample the instances of a downgrade by a few notches are more common than an upgrade by more than one notch, which could partially explain insignificant results for the positive sub-sample. It could be seen that the reaction for the downgrades is statistically significant for both downgrades by one notch and multiple notches. Moreover, as predicted, the coefficient for multiple notches is higher, yet they are not statistically different.

Moreover, we divided all companies into two groups: below and above the median market capitalisation of the sample. We expected more pronounced reaction for rating transition of smaller companies, as they are likely to be less covered by analysts, and consequently, the information associated with rating changes could have a bigger effect. For the large companies, the analysts may act as agents mitigating the information asymmetry, while in case of the small companies, the rating agencies could take on that role. Nevertheless, the results reveal that there is no significant difference between the reaction of large and small companies. Furthermore, the share price reaction of large companies does not show significant results and therefore the CAR are not presented.

Finally, we divided the sample into the rating changes that were preceded by watch or outlook in the same direction (anticipated ratings) and the rating changes that were not preceded

[17] Emerging Europe and countries most affected by the Euro-debt crisis after 2009: Bulgaria, Croatia, Cyprus, Hungary, Ireland, Italy, Poland, Portugal, Romania, Slovak Republic, Spain.

[18] DM countries: Austria, Belgium, Denmark, Finland, France, Germany, Liechtenstein, Luxembourg, Malta, Netherlands, Norway, Sweden, Switzerland, United Kingdom.

by either watch or outlook (non-anticipated rating change; see Table 9). As credit watch or outlook inform the market about the expected deterioration or improvement in creditworthiness of a company in a short or medium-term respectively, when a company is placed on watch or outlook, the market could anticipate a future credit rating change. Holthausen and Leftwich (1986) and Norden and Weber (2004) provided evidence that watch-preceded rating changes affect stock prices to a lower extent than credit rating changes not preceded by a formal review process. Therefore, we would expect the share price reaction to anticipated ratings to be smaller than to non-anticipated ratings. Nevertheless, the z-test results reveal that watch-preceded credit rating change does not have a different effect on share prices than a direct credit rating change. This is consistent with the findings of Finnerty et al. (2013). Additional investigation of the anticipation by watch and rating separately lead to the same results (see Table 14 in the appendix). Therefore, we conclude that anticipated rating changes are neither more nor less informative than unanticipated.

Table 9 presents CAR over a two-week period for the whole period from 1989 till 2017. The table shows the market reaction to rating downgrades "Negative" and upgrades "Positive". On the left-hand side, in the section called "Country Group", we distinguish between two country groups. "EM countries" represent Emerging Europe and countries the most affected by the Euro-debt crisis after 2009 – Bulgaria, Croatia, Cyprus, Hungary, Ireland, Italy, Poland, Portugal, Romania, Slovak Republic, and Spain. "DM countries" include the remaining countries from our sample – Austria, Belgium, Denmark, Finland, France, Germany, Liechtenstein, Luxembourg, Malta, Netherlands, Norway, Sweden, Switzerland, and the United Kingdom. In the section "Magnitude in Notches", we distinguish between two groups – where the magnitude of the downgrade (upgrade) is one notch and where the magnitude of the downgrade (upgrade) is more than one notch. Finally, in the section "Anticipation", we present CAR broken down by anticipation by outlook or watch. A rating change is defined as "anticipated" when it has been directly preceded by watch or outlook. Correspondingly, a rating is defined as "non-anticipated" when it has not been proceeded by either outlook or watch. Statistical significance is denoted by stars and is presented underneath the table. The results are presented in percentages.

FURTHER RESULTS ON RATING ANALYSIS

	COUNTRY GROUP				MAGNITUDE IN NOTCHES				ANTICIPATION			
	EM Countries		DM Countries		One Notch		Multiple Notches		Anticipated		Non-Anticipated	
	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive
CAR[-7 ,-1]	-0.12	-0.06	0.03	-0.11	0.03	-0.13	-0.08	0.23	-0.07	-0.18	0.05	-0.08
(z-test)	*(-0.34)*	*(-0.15)*	*(-0.14)*	*(-0.63)*	*(-0.13)*	*(-0.83)*	*(-0.15)*	*(-0.24)*	*(-0.24)*	*(-0.80)*	*(-0.13)*	*(-0.31)*
N	323	98	796	486	925	543	186	40	572	242	332	250
CAR [0, +1]	-1.07***	0.22	-0.23	0.30**	-0.39***	0.30**	-1.04***	0.23	-0.54***	0.49***	-0.67**	0.09
(z-test)	*(-6.01)*	*(-0.71)*	*(-1.70)*	*(-2.75)*	*(-3.38)*	*(-3.00)*	*(-3.71)*	*(-0.35)*	*(-3.70)*	*(-3.80)*	*(-3.27)*	*(-0.53)*
N	323	98	796	486	925	543	186	40	572	242	332	250
CAR [+2,+7]	-0.14	0.19	0.69***	-0.33*	0.41*	-0.18	0.48	-1.06	0.52*	-0.4	0.40	-0.09
(z-test)	*(-0.42)*	*(-0.48)*	*(-3.37)*	*(-2.21)*	*(-2.19)*	*(-1.28)*	*(-1.13)*	*(-1.47)*	*(-2.20)*	*(-1.81)*	*(-1.28)*	*(-0.40)*
N	323	98	796	486	925	543	186	40	572	242	332	250

** p<0.05, ** p<0.01, *** p<0.001*

3.6 Robustness of the Results

In order to attain the presented results, we make series of adjustments to the data addressed throughout the paper. Nevertheless, it is important to discuss the influence the adjustments have on the results.

First of all, the results derived from the contaminated sample (which includes contaminated events and Greece) show similar trends to the results derived from the non-contaminated sample – they are stronger for the negative than positive sub-sample, there is an anticipation of negative events, and subsequent reversal from day 2 (see Figures 10, 11, 12 in the appendix). Even though coefficients for the share price reaction on the event day to all event types (excluding watch) from the contaminated sample are slightly higher, they still range from approximately -2% to 0.5% for the negative events (see Tables 16, 17, 18 in the appendix). Nevertheless, credit watch provides interesting insights (see Table 10). For the credit watch from the contaminated sample we could observe short term anticipation of approximately +/- 2-3%, which is significant on at least 10% significance level. This finding could be explained by the nature of watch, which in many cases, is event-driven. The market anticipation a week before the event could simply be investors´ response to certain events. Interestingly, we still observe a stock price drop on the event day for the negative revisions and no immediate reversal afterwards. This finding suggests that either the market reacts to negative watch announcements on the event day (even if it is preceded by some adverse news) or there are simply other events that negatively affect the stock prices on the event day.

Galil and Soffer (2011) criticised the standard procedure of "uncontaminating" the data and only using the observations that are neither preceded nor succeeded by other rating events within a certain time span. The research claimed that this procedure could result in underestimation of results. As discussed in section 2.2.2, we address this problem and do not "uncontaminate" the whole sample. Instead, we leave the first event in an event series and remove all succeeding ones with less than 7 days difference in between.[19]

[19] Initially, we used a smaller data sample and "un-contaminated" it removing all rating, watch or outlooks that occurred within less than 30 days from each other. For instance, on day -10 -S&P put company X on negative watch, on day 3 - Moody's put it on negative outlook and on day 20 - S&P downgraded the company. All of these events would be deemed as "contaminated" and eliminated from the data. This procedure indeed resulted in less conclusive results and smaller sample size. Nevertheless, while the results for rating were insignificant, yet for watch and outlook the results were comparable to presented above.

Table 10 exhibits mean CAR during the period immediately before the event window (days -7 to -1), the event window (days 0 to + 1) and the immediate period after the event window (days +2 to +7). The results cover the period from 1989 to October 2017, pre-regulation era covering 1989 to mid-October 2009, and post-regulation era covering mid-December 2009 to October 2017. The sample is contaminated. The table covers positive and negative watch. The significance level is denoted by stars and described below the table. All numbers are presented in percentages.

Watch - Contaminated Sample

	Whole Period		Before Regulation		After Regulation	
	Negative	Positive	Negative	Positive	Negative	Positive
CAR[-7,-1]	-2.56***	2.63**	-2.46**	1.99	-2.64***	3.19*
(z-test)	*(-5.37)*	*(-2.81)*	*(-3.16)*	*(-1.68)*	*(-4.38)*	*(-2.24*
N	494	77	202	36	292	41
CAR [0,+1]	-1.08**	0.31	-1.79*	0.83	-0.59**	-0.14
(z-test)	*(-3.06)*	*(-0.85)*	*(-2.24)*	*(-1.23)*	*(-2.63)*	*(-0.37)*
N	494	77	202	36	292	41
CAR [+2,+7]	0.04	-0.07	-0.02	0.00	0.08	-0.04
(z-test)	*(-0.14)*	*(-0.12)*	*(-0.04)*	*(-0.11)*	*(-0.20)*	*(-0.05)*
N	494	77	202	36	292	41

** p<0.05, ** p<0.01, *** p<0.001*

Furthermore, we excluded Greece from the non-contaminated sample. We repeated the analysis with non-contaminated sample including Greece and found that the elimination of this country does not have major effect on the results in terms of coefficients or statistical significance in the investigation window of -7 to +7 days around the event. Nevertheless, we could observe a larger dip on negative event days for both rating and outlook.

Finally, since the market performance of various countries in Europe was studied, one could question the choice of the proxy for the underlying market. A more precise approach would be to use individual country's underlying market to compute abnormal returns. We make a sample test and calculate AR for Spanish companies, using the IBEX 35 Index as the underlying market, and conclude that there are no significant differences between the abnormal returns due to underlying market choice.[20] Moreover, other counties whose AR could be distorted by the choice of the underlying market, such as Hungary or Romania, have relatively few observations in our sample.

[20] Mean difference between AR calculated with Stox600 and IBEX 35 as underlying markets is about -0.007% with standard deviation of 0.008.

4 CONCLUSION

In general, the paper finds a share price reaction on the announcement day of watch, outlook, and rating changes, with the results more pronounced for negative than positive events. A significant negative market reaction for all negative announcement types including watch, outlook, and rating changes is observed. However, the magnitude of the coefficients is rather small, and a post-announcement reversal is noted after outlook and rating change announcements. Nevertheless, we conclude that the rating events bring some new information to the market. Furthermore, the negative announcements seem to have more informational value than the positive.

While minor improvements of the informational value of the announcements after the regulation could be seen, we do not have sufficient evidence to conclude that the regulation enhanced the quality of the new information that rating event announcements bring to the market. The results indicate that there are no differences in share price reactions to watch, outlook, and rating changes between investment grade and non-investment grades firms. Neither differences in other factors used to distinguish between groups such as geography, the magnitude of the rating change, and anticipation are found.

Due to data limitations, the study was not able to distinguish observations based on the reason for the rating actions. It is worth noting that there has been evidence in the US market that the reason for a rating action has a significant effect on the results (Goh & Ederington, 1993). Therefore, it would be interesting to repeat the study taking into account the reason for the outlook, watch, and rating changes.

5 APPENDIX

Table 11 presents rating scales by Moody's, S&P and Fitch. It also provides a numeric S&P equivalent number between 0 and 27. Note, that we present the numeric scale only for the ratings that are present in our data.

Moody's	**S&P**	**Fitch**	**S&P Equivalent**	**Grade**
Aaa	AAA	AAA	27	Investment Grade
Aa1	AA+	AA+	25	
Aa2	AA	AA	24	
Aa3	AA-	AA-	23	
A1	A+	A+	22	
A2	A	A	21	
A3	A-	A-	20	
Baa1	BBB+	BBB+	19	
Baa2	BBB	BBB	18	
Baa3	BBB-	BBB-	17	
Ba1	BB+	BB+	16	Non-Investment Grade
Ba2	BB	BB	15	
Ba3	BB-	BB-	14	
B1	B+	B+	13	
B2	B	B	12	
B3	B-	B-	11	
Caa1	CCC+	CCC+	10	
Caa2	CCC	CCC	9	
Caa3	CCC-		8	
Ca	CC	CC	7	
	C		4	
C	SD	RD	0	In Default
	D	D	0	

Table 12 presents the number of observations in the non-contaminated sample, broken-down by the pre- and post-regulation era, type, outcome, and credit rating agency. Pre-regulation era covers the period from 1989 to mid-October 2009, and post-regulation era covers the period from mid-December 2009 to October 2017. Types of events include outlook, watch and rating changes. Positive direction of the outcome is designated as "Up" and negative as "Down". Finally, "FDL" corresponds to Fitch, "MIS" to Moody's and "SPI" to Standard and Poor's.

Time and Type of the Event	Rating Source and Direction of the Outcome											
	FDL			MIS			SPI			Total		
	Down	Up	Total	Down	Up	Total	Down	Up	Total	Down	Up	Total
pre-regulation era												
Outlook	147	79	226				327	172	499	474	251	725
Rating	144	71	215	82	36	118	316	138	454	542	245	787
Watch	39	5	44	21	1	22	62	13	75	122	19	141
Total	330	155	485	103	37	140	705	323	1,028	1,138	515	1,653
post-regulation era												
Outlook	187	163	350	24	18	42	399	328	727	610	509	1,119
Rating	177	89	266	69	49	118	323	200	523	569	338	907
Watch	25	3	28	39	7	46	116	23	139	180	33	213
Total	389	255	644	132	74	206	838	551	1,389	1,359	880	2,239

Table 13 exhibits geographic distribution of non-contaminated observations. According to Thompson Reuters (2017), "Primary country of risk" is based on an algorithm that takes into account factors such as the domicile of a firm, its headquarters location, the countries in which its revenue is generated, the countries in which its securities are traded, and the base currency used in its financial reports.

Primary Country of Risk	Freq.	Percent	Cum.
France	659	16.93	16.93
United Kingdom	636	16.34	33.27
Germany	525	13.49	46.76
Italy	374	9.61	56.37
Spain	373	9.58	65.96
Sweden	186	4.78	70.73
Netherlands	185	4.75	75.49
Switzerland	171	4.39	79.88
Portugal	143	3.67	83.56
Norway	98	2.52	86.07
Poland	96	2.47	88.54
Finland	89	2.29	90.83
Belgium	73	1.88	92.70
Luxembourg	58	1.49	94.19
Denmark	50	1.28	95.48
Czech Republic	44	1.13	96.61
Austria	42	1.08	97.69
Hungary	22	0.57	98.25
Ireland; Republic of	21	0.54	98.79
Cyprus	14	0.36	99.15
Croatia	13	0.33	99.49
Romania	7	0.18	99.67
Bulgaria	5	0.13	99.79
Liechtenstein	4	0.10	99.90
Malta	2	0.05	99.95
Slovak Republic	2	0.05	100.00
Total	3,892	100.00	

Table 14 shows CAR for upgrades ("positive") and downgrades ("negative") broken-down by anticipation by outlook and watch. A rating change is defined as "anticipated" when it has been directly preceded by watch or outlook. All numbers are in percentage (%). Significance level is denoted by stars and presented underneath the table.

ANTICIPTED RATING

	By Watch		By Outlook	
	Negative	**Positive**	**Negative**	**Positive**
CAR[-7 ,-1]	1.07*	-0.47	-1.03**	-0.08
(z-test)	*(-2.57)*	*(-0.86)*	*(-2.86)*	*(-0.35)*
N	263	62	309	180
CAR [0, +1]	-0.43*	0.84**	-0.63**	0.37**
(z-test)	*(-2.34)*	*(-2.86)*	*(-2.88)*	*(-2.63)*
N	263	62	309	180
CAR [+2,+7]	0.51	-0.12	0.53	-0.50*
(z-test)	*(-1.5)*	*(-0.23)*	*(-1.61)*	*(-2.08)*
N	263	62	309	180

** p<0.05, ** p<0.01, *** p<0.001*

Table 15 presents CAR over a two-week period for the whole period from 1989 till 2017. The table shows the market reaction to rating downgrades "Negative" and upgrades "Positive". On the left-hand side, in the section called "SECTOR", we distinguish the companies in financial and non-financial sector. In the section "RELATION", we distinguish between two groups: parent and subsidiary. Parent is when the listed company is the ultimate parent, or in other words, is not owned by any other companies. Subsidiary is when the ultimate parent is different than the listed company. Finally, in section "CRISIS", we present CAR for rating migrations that happened during the financial crisis and in any other period. Here, we define the financial crisis from the collapse of Lehman Brothers on 15 October 2008 to the end mid-June following year (2009).

FURTHER RESULTS - SECTOR, CRISIS, SUBSIDIARY

	SECTOR				RELATION				CRISIS			
	Financial		Non-Financial		Parent		Subsidiary		YES		NO	
	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive
CAR[-7,-1]	0.15	-0.09	-0.09	-0.11	0.28	0.11	-0.83	-0.42	-0.40	1.29	0.04	-0.14
(z-test)	*(-0.42)*	*(-0.35)*	*(-0.40)*	*(-0.54)*	*(-1.18)*	*(-0.56)*	*(-1.64)*	*(-0.96)*	*(-0.46)*	*(-0.68)*	*(-0.19)*	*(-0.86)*
N	376	198	743	386	796	405	168	93	126	14	993	570
CAR [0,+1]	-0.63***	0.25	-0.39**	0.30*	-0.38**	0.39**	-0.78**	0.00	-0.8	0.18	-0.43***	0.29**
(z-test)	*(-3.33)*	*(-1.59)*	*(-2.93)*	*(-2.24)*	*(-2.88)*	*(-3.08)*	*(-2.72)*	*(-0.01)*	*(-1.79)*	*(-0.13)*	*(-3.95)*	*(-2.83*
N	376	198	743	386	796	405	168	93	126	14	993	570
CAR [+2,+7]	0.27	-0.38	0.55*	-0.17	0.56**	-0.38*	-0.12	-0.3	0.90	0.37	0.40*	-0.26
(z-test)	*(-0.90)*	*(-1.63)*	*(-2.57)*	*(-0.96)*	*(-2.60)*	*(-2.27)*	*(-0.30)*	*(-0.77)*	*(-1.16)*	*(-0.35)*	*(-2.35)*	*(-1.80)*
N	376	198	743	386	796	405	168	93	126	14	993	570

** p<0.05, ** p<0.01, *** p<0.001*

Figures 10, 11, 12, 13 present the cumulative abnormal returns for the period from 30 days before to 30 days after a rating event marked by 0. The graphs cover contaminated events, including Greece. Figure 10 includes 3,819 negative and 1,936 positive events from 1989 to 2017. The CAR is presented for all rating event types together – rating, outlook and watch. Figure 11 shows CAR due to rating changes. It includes 1,739 downgrades and 830 upgrades from 1989 to 2017. Figure 12 shows the stock price reaction to announcements. It includes 494 negative and 77 positive observations. Figure 13 shows the stock price reaction to outlook announcements. It includes 1,586 negative and 1,029 positive watch observations.

Figure 10

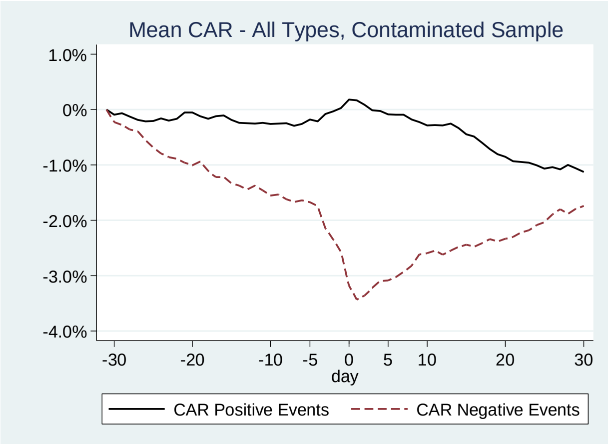


Figure 11

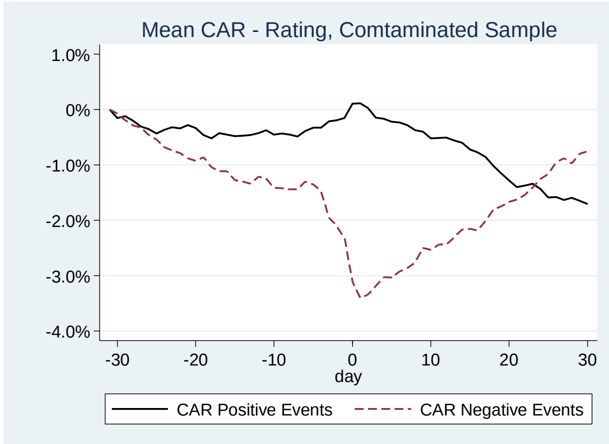


Figure 12

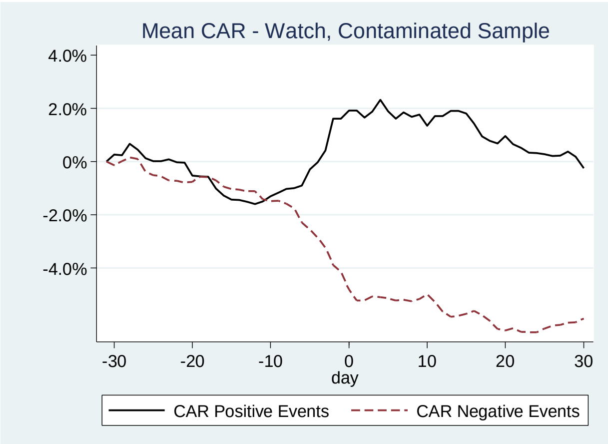


Figure 13

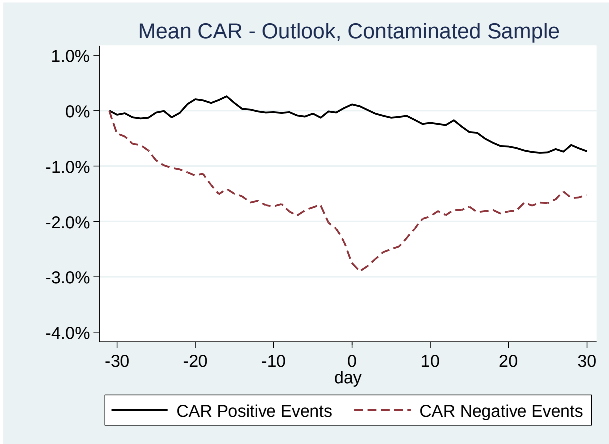


Table 16 exhibits mean CAR during the period immediately before the event window (days -7 to -1), the event window (days 0 to + 1), and the immediate period after the event window (days +2 to +7). The results cover the period from 1989 to October 2017, pre-regulation era covering 1989 to mid-October 2009, and post-regulation era covering the time mid-December 2009 to October 2017. The sample is contaminated (including Greece). The table covers rating upgrades "positive" and downgrades "negative". The significance level is denoted by stars and is described below the table. All numbers are presented in percentages.

All Types - Rating, Watch, and Outlook, Contaminated Sample

	Whole Period		Before Regulation		After Regulation	
	Negative	**Positive**	**Negative**	**Positive**	**Negative**	**Positive**
CAR[-7,-1]	-0.96***	0.27	-0.42	0.19	-1.41***	0.33
(z-test)	*(-5.72)*	*(-1.95)*	*(-1.70)*	*(-1.01)*	*(-6.27)*	*(-1.67)*
N	3,819	1,936	1,756	768	2,063	1,168
CAR [0,+1]	-0.85***	0.14*	-1.27***	0.08	-0.50***	0.18*
(z-test)	*(-7.35)*	*(-2.01)*	*(-5.77)*	*(-0.72)*	*(-4.74)*	*(-1.98)*
N	3,819	1,936	1,756	768	2,063	1,168
CAR [+2,+7]	0.50***	-0.26*	0.53*	-0.30*	0.50**	-0.24
(z-test)	*(-3.86)*	*(-2.55)*	*(-2.53)*	*(-2.13)*	*(-2.94)*	*(-1.65)*
N	3,819	1,936	1,756	768	2,063	1,168

** p<0.05, ** p<0.01, *** p<0.001*

Table 17 exhibits mean CAR during the period immediately before the event window (days -7 to -1), the event window (days 0 to + 1), and the immediate period after the event window (days +2 to +7). The results cover the period from 1989 to October 2017, pre-regulation era covering 1989 to mid-October 2009, and post-regulation era covering the time from mid-December 2009 to October 2017. The sample is contaminated (including Greece). The table covers rating upgrades "positive" and downgrades "negative". The significance level is denoted by stars and described below the table. All numbers are presented in percentages.

Rating - Contaminated Sample

	Whole Period		Before Regulation		After Regulation	
	Negative	**Positive**	**Negative**	**Positive**	**Negative**	**Positive**
CAR[-7,-1]	-0.88**	0.30	-0.16	0.03	-1.56***	0.51
(z-test)	*(-3.27)*	*(-1.20)*	*(-0.40)*	*(-0.11)*	*(-4.29)*	*(-1.27)*
N	1,739	830	846	363	893	467
CAR [0,+1]	-1.08***	0.27*	-1.58***	0.07	-0.61**	0.41*
(z-test)	*(-5.12)*	*(-2.04)*	*(-4.13)*	*(-0.45)*	*(-3.17)*	*(-2.14)*
N	1,739	830	846	363	893	467
CAR [+2,+7]	0.54*	-0.39*	0.00	-0.39*	0.61*	-0.39
(z-test)	*(-2.40)*	*(-2.19)*	*(-1.29)*	*(-1.97)*	*(-2.20)*	*(-1.40)*
N	1,739	830	846	363	893	467

** p<0.05, ** p<0.01, *** p<0.001*

Table 18 exhibits mean CAR during the period immediately before the event window (days -7 to -1), the event window (days 0 to + 1) and the immediate period after the event window (days +2 to +7). The results cover the period from 1989 to October 2017, pre-regulation era covering 1989 to mid-October 2009, and post-regulation era covering the time from mid-December 2009 to October 2017. The sample is contaminated. The significance level is denoted by stars and described below the table. All numbers are presented in percentages.

Outlook - Contaminated Sample

	Whole Period		Before Regulation		After Regulation	
	Negative	**Positive**	**Negative**	**Positive**	**Negative**	**Positive**
CAR[-7 ; -1]	-0.55*	0.07	-0.16	0.17	-0.86**	0.02
z-test	*(-2.36)*	*(-0.48)*	*(-0.49)*	*(-0.60)*	*(-2.67)*	*(-0.10)*
N	1,586	1,029	708	369	878	660
CAR [0; +1]	-0.54***	0.03	-0.76***	0.01	-0.36**	0.00
z-test	*(-4.74)*	*(-0.40)*	*(-3.93)*	*(-0.09)*	*(-2.70)*	*(-0.47)*
N	1,586	1,029	708	369	878	660
CAR [+2 ; +7]	0.61***	-0.18	0.76**	-0.23	0.49*	-0.14
z-test	*(-3.54)*	*(-1.42)*	*(-2.88)*	*(-1.15)*	*(-2.15)*	*(-0.92)*
N	1,586	1,029	708	369	878	660

** p<0.05, ** p<0.01, *** p<0.001*

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