How does firm transparency affect investors' reaction around rating changes?

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How does firm transparency affect investors' reaction around rating changes?

Jury

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Abstract

This paper investigates the effect of corporate transparency on the market reaction following a rating change. A regression analysis on several samples constituted of rating actions is used to examine the characteristics that might foster corporate transparency. The purpose is to identify the degree of influence that it could have on the investors' perception following a rating change. Our findings show that corporate transparency actually influences the market response to a rating change. There are two significant relations between its proxies and rating changes in the regression of the cumulative abnormal returns. The results also reveal that there is no significant response to rating upgrades as widely acknowledged in the literature. Finally, the absolute versions of the discretionary accruals do not present any significant influence contrary to the raw and adjusted versions proposed by Kothari et al. (2005) of the discretionary accruals.

Keywords: Corporate transparency – Event study – Market reaction – Rating changes – Discretionary accruals – Winsor – Cumulative abnormal returns

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Introduction

As a general rule, publicly traded firms have to comply with a certain degree of transparency. In the U.S., companies aiming to raise funds on the financial markets have to register first with the Securities and Exchange Commission (hereafter 'the SEC'). This regulatory body then ensures the proper disclosure of subsequently published financial information. It constitutes the basis of corporate transparency. However, it remains a heterogeneous characteristic as companies are the ones that inevitably decide the most beneficial degree of their transparency. Theoretically, the less transparent a company, the more abnormal its trading volume and, thus, thus the volatility of its security price. This phenomenon is characteristic of a situation in which information is asymmetric. The resolution of this market failure requires greater transparency in the disclosure of information. This last statement is enough in itself to explain the raison d'être of the SEC. The latter may get close to the century of existence; there remain, however, current occurrences for this stake in the U.S as it is evidenced by the Corporate Transparency Act, a significant piece of regulation passed by Congress on January 1, 2021.

In a nutshell, all companies (issuers) whose securities are traded on the financial markets are assessed[1]. Then their credit quality rests in the form of a rating reflecting the forward-looking opinion of an agency. The word 'opinion' is essential here as in spite of all the expertise that rating agencies have accumulated over time, it will never be anything like an investment recommendation. There may be various ratings for a single security, each tackling the evaluation from a different perspective or at least methodology. The latter are generally split into model-driven ratings and analyst-driven ratings (Guide to Credit Rating Essentials by Standard's and Poor's). In the context of this study, only one of the top leading rating agencies will be considered, Standard & Poor's. This private player has a widely documented credibility among investors and offers a reassessment of a company's credit quality whenever it proves necessary. Once the information is disseminated in the markets, the magnitude of the impact varies according to several firm-specific factors, amongst which one of them, transparency, will be our subject of study. The influence of rating changes on stock prices is well established (Norden and Weber 2004, 2009; Hull et al. 2004) and has made it possible, in particular, to quantify the confidence that investors place in rating agencies. As a matter of fact, positive abnormal stock returns have been empirically outlined around credit rating changes and specifically downgrades (Griffin and Sanvicente, 1982; Cornell et al., 1989; Hand et al., 1992; Holthausen and Leftwich, 1986; Choy et al., 2006; Jorion and Zhang, 2007). Cross-referencing these results with an assessment of corporate transparency should define the extent to which this notion can influence the stock price evolution.

The study of the impact of rating changes or, even more generally, on rating agencies' influence is a well-documented subject. However, as we will see later in the literature review,

[1] It is more a norm than a rule given that companies are not legally binded to be rated. However, since it is highly convenient for many criteria and because it results in win-win situations for both the issuer and the investors, the reality is that all securities, as of a certain size, benefit from a rating.

there remain ongoing debates, notably on the market's reaction. This paper’s contribution consists of adding a prism to approach an area of study that already benefits from abundant sources, respectively corporate transparency and the event studies of rating agencies' influence on financial markets and, more particularly, on U.S. equities. In practical terms, the approach involves recording rating changes occurring on securities contained in the S&P 1500 over a period during which prices are a priori not likely to be influenced by notable exogenous factors, 2010-2017. As for minor noises, other control variables such as the notion of contamination, some industries fixed effects, as well as the size and the return on assets, should make it possible to isolate the impact of a rating change event on the price of a security through cumulative abnormal returns. Once the market reaction has been highlighted, a more qualitative layer of analysis, i.e., corporate transparency, should partly explain the disparity that characterises the price movements following a rating change regardless of its nature. This paper investigates the reason for this unpredictability in the stock prices evolution surrounding its rating change. The approach proposes to extend forecast models seeking to comprehend market abnormalities in the context of an event study.

This thesis investigates the role of corporate transparency on trades using credit ratings as a variable and stock prices as the identifier of the market reaction. As it is a typical example of an event study, one of the most challenging parts in carrying out this study will be at the moment of the data collection. Indeed, not only corporate transparency of many security issuers will have to be assessed, but this one should reflect the fair view at the exact occurrence of the events. Before any further development, it appears necessary to point out that, regardless of the database used in the analysis, it is impossible to develop a precise figure that would fully grasp the degree of transparency of a given company. Several proxies have been designed in the literature that should nevertheless make it possible to highlight the influence of transparency on the financial markets. In this respect, it appears necessary to introduce a dependent variable that should highlight this influence all other things being equal. In our case, it is the change in the credit rating of diverse securities that plays the role of the variable factor. Moreover, it should be noted that there are three types of rating events that can induce significant price movements over the revised securities, rating outlooks, credit watches, and unannounced rating changes (Linciano, 2004). Considering that we focus on rating changes, the bigger the event window, the higher the probability for it to comprise the investors’ reaction. Obviously, none of the extreme is desirable as the bigger the event window, the less precise the analysis.

This paper's remainder proceeds as follows: the literature review will be split into four different parts. The first one will delimit the credit rating agencies influence on the financial markets, followed by the recapitulation of the event studies dealing with market reaction around rating changes. The third part will describe the concept of corporate transparency as a whole, i.e., in a qualitative as well as a quantitative approach. The last part will briefly tackle the notion of information asymmetry, given how it is closely related to rating agencies and corporate transparency. The next section will describe the data collection and the methodology. The results will then be analysed and organised into two main parts; each of them will comprise a thorough interpretation, followed by the limitations that might arise.

Literature review

This literature review will be developed by endeavouring to take into account the current state of research on the aforementioned topics.

The influence of credit rating agencies on the financial markets and its drifts

Now that the subject's boundaries have been defined, it is appropriate to explain the current state of research on specific concepts. Let's start with the rating agencies, their function and their influence on financial markets. We will then tackle the contentious part, i.e., the inconsistency in interpreting the market reaction following a rating change.

Investors are aware of the asymmetry of information between them and the companies whose debt securities are issued and traded on the financial markets. Between these two edges of the marketplace resides the credit rating agencies. In order to grant a credit rating, the issuer usually has access to an extensive data set that remains unavailable to investors. The issuer could disclose these data; however, it wouldn't be as trustworthy as if an intermediary does it, assuming the respectability of the latter and the incentive effect for the issuer not to be fully transparent. Indeed, as Hermalin and Weisbach (2007) suggest, there are likely to be both costs and benefits to increased transparency. That is why the due diligence work achieved by CRAs is so much valuable. It allows investors to have a view about a company over the horizon of time that suits their needs without disclosing any additional documents than those already available to the public. To diminish this risk premium and, therefore, the cost of borrowing, issuers call upon rating agencies. Another argument that follows the same logic concerns issuers with low credit risk and low returns that might not be able to obtain any credit due to adverse selection. Rating agencies aim at easing this problem by giving investors a risk-screening instrument to diminish the asymmetry of information and uncover hidden data. Thanks to their activity, the higher the creditworthiness of an issue, the lower the interests that the issuers have to pay. This notion of bridge is particularly relevant as they create value by reducing the cost of information (Dittrich, 2007).

Concretely, credit rating agencies provide an alphabetical letter score symbolising their forward-looking opinion on the creditworthiness of the rated issuer on a precise date (see Appendix-A). The influence then arises to the extent of the agency's reputation[2]. Indeed, a credit rating constitutes a decisive sorting criterion for investors if and only if, from a statistical point of view, i.e. following an ex-post analysis, a credit rating agency can testify of robust reliability. CRA measure their own performance by tracking default rates and the frequency of transitions. It helps them to recalibrate their analytical methods. Beyond their function, this

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2 Standard & Poor's Ratings Service, U.S. Securities and Exchange Commission Public Hearing - November 15, 2002 Role and Function of Credit Rating Agencies in the U.S. Securities Markets. The report mention the follwing sentence: "*the ongoing value of Standard & Poor's credit ratings business is wholly dependent on continued market confidence in the credibility and reliability of its credit ratings*"

convenience is the second element that explains their influence. It is worth noting that the respectability is not evenly distributed among the rating agencies. In this regard, Li et al. (2006) focus on the Japanese market and demonstrate that international agencies have a more significant impact overall on securities price movements than local agencies, reporting specifically, a greater reaction to downgrades.

Beyond the primal informative aspect of credit ratings, the 'license' they bring to the issuers, which is the result of expertise, allows them to access the capital markets or lower regulatory burdens (Partnoy, 1999, p 683). Apart from an influence that would rather be towards issuers than investors, this function serves as a risk management tool for institutions. Indeed, the existence of ratings-based regulations like the Basel Accords, only to cite an example, provides a new approach to credit ratings which are no longer seen as information but rather as certifications. Partnoy (1999) argue that this function is the one that brings the most value to the rating agencies. This argument suffices in itself to explain why rating agencies suffered that much from the subprime crisis of 2007-2008. The ECB words in the edition of June 2004 of its occasional paper series might appear premonitory insofar as it mentions an apparent lack of transparency of the rating industry and, despite some efforts made, a stated willingness to "keep pace with the needs of market participants". Claire A. Hill (2010) paper *Why did rating agencies do such a bad job rating subprime securities?* reveals the ceiling of such an ambition. As White (2009) underlines, the CRAs judgments attained the force of law ahead of the crisis. By the early 2000s, the influence of rating agencies on financial markets was at its peak. Partnoy (2009) mentions the overdependence of the markets upon the CRAs as the main trigger of the financial crisis. It naturally dropped as a result of their indisputable involvement in the crisis (see the minutes of the Financial Crisis Inquiry Commission of 2011[3]), it is mainly their role of ratings as contractual triggers (e.g., Manso (2013), Kraft (2015)) that has deteriorated as evidenced by the Dodd-Frank Act that removes regulatory references to ratings in the U.S.

A stream of the literature investigates the potential emergence of conflicting interests between issuers and CRAs in the course of their business. As Dittrich (2007) stresses: "every credit contract constitutes a principal-agent relationship", demonstrating that approaching the credit rating activity through the agency theory is legitimate and the arising of agency conflicts plausible if not foreseeable. CRAs benefit from reputation; it is the central element of their influence on the financial markets. Wakeman (1981) recognises in them a "reputable auditor". One speaks about the "reputational capital" model (Macey, 1998). However, no reputation mechanism can hold if conflicts of interest are publicly revealed (Smith and Walter, 2002). Dittrich (2007) points out that the incentives for CRAs of misconducting are strong given how profitable the lack of honesty can turn. Despite these incentives, as Hill (2004) observes, there is an immense majority of ratings for which the agencies did a good job. Nonetheless, even a negligible part of infringements suffices to endanger the complete structure, as post-crisis studies evidenced later. Efing et Hau (2013) prove that asset- and mortgage-backed securities have been treated advantageously depending on the strength of their business relationships with CRAs. Many studies have identified the wrongdoings of CRAs (Benmelech et Dlugosz, 2009;

[3] "Investors relied on them, often blindly. [...] This crisis could not have happened without the rating agencies." The Financial Crisis Inquiry Commission (2011) page xxv.

Griffin et Tang, 2011; Hau et al., 2013; Pagano et al., 2010); some authors even tried to reconsider the whole "reputational capital" model. Mathis et al. (2009) argue that reputation concerns are powerful to discipline CRAs if and only if a major fraction of their income is derived from other sources than rating complex products. Bolton et al. (2009) describe the three sources of conflicts of interest in the credit rating industry: "(1) CRAs conflict of understating risk to attract business, (2) issuers' ability to purchase only the most favourable ratings, and (3) the trusting nature of some investor clienteles". These circumstances are the perfect tracks for what Golan et al. (2015) designate as "race-to-the-bottom" phenomena that inexorably attain industries in which there is a principal-agent relationship that is driven by the risk aversion of the agent. In the credit rating industry, it results in the deterioration of the long-term rating quality.

For a long time, the three primary players, Standard & Poor's, Moody's and Fitch, have levelled their market share within the credit rating industry in excess of 90% (Hill, 2004) which hold true even nowadays[4]. Yet as Samuelson and Nordhaus (1998) show, in an oligopoly, all rating agencies sell at the monopoly price in order to maximise profits. On the basis of that postulate, many argued that the only adequate response to the oligopolistic issue of the credit rating industry was to foster competition. Some scholars like Becker and Milbourn (2008) challenge this idea by disclosing unforeseen results of the industry's reaction following the rise of Fitch. They discover that it led to lower the quality of the ratings within the industry in three aspects: rating level went up on average, the correlation between ratings and market-implied yields fell, and the ability of ratings to predict default deteriorated. Fitch's expansion at the beginning of the 1990s therefore coincided with the production of inflated ratings. The nature of the credit rating industry turns any attempt to incorporate competition in a struggle that eventually works to the detriment of the investors, rating agencies levelling down their requirements and severity to stay competitive. For purposes of countering this drawback, a few academics tried to reconsider the income model of the CRAs. Bolton et al. (2009) critique the issuer-pay model, which is the preeminent source of income for CRAs. The latter enables the issuer to pay their fees after receiving the rating. According to the authors, an upfront payment should mitigate the conflict of interest of both issuers and CRAs. This would put a stop to 'credit shopping', a phenomenon that is identified for a long time in the literature and that participate in lessening the CRAs' influence.

With all the light shed upon these concerns, the reputation of CRAs has been threatened, but the message that credit ratings convey persist in carrying critical signals towards the markets. Indeed, with regards to the ratings as a piece of information, recent studies suggest that CRAs keep a considerable influence on the financial markets (Yang et al., 2017).

Market reaction following a rating change

[4] The European Securities and Markets Authority (ESMA) as well as the Securities and Exchange Comission (SEC) respectively account for 91,07% and 93,3% of market share for the three largets CRA according to their 2020 annual report.

Although a majority of researchs argues for a long time now that the market's reaction to a downgrade is statistically more significant relative to an upgrade (see Hand et al. (1992), Ederington et al. (1996)), recent papers make an opposite observation (Abu et al., 2018), yet building on a similar methodology. However, it is necessary to specify that the former studies take place in the U.S. equity market, while the latter focuses on the Bangladeshi market. According to Barron et al. (1997), possible reasons for the mixed results in the market reaction come from five differences in the frequency of observations (daily, weekly or monthly), contamination of data with other firm-specific news, and the sample periods. In the context of U.S. equities, a consensus has now been reached for years, but some specific firm factors could reanimate an area of study that remains linear in its approach of their data. Additionally, many country-specific pieces of evidence continue to be presented, such as the previously mentioned study of Abu et al. (2018) but also Mutize and Nkhalamba (2020) for South Africa, Livingston et al. (2018) for China or Hitz and Lehmann (2015) for the U.K. and Germany.

As far as the filtering processes are concerned, Yang et al. (2017) build on the work of Holthausen and Leftwich (1986) and Stickel (1986) pertaining to "contaminated" or "uncontaminated" rating change announcements in their data. Here the term of contamination refers to potential confounding effects that might arise due to other concurrent news releases. We will see how it materialises in the methodology part. Other authors also employ the term of contamination but in reference to other events that might parasite a market reaction analysis based on rating changes. Yang et al. (2017) speak about "contaminated announcement" that would either be attributed to a prior rating review or the occurrence of a further rating change announcement from another rating agency.

Linciano (2004) takes an in-depth approach by taking rating changes and credit watches and sorting them according to several criteria, including contamination. On the other hand, Jorion and Zhang (2007) point out that the market's reaction to a company's rating revision is not a linear process but rather depend on factors such as the quality of the rating. They find much stronger information effects for rating changes of low-rated firms in comparison with high-rated firms.

The conflicting results of prior studies that question a long-term established literature calls for more research and a better understanding of the relationship between rating changes and market reactions. Particularly, the mixed evidences documenting the investors' reaction to a rating upgrade lead us to test it within the context of a first hypothesis.

H1*: Positive rating changes are associated with more positive market reactions*

Corporate transparency and its proxies

Taking corporate transparency into account in this study's development could highlight the role of a firm-specific factor on the evolution of a company's share price in the financial markets. Bushman and Smith (2003) present the financial accounting information dataset and the extent to which it is linked to corporate governance. Basically, they list all the firm-specific information available to investors to obtain a fair representation of firm financial health. Although this method requires a substantially longer data collection period, it provides a holistic approach to evaluating corporate transparency that could be a best-fitted alternative than the recurrent earning management utilisation. The latter is indeed often used as a proxy in the literature when it comes to assessing corporate transparency. In essence, it is an inverse indicator of the quality of disclosure. Chtourou et al. (2001) measure earning management by isolating the discretionary accruals. This proxy is notably used in Chin (2016), together with timely loss recognition (TLR) and asymmetric timely loss recognition (ATLR). It constitutes, nevertheless, a shortcut that doesn’t encompass the concept of transparency in its globality. To remedy this issue, Lang and Maffett (2011) add, besides earnings management, the accounting standards, the auditor choice, the analyst following and the forecast accuracy. Despite its apparent completeness, this measure seems to lack a notion of time. Indeed, the time lag between the occurrence of an event, whatever its nature, and its disclosure to the shareholders characterises a company's willingness to be transparent or not. Chin's work (2016) attempts to fill this gap by providing the following two measures: timely loss recognition (TLR) and asymmetric timely loss recognition (ATLR). Kim et al. (2012) break down earning management into three different proxies: discretionary accruals, real activities manipulation, and the incidence of Accounting and Auditing Enforcement Releases (AAERs) that regularly originate from the SEC. These last three studies pinpoint the two main obstacles in the comprehension of corporate transparency, i.e., data availability and proxies’ selection. Considering the significance of the results these authors obtained through their studies, we can assume that they succeed in outlying the qualitative concept that is corporate transparency.

One measure that mechanically emerges in the papers tackling corporate transparency is discretionary accruals. Ashbaugh-Skaife et al. (2006), in one of the few papers that associate the notion of credit rating with corporate transparency, argue that credit ratings positively affect accrual quality after controlling for firm-specific risk profiles. This highlight the point that corporate transparency is often, if not always, to be tracked down thanks to accounting. The latter, jointly with financial reporting systems, is a critical source of verifiable information that is useful to the managers’ oversight (Bushman and Smith, 2001). The reason of the overuse of discretionary accruals as a measure of transparency can be found in DeFond and Park (1997) and, more precisely, in the reasons they give to the presence of discretionary accruals in the accounting of many firms. According to the authors, they can be used either to save current earnings for potential use in the future or to cover up poor performance. Kasznik (1996) accentuates the underlying notion of willingness regarding corporate transparency[5] and concludes from his study that managers use discretionary accruals to reduce their forecasting errors. Dechow (1994) documents the opportunities to manipulate earnings due to the flexibility that enable the use of discretionary accruals. In this regard, one often distinguishes positive

[5] Even though the author never clearly mentions it in its paper but rather uses earnings management which fit in our context .The joined terms “corporate transparency” are widely recognized after 2003. *See Bushman, Robert M. and Piotroski, Joseph D. and Smith, Abbie J., What Determines Corporate Transparency? (December 1, 2003). Journal of Accounting Research 2004, 42 (2). Anteriorly but still nowadays, the terms are observed as a process included in corporate governance and thusly refered to in that manner.*

discretionary accruals associated with aggressive accounting policy from negative ones linked with conservative accounting policy. While aggressiveness in accounting policy is arguably motivated by the above-mentioned reasons, **Karjalainen** (2011) notes that companies adopt a conservative approach in order to avoid the risk of assets'overvaluation vis-à-vis the creditors and the shareholders. Although this remains a lack of transparency as documented in the literature, subsampling on the basis of the discretionary accruals sign might bring interesting results considering the opposition of these policies and what it reveals of their risk profiles.

Transparency at the company level has been widely studied in the literature; that is why its shapes and its stakes are clearly identified. Despite the prima facie vague aspect of corporate transparency, Bushman and Smith (2003) tries to grasp it with the following: "the widespread availability of relevant, reliable information about the periodic performance, financial position, investment opportunities, governance, value, and risk of publicly traded firms". This definition will be the prevailing one. It makes a direct link with the role of rating agencies, as Kuhner (2001) acknowledges it, i.e. an "informational intermediary". Corporate transparency is crucial to investor confidence. By transitivity, it is understandable that the degree of transparency can impact the reaction of investors when a change in the credit rating of a company is announced. Investors must base their decisions on a sample of information of varying sizes. Considering the rating as the aggregation of several critical data in a single piece of information (see Appendix-B for all the areas overseen by a Standard & Poor's rating), the marginal value of the rating change announcement for a company with low transparency should, other things being equal, be greater than for a company with a higher transparency. Hence, the latter should demonstrate higher abnormal returns. These last two sentences constitute the following two hypotheses:

H2*: There is a negative correlation between corporate transparency and the cumulative abnormal returns triggered by rating changes.*

H3*: Corporate transparency impacts significatively the market response to a rating change*

Information asymmetry as the cause for CRAs activities and the corporate transparency ideal

This study, though quantitative in the sense that the hypotheses will only be supported by patterns found in the stock prices, is all about information and how the market perceives it. This last statement offers a perfect transition for a concept that lies at the opposite of transparency, information asymmetry. This concept benefits likewise, and maybe even more, of the necessary documentation. Healy and Palepu (2000) argue that demand for financial reporting and disclosure arises from information asymmetry and agency conflicts between managers and outside investors. At the firm level, it is made manifest in miscellaneous ways. Chambers and Penman (1984) acknowledge, for instance, early announcements of good news, whereas announcements of bad news regularly display reporting lags. Typically, the managers-stakeholders relationship is the one that provides the most shreds of evidence of information asymmetry, as documented in the previous section.

Yang et al. (2017) are among the few studies to examine the link between information asymmetry and investor reaction to a rating change announcement. To identify the effect of information asymmetry, they divided their study sample into three categories, each corresponding to a type of investor: domestic individuals, domestic institutions, and foreign investors. Doing so, they analyse the trading responses of each investor group. The presence of discrepancies would then testify of asymmetry of information given that they confront different datasets to the same events, ceteris paribus.

In a principal-agent relationship such as the one issuer-investor, the agency theory places the asymmetry of information as an assumption (Eisenhard, 1989). CRAs are consulted in the course of a market transaction in order to overcome informational asymmetries between both market sides (Dittrich, 2007). Indeed, the issuer is unwilling to transmit critical information about his own credit risk to the investor at no cost. In any case, investors will generally not trust the accuracy of such information since the issuer may find benefits from supplying the investor with wrong information. As a result, the cost of the transaction will tend to comprise this risk and thus be higher (Merton, 1987). This situation is detrimental for both parties. Healy and Palepu (2000) note that CRAs, along with financial analysts, can help to reduce this asymmetry of information by revealing the hidden information in the form of a rating.

Focusing on the reasons that lead thorough corporate transparency not to be ideal, many papers document the link between this concept and the board of managers independence within the company. Newman (2000) defines managers' strategic independence as their autonomy in strategic decision making and absence of direct interference and constraints imposed by the owners. As Goh et al. (2014) demonstrate, greater board independence leads to lower information asymmetry. The papers of Ortega and Grant (2003) and Burgstahler and Eames (2006) reinforce this idea that managers find an incentive to manipulate earnings by choosing an accounting method so that earnings level meets the expectation from the financial analyst or investor and then alters company stock price. Nonetheless, as Hermalin and Weisbach (2012) nuance, none of the two extrema is desirable in respect of corporate transparency. Even beyond the scale of a company, transparency has its limits in the matter of added value, and the two authors mention in this regard the aggravation of agency problems and the costs associated with them. They argue that: "a point can exist beyond which additional disclosure decreases firm value". This argument resonates with the founding law of diminishing returns and thusly calls for more nuance in approaching corporate transparency.

A transparent organisation provides information in such a way that any stakeholder can obtain a proper insight into the issues that are relevant for her (Kaptein, 2003). In the case of the credit rating industry, the rating is an alternative way of conveying information but obviously not always efficient and primarily because of the conflict of interests that may arise. In addition, CRAs generally have a strict policy with regards to the data utilised within the framework of their computation[7]. Hence, one can perceive the information asymmetry as irremediable on the financial markets, at least, for a vast majority of the issuers. That is why scholars like Roberts (2018) acknowledges transparency as 'an alluring but deceptive ideal'. Christensen and Cheney (2015) challenge the ideal that represents the actual model of transparency in the literature. They critique the ambivalence which is generally associated with the implementation of transparency. This ambivalence is particularly visible in Vaccaro and Echeverri (2010) who observe that the objective of corporate transparency may be self-defeating, as more information released to the public may diminish stakeholders' desire to participate, therefore lowering the effectiveness of future social responsibility.

Data and methodology

Data summary

As this is an event study, a time series data frame should be developed. The data will cover the U.S. stock prices and, more specifically, the S&P1500. This index is comprising small, middle and large capitalisations of U.S. equities. Such diversity in the sample enriches the study insofar as certain firm characteristics might foster transparency. The study uses daily stock transaction data from January 31, 2010, to February 28, 2017. This timeframe should deliver a fair representation of the market under normal conditions, i.e. removed from exogenous factors that could blur its interpretation. As far as concerns the rating agency, only Standard & Poor's will be considered. The rating system is the S&P domestic Long Term Issuer Credit Rating (SPLTICRM). Each firm's rating history is retrieved from WRDS whereas the firm specific data originate from Compustat, including performance, size, valuation and transparency measures on a yearly basis. Finally, we merge this dataset with the event study output for each window to obtain the raw study samples.

The aim of an event study is to determine whether there are any abnormal returns associated to a specific event (Peterson, 1989). In order to evaluate the expected returns and then assess the abnormal ones, we use a market adjusted model. An estimation window of 200 days[8], including at least 50 valid observations, is set up for each security of the dataset. A one-month gap separating the estimation window from the starting date of the event window ensures avoiding potential noises that might perturb the stock prices and thus render impossible any interpretation. The samples are built around rating changes being defined as 'events' ($t = 0$) with continous reaction windows such as $t = 20$ and $t = 30$ in [-*t*;*t*]. This should fully capture the market reaction while being coherent with the event studies focusing on rating changes. As a matter of fact, the event window's length commonly ranges between 35 and 60 business days[8].

7 Public hearings held by the Securities and Exchange Commission on the role and function of credit rating agencies in the U.S. November 15, 2002.

8 Peterson (1989) reports the typical length of the estimation windows between 100 and 300 days and the one of the event period from 21 to 121. Specifically, the studies of Linciano (2004), Taib et al. (2009), Yang et al. (2017), Abu et al. (2018) use event windows that range from 35 to 60 business days.

As far as concerns data processing, again, two approaches confront each other. On the one hand, Yang et al. (2017) limit themselves to the work of Holthausen and Leftwich (1986) and Stickel (1986) with the concepts of "contaminated" and "uncontaminated" rating change announcements. Stickel (1986) defines a contaminated (uncontaminated) announcement as a rating change announcement that is (not) accompanied by other concurrent firm-specific news released during days −1 to +1 (where day 0 is the rating change date) that may have an impact on the stock price. On the other hand, some authors consider three or even more sorting criteria in order to fine-tune their samples. In the context of this study, given that we assess the market reactions on long-term windows, we can't take into account all the corporate actions. Instead, we focus on earning announcements which are, together with acquisitions and targets announcements the major corporate actions in terms of market reaction (Chae, 2002), the latter being nonetheless much less frequent. Besides contamination, we add the continuous ratings disclosure for a period of at least two years around the event date. This criterion leads to remove from the sample, the companies whose potential rating changes occured at an unknown time, i.e., at a time for which there are no data available. As this step is part of the data collection, the criterion does not appear in table 1, which recapitulates the filtering process.

The initial sample covered 1,038 rating changes, including 671 upgrades and 367 downgrades, giving a downgrade ratio of 0,35, coherent with a study period exempt from financial turmoils[9]. Yet, the event study followed by its merging with the dataset cumulatively removes 391 events because of data availabilities. Ultimately, the study sample is comprised of 487 companies accumulating 647 rating actions, including 442 upgrades and 205 downgrades. Amongst these 487 companies, 177 underwent more than one rating change. With respect to the contamination filter, 77,6% of the events for the [-30;30] event window are concerned, which falls to 51,6% for the [-20;20] event window. Though consequent, these proportions were expected given the amplitude of the windows. Regarding corporate transparency, 250 companies present positive discretionary accruals (38,64%) while the rest, 397 companies, present negative discretionary accruals (61,36%).

< Insert Table 1 about here. >

Table 2 provides the distribution of rating changes by industry. These figures are required for the adjustment of the discretionary accruals. Independently of the model used for the computation of discretionary accruals, more recent studies adjust their results with respect to the ROA of companies belonging to the same industry (Tehranian et al., 2006; Demirkan et al., 2011). Following Kothari et al. (2005), each two-digit SIC industry comprising at least 20 firms for a year *t* allows to adjust their discretionary accruals by matching with the 'companion firm', i.e. the one with the closest ROA. It results in a new variable called PADTA which stands for performance adjusted discretionary accruals, ABSDA being the absolute value of PADTA.

[9] The link between the downgrade ratio and the state of the economy is well identified and notably in Raffestin (2017). From his own sample of rating actions, the author associates 2010 with the year from which the ratio steadily came back to normal (around 40 %) as the economy recovered from the subprimes crisis.

An inverse relationship between ABSDA and accruals quality is documented in the literature. Theoritically, the higher ABSDA, the lower the accruals quality and conversely.

< Insert Table 2 about here. >

Table 3 summarizes the key statistics for our dependent, independent and control variables. *CAR* represents the [-30;30] event window while *CAR** represents the [-20;20] event window. As suggest in the previous section, *CAR* seems to capture a bigger picture of the market response as it is evidenced by the amplitude of the windows (1,324 < 1,729). The mean value of the ratings is 10,185, the equivalent of a BBB-, which involve that the barrier between investment grade and speculative grade divide almost perfectly our sample into two parts. Raising such point is interesting in view of the subsampling analysis. Though relatively low considering a study sample spanning the S&P 1500, this is coherent with the conservatism in the ratings observed by Baghai et al. (2013). Besides, the standard deviation of *ROA* is very low, which endorse the asumption regarding the time frame, i.e. a period free of major economic shocks. Obviously, the variable is winsorised which participate to lower the standard deviation, but this function has a minor influence on the distribution. Finally, it is noteworthy to stress that, on average, *DA* is slightly negative whereas *PADTA* is not. Therefore, the adjustement tends to somewhat increase the overall value of the accruals. This is explicited in the maximum value that more than doubled with the adjustment. It calls for caution in interpreting *PADTA* and consequently *ABSDA* as the adjustment can strongly alter the discretionary accruals value.

< Insert Table 3 about here. >

As far as the limitations of the dataset, the rating events are, by default, dated at the end of a month because of data availability concerns. This problem undoubtly alters the accuracy of the study. The implications will be detailed in the limitations section. Additionnaly, 181 securities over the 1.508 are missing. It has no particular influence on the dataset as the missing securities do not concern either a specific sector or a specific capitalisation group.

Methodology

As the majority of the event studies focusing on stock prices evolution (Linciano, 2004; Yang et al., 2017; Amin et al., 2018), the investors' reaction will be captured thanks respectively to the log return $R_{i,t}$, the cumulative total return CTR_t, the abnormal return $AR_{i,t}$, and the cumulative abnormal returns CAR_t formulae:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}$$

$$CTR_{(i,t_1,t_2)} = \sum_{-t_1}^{t2} R_{i,t}$$

$$AR_{i,t} = R_{i,t} - \alpha_i - \beta_i R_{m,t}$$

$$CAR_{(i,t_1,t_2)} = \sum_{-t_1}^{t2} AR_{i,t}$$

where:

$R_{i,t}$ = Capital asset pricing model

$t_n \in [20, 30]$

With regard to corporate transparency, we will use discretionary accruals as a proxy. There exist different ways of calculating them but this study will concentrate on the modified Jones cross-sectional model (Jones, 1991; Defond and Jiambalvo, 1994; Dechow et al., 1995). This technique is largely accepted and well established in the literature (Zhou and Lobo, 2001; Chtourou et al., 2001). Basically, it corresponds to the residual from the regression of total accruals on two factors that explain non-discretionary accruals, the level of fixed assets and the shifts in revenue.

$$DAC_{it} = TAC_{it}/A_{i,t-1} - \left[\beta_0(1/A_{i,t-1}) + \beta_1(\Delta REV_{it}/A_{i,t-1}) + \beta_2(PPE_{it}/A_{i,t-1})\right]$$

where:

DAC_{it} = Discretionary accruals for firm *i* in year *t*;

TAC_{it} = Total accruals for firm *i* in year *t*;

$A_{i,t-1}$ = Total assets for firm *i* at the end of year *t – 1 (Assets-Total* in *Compustat*);

ΔREV_{it} = Change in net sales for firm *i* between year *t – 1* and *t (Sales (Net)* in *Compustat)*;

PPE_{it} = Gross property, plant and equipment for firm *i* in year *t (Property, Plant and Equipment (gross-Total)).*

β_n = Industry-specific coefficients

Considering that the differences between the companies within the S&P 1500 might be important, it is essential to control for some firm-specific situations. Such a practice can be justified by the fact that the market response can be driven by various factors other than corporate transparency. Hence, controling for these factors' influence aims at better isolating the effect of our independent variables and, therefore, understand the extent to which it can affect the market response, measured in our regression by the *CARs*.

The regression model used to test the hypotheses is as below:

$$CAR_{i,t} = \delta_0 + \delta_1 RCHANGE_{i,t} * \delta_2 DA_{i,t} + \delta_3 RATING_{i,t} + \delta_4 ROA_{i,t} + \delta_6 LOSS_{i,t} + \delta_5 MTB_{i,t} + \delta_7 LOGTA_{i,t} + YEAR + INDUSTRY + \varepsilon_{i,t}$$

The variable of interest is the interaction between the dummy variable $RCHANGE_{i,t}$ and $DA_{i,t}$. Allison (1977) argues that “the inclusion of a product term in a multiple regression is a legitimate way to test for interaction”. The resulting estimate, combined with its significance, should enable us to draw the necessary conclusions with regard to the hypotheses. It is important to precise that $DA_{i,t}$ can be replaced by its absolute version, $ABS.DA_{i,t}$, but also the adjusted versions that are $PADTA_{i,t}$ and $ABSDA_{i,t}$ in order to refine the model. Following Jorion and Zhang (2007) $RATING_{i,t}$ is added to control the magnitude of the reaction with respect to the rating of a company *i* at year *t*. It is calculated by assigning each letter grade a numerical value between 1 and 21, with the highest letter grade receiving the lowest value (see appendix-A for cardinal scores matching). The two variables $ROA_{i,t}$ and $LOSS_{i,t}$ are used to control for performance effects. This is interesting as bad-performing companies might find incentives to cover their poor results, and, in particular, from the shareholders. $MTB_{i,t}$ is added to control that the level of valuation on the markets has no influence on the level of transparency. The reverse being documented in the literature[10]. Finally, firm size may affect the level of earnings management (Becker et al. 1998). As a result, the variable $LOGTA_{i,t}$ is used to control for this effect. It represents the log of companies’ total assets. The logarithm function is utilised to correct the skewness of the distribution.

In accordance with Wilcox and Rand (2005), all continuous variables including $CAR_{i,t}$ are Winsorized so that the tails of the distribution do not influence too much the outcome and thusly ensure qualitative robustness. Assuming x_γ and $x_{1-\gamma}$ to be the γ and $1-\gamma$ quantiles. Then a γ-Winsorized analog of CAR is the below distribution:

$$CAR_w(x) = \begin{cases} 0, & if\ x < x_\gamma \\ \gamma, & if\ x = x_\gamma \\ CAR(x) & if\ x_\gamma < x < x_{1-\gamma} \\ 1, & if\ x \geq x_{1-\gamma.} \end{cases}$$

For the sake of robustness, the regression model will be tested against various subsamples built around common characteristics. Even though it remains a non-random sampling method, each subsample construction is motivated by findings that are well established in the literature. As regards the statistical significance, we will rely on the t-tests. Finally, to ensure avoiding multicollinearity issues, we will check the variance inflation factors (VIF), which basically return what percentage of the variance (i.e. the standard error squared) is inflated for each coefficient.

10 Damodaran (2002) argues that the less transparent a firm is, the more complex its valuation results.

Empirical results

In this section, the estimation results of abnormal returns are reported for the five subsamples: uncontaminated events, positive discretionary accruals, negative discretionary accruals, investment and speculative grades for the two event windows, [-20;20] and [-30;30]. However, only the most relevant results will be presented and discussed. The other samples are added in appendices.

The stock market response to rating changes

Table 4 shows the correlation coefficients between each of the dependent, independent and control variables. Oddly, the first element we notice is CAR's correlation with RATING that rejects the null hypothesis, whereas CAR* does not. This evidence constitutes the first argument to rather rely on the [-30;30] window. Another interesting comment to retrieve from this table is that none of the modified discretionary accruals' measures shows significance in their correlation with the other variables except between each other. While $DA_{i,t}$ and $PATDA_{i,t}$ are the two proxies that present meaningful interactions with $RCHANGE_{i,t}$ in the regression models, only *DA* demonstrates significant correlations with other variables. The latter are *RCHANGE, RATING, LOGTA and ROA*. Since there exist repeated significant correlations, we can assume that *DA* fits well in the model. Even though correlation does not necessarily mean causation, the high significance in the correlation of *DA* with *RCHANGE* suggests that this study investigates an actual path that calls for further research. Despite its relative weakness, a 0,159 correlation still seems to be rather high considering that a corporate transparency proxy has, to our knowledge, never been taken into account in an event study focusing on rating changes. Nevertheless, one has to point out one conflicting result that number with this table. The correlations of *DA* with *LOGTA* and *ROA* being both positive and assuming these two variables to be proxies for size and performance, it is interesting to note that in our sample, the bigger or the more performant companies are, the less transparent they tend to be. While the negative correlation between transparency and performance have been outlined (Che Haat et al., 2008), size proxies and transparency are observed as being positively correlated in the literature. Patel and Dallas (2003) report that the size premium is linked to a lack of information available on small companies. They claim that larger companies tend to provide more reliable disclosure in their annual reports. Notwithstanding this state of fact widely acknowledged within the scientific community, we can supply three nuances to explain this inconsistency with our observations. Firstly, their proxy for transparency is different; they use the Standard & Poor's Transparency and Disclosure ranking. Regardless of its accuracy as a proxy, this measure is qualitative in the sense that it focuses on firms' corporate governance and disclosure practices. Discretionary accruals present limits that will be exposed in the remainder of this study. Likewise, disclosure practices utilisation as a proxy also faces limitations. The main one probably is the managers' potential reports manipulation (Beyer and Guttman, 2012). Secondly, even though their sample comprises the S&P 500, they add equities from all over the world, including emerging market equities, which make the sample substantially diverge from the S&P 1500 with respect to market capitalisations between other characteristics. Thirdly, the correlation is only significant to the first level, which doesn't permit the rejection of the null hypothesis.

< Insert Table 4 about here. >

As far as concerns the model, it appears relatively resilient with respect to the overall statistical significance. Nonetheless, it is critical to highlight that the results are much more conclusive over the event window [-30;30]. This is consistent with the literature, as the 40-trading day window is too short to capture a complete market response in the aftermath of a rating change. For the sake of completeness, the regressions will nonetheless be added in appendices (see appendices D). The choice to report two different event windows has mainly been motivated by its value as a robustness test. Regarding the control variables, all of them demonstrate satisfactory levels of statistical significance. Some variables like $RATING_{i,t}$ and $MTB_{i,t}$ almost always present the highest levels of significance. $RATING_{i,t}$ displays positive estimates for the two event windows (0.006 and 0.012) that reject the null hypothesis. Although close to 0, this is coherent with Jorion and Zhang (2007); the market's reaction depends on the initial quality of the rating. The coefficients of $MTB_{i,t}$ (0.025 and 0.012) indicate that when the companies' valuation level slightly increases, the cumulative abnormal returns tend to do likewise. Lastly, the model never demonstrates severe issues related to multicollinearity, which confirm its suitable construction, especially in the control variables selection.

With regards to the measure of corporate transparency, $ABS.DA_{i,t}$, $ABSDA_{i,t}$ are non-significant over all the samples. One couldn't conclude about their weakness as measures of corporate transparency given that the methodology isn't oriented towards proving such a statement. Factually, one can only reckon that the absolute values of the adjusted and non-adjusted versions of the discretionary accruals are meaningless in the context of this regression model, given the absence of significance. A reason, amongst others, could be that companies accounting policies can be dissociated on the basis of their discretionary accruals sign. Whether the latter is positive or negative, respectively induce an aggressive policy or a conservative one (Martinez-Ferrero et al., 2013). We will observe that effect in the subsampling analysis. Nevertheless, it is worth noticing that many studies and even recent ones, use discretionary accruals as a proxy for corporate transparency regardless of their sign (Comprix and Huang, 2015; Li and Kuo, 2017; Safari, 2017).

Neither of the full samples for both windows provides interpretable results vis-à-vis a potential corporate transparency influence (Appendix C and D). This was expected considering that other corporate announcements contaminate a majority of events in these samples. Once removed from the sample, the outcome permits to answer to hypothesis 2 positively. Indeed, Table 5 shows that the interaction between $DA_{i,t}$ and $RCHANGE_{i,t}$ is statistically significant. A decrease in discretionary accruals is associated with an increase in corporate transparency; therefore, this interaction can be interpreted in the following way: the market reaction to upgrades is lower when the firm is less transparent. The estimate of -0.302 indicates a rather substantial correlation which has to be checked using other datasets. The independent variable *DA* appears significant while showing a positive relationship. This is not contradictory as interpreting the DA estimate does not make sense in this specific context. Indeed, addressing hypotheses 2 and 3 requires adding an interaction term.

The intercept is not significant with this subsample which does not prevent the interpretation of the results. It simply suggests that the mean effect of all omitted variables may not be important. As we will observe further in the analysis, the intercept gains significance as from a certain number of observations. Finally, it is relevant to point out that $PADTA_{i,t}$ is far from being significant in this sample either.

< Insert Table 5 about here. >

The most significant result that enables us to answer the first hypothesis is found in the uncontaminated subsample of the [-30;30] event window. The regression coefficient of the independent variable $RCHANGE_{i,t}$ (which is a dummy variable, 1 = upgrade and 0 = downgrade) being the most significant among all the subsamples and panels. First of all, it appears necessary to point out that it is not significant (t value of 0.11). In any case, the output (-0.054) suggests that the relationship is not positive. Though contradictory to hypothesis 1, this result supports the non-significance in the market response to rating upgrades documented in the literature.

Robustness checks

This study aims at proving the existence of a significant influence that a firm-specific factor, corporate transparency, may have over the financial markets. Rating changes then have solely to be observed as the occurrence of an event allowing to highlight this influence. Given that it has never been pointed out in a similar context, the approach of this study is to rely on subsampling analysis primarily to check the robustness of the results but also to play on some firm characteristics, based on recognised findings, that could foster the lack of transparency.

The discretionary accruals sign as a subsampling criterion

Table 6 represents the outcome of the regression of the first subsample. The latter is constructed based on the discretionary accruals sign. It provides an exemple to the above-mentioned reason regarding the non-significance in the discretionary accruals' absolute measures. $ABSDA_{i,t}$ and $ABS.DA_{i,t}$ has been removed given that we want the sign to matter in this particular context. Surprisingly, $RCHANGE * DA$ is not significant anymore, whereas

*RCHANGE * PADTA* is. This interaction shows a correlation coefficient that is divided by more than two (0.134 < 0.302) with respect to the other significant interaction in table 5. However, it is necessary to note that the model is weaker with this subsample. The interaction remains open to interpretation as the only possible answer to a significant interaction within a non-significant regression analysis is the presence of a cross-over interaction (Loftus, 1978). As far as the differences in the outcomes are concerned, one reckons the absence of any significative result for the negative discretionary accruals sample (regressions 3 and 4). It would be erroneous to conclude anything else regarding these subsamples insofar as discretionary accruals present limitations in proxying corporate transparency. As Baber et al. (2011) state: "income-increasing (decreasing) discretionary accruals initiated in a prior period reverse to become income-decreasing (increasing) accruals in the current period". As a result, discretionary accruals have to be analysed regardless of their signs. Even though subsampling upon this criterion significantly results in our particular case, it needs to be interpreted with great caution. All the more so, the anterior analysis of the Khotari's accruals adjustment already suggests being watchful.

< Insert Table 6 about here. >

The rating class as a subsampling criterion

Table 7 provides another robustness check. The motivation for its construction emerges in Jorion and Zhang (2006). These authors highlight the non-linearity in the market response when taking into account the issues initial rating. Their central finding is that stronger information effects are measured for rating changes of low-rated firms with respect to high-rated firms. Considering that *RATING* is significatively correlated with *CAR* (0,106), the construction of a subsample upon this criterion could bring meaningful results. Overall, the model appears to explain relatively well the investment grades subsample (regressions 1, 2, 3 and 4), whereas it fails to do so with the speculative grades subsample (regressions 5, 6, 7 and 8). This is outlined by the adjusted R2, which is, on average, almost divided by five coupled with the decrease in the significance level across the different variables. To illustrate this issue, *RATING* and *LOGTA* lose their statistical significance. Pettit (2004) proves that companies' size is the metric that matters the most in credit ratings. Building on that statement, we could expect *LOGTA* not to be significant in the investment grades subsample because of a cluster effect. Given that our results show the opposite, we can only attribute *LOGTA* non-significance in the speculative grades subsample to fewer observations.

< Insert Table 7 about here. >

The interaction between *RCHANGE* and *DA* is, yet again, close to being significant. Due to limitations in the sample size, isolating uncontaminated events within the subsamples is impossible. It has to be remarked as the uncontaminated sample of the [-30;30] window provides significant results.

The absolute discretionary accruals level as a subsampling criterion

Even though the last paragraphs already answer hypothesis 3, one robustness check that could be interesting to run is to divide the sample in quarters, take the two extrema (high-level accruals), merge them and compare the response it gives with respect to the middle two quarters (low-level accruals). Underneath, table 8 presents the outcome of the regression for these two subsamples. It is only performed for the [-30;30] event window and the independent variables $DA_{i,t}$ and $PATDA_{i,t}$ in accordance with the aforementioned significance report.

< Insert Table 8 about here. >

The interaction between $RCHANGE_{i,t}$ and $PADTA_{i,t}$ does not reject the null hypothesis. Therefore, it is impossible to validate hypothesis 2. However, as it is quite close to the first significance level (0.1 < 0.121), while for the same interaction, the other subsample returns a value that can't be interpreted, we can imagine that the third hypothesis could be confirmed with additional observations with this subsample too. Nonetheless, obtaining another result nearly significant and close to the previous estimates obtained in table 6 drastically diminish the possibility that chance played a role in this achievement. Both *DA* and *PADTA* provide a promising outcome within the context of this study. We can question the reliability of such results since they are not reproduced using other subsamples event though one must stress two critical points. First, they are both close to reach the first level of statistical significance. Secondly and most importantly, both measures being proxies of the same concept, it would not be erroneous to conclude that the results are robust. This is the reason, by the way, that allows us to answer to hypotheses 2 and 3 positively. At least, these variables provide statistical significance in contrast to *ABS.DA* and *ABSDA.*

Limitations

Like any other research paper, this study suffers from a certain number of limitations. We will tackle them in this section by descending order of seriousness.

The main issue with this study resides in the data collection method. In fact, an observation of a rating change in our dataset corresponds to a change that occurs from one month to the next. Since there is no database available that enable us to retrieve a list of the rating change dates for the target sample, i.e. the S&P1500, the best alternative was to deduct these changes from one month to the following one. Thus, by default, the change dates all fall on the last business day of a given month. As a result, the dates of the rating actions do not correspond to the actual date of the change. While this may seem like a serious obstacle, the subject of this thesis offers a broader framework with respect to the studies dealing with the market response to a rating change. Indeed, the aim here is not to decompose a reaction but rather to identify the influence that a factor might have on this reaction. In addition, a sufficiently large event window such as the one used in this study still inevitably capture the market reaction, although incorporating more noises.

Another problem stems from the data periodicity. Indeed, instead of being contextualised with data specific to their date of occurrence, the events are associated with the company's financial state at the end of the calendar year. In other words, these data are in annual terms, which does not allow a perfect match with the financial state of the companies at the date of their rating change. The dataset was initially comprised of varying reporting frequencies. The quarterly data were then turned into annual data to put them all on the same basis and allow the merging. For some variables, the variation is relatively marginal, but others can sometimes obscure the reality of a company's situation at the time it undergoes a rating action. For example, a financial loss can be the trigger for a rating agency to downgrade a security. However, because of their significant impact on shareholders' perception, losses are corrected as quickly as possible and often as of the following fiscal period. Consequently, assuming quarterly reports, the data put in annual terms might not present any loss, whereas it justified the rating action.

There is also a problem with the notion of contamination. The latter is not used in the same way as in the literature. Indeed, most researchers rely on the work of Holthausen and Leftwich (1986) and Stickel (1986). Given the data collection method for rating actions, it was necessary to find a way of retaining the contaminated nature of the observations, which is essential in an event study without having a precise date on which to base it. The solution found is to determine whether an earnings announcement occurs within the event window. Of course, this poses several minor problems. Firstly, there are way more contaminated observations since the contamination window is no longer three or five days long as in the literature, but forty and sixty. Secondly, many other corporate actions can present a considerable impact on the evolution of a stock price. Even though it might seem arbitrary only to focus on earnings announcements, one must stress that it represents a major corporate action with respect to the magnitude of its impact on the security price considering that it occurs regularly, that is, once per fiscal period.

As announced, highlight corporate transparency as a whole is a tedious task. The exercise of quantifying such a qualitative notion is delicate. In this study, discretionary accruals were selected, but they have many limitations in their interpretation as a proxy for corporate transparency. In fact, it does not incorporate any of the three dimensions of the information structure as documented by Damodaran (1985). The author designates the frequency with which information is disseminated, their accuracy and the bias in information release as the sources of imperfect information. The latter could be observed as the three pillars of corporate transparency since they resonate with the definition provided by Bushman and Smith (2003) and notably “the widespread availability of relevant, reliable information”. Thus, monitoring compliance with these three dimensions for each of the observed companies would probably result in a more pertinent proxy for quantifying corporate transparency. Obviously, it is unrealistic in terms of data collection. On the other side, discretionary accruals correspond to the amount of asset or liability that is not mandatory but is recorded in the system. They represent an aspect of transparency, which, building on Damodaran's work, could be associated with frequency in the sense that discretionary accruals offer the managers the opportunity to avoid for some time the disclosure of information. Therefore, discretionary accruals proxy, at best, one-third of the corporate transparency concept. Besides, their value can differ in accordance with the computation method. Finally, it is odd not to observe any significance for the absolute versions of the discretionary accruals as they benefit from a greater recognition in the literature.

The last issue has to be related to data availability. Even though we documented 1.038 rating changes, 391 of them could not be exploited due to the absence of relevant data. On top of that, the contamination filter removes a major part of the observations. The ultimate samples of uncontaminated events amount to 122 for the [-30;30] event window. This sample size does not allow the observations to be crossed with the sub-sampling criteria, which somewhat weakens the study.

Conclusion

This paper investigates the effect of corporate transparency on the market reaction following a rating change. The central point of the study resides in the way data are processed. All other things being equal, the reaction to a rating change can't be the same for two companies showing different degrees of transparency. This study contributes to removing some linearity in the approach of the market response. Each company is unique with respect to its governance, financial position, value proposition, etc. Our findings suggest that corporate transparency should lie among the various reasons that could explain the contradictory results in the investors' reaction following a rating change. Indeed, one shouldn't apprehend it as the decisive specific firm factor that could explain the blur. This paper posits that corporate transparency is one of these explanatory variables, evidenced by the modest yet significant results highlighted within the study. As a matter of fact, we found two significant relations between the corporate transparency proxies that are *DA* and *PADTA* and rating changes in the regression of the cumulative abnormal returns. Besides, the absolute versions that are *ABS.DA* and *ABSDA* do not present any significant influence contrary to the raw version and the adjusted versions of the discretionary accruals proposed by Kothari et al. (2005). The subsampling analysis presents mixed results. On the one hand, it validates the previous results, thus confirming hypotheses 2 and 3. On the other hand, this result does not come from the same measure of the discretionary accruals. Indeed, *DA* does not show a statistically significant interaction with *RCHANGE* while *PADTA* does. Additionally, the results reveal that there is no significant response to rating upgrades as widely acknowledged in the literature. Overall, the results are consistent with the literature.

Considering the innovative character of the study, these results call for deeper investigations. Among other things, the different proxies of corporate transparency used in the literature could be confronted with the same hypotheses. Only to mention the most practical ones, there could be some companies' indexes like the S&P T&D rankings (Patel and Dallas, 2002) or the Bloomberg ESG disclosure scores (Tamimi and Sebastianelli, 2017), there is also the SEC-based proxy, i.e. the Accounting and Auditing Enforcement Releases (Kim et al., 2012) and finally the Disclosure level (Che Haat et al., 2008). Regardless of the proxy nature, it should theoretically be a combination of several of them to grasp the concept of corporate transparency in its globality. The concept of corporate transparency already benefits from abundant sources and is complemented by the researchs on corporate social responsibility (CSR) and corporate governance.

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Table 1. Filtering process

Sample selection criteria		Num. obs.
Original sample		1.038 (671 upgrades, 367 downgrades)
Criteria:		
1. At least 60 days of trading information		864 (566 upgrades, 298 downgrades)
		647 due to missing data for specific year/company during the merging
2. No earnings announcement within the window	[-20;20]	313 (212 upgrades; 101 downgrades)
	[-30;30]	145 (100 upgrades; 45 downgrades)

Table 1 presents the filtering process as well as the funnel leading to the utlimate numbers of observations per study sample.

Table 2. Industry-wise distribution of rating changes.

Industry	Rating Changes	Upgrades	Downgrades	Frequency		
Mining	33	16	17	5,10%	2,47%	2,63%
Construction	11	7	4	1,70%	1,08%	0,62%
Manufacturing	276	184	92	42,66%	28,44%	14,22%
Transp. & Public Utilities	111	84	27	17,16%	12,98%	4,17%
Wholesale Trade	13	10	3	2,01%	1,55%	0,46%
Retail Trade	75	55	20	11,59%	8,50%	3,09%
Finance, Insurance, Real Estate	49	36	13	7,57%	5,56%	2,01%
Services	78	50	28	12,06%	7,73%	4,33%
Public Administration	1	0	1	0,15%	0,00%	0,15%
Total	647	442	205	100%	68,32%	31,68%

Table 2 presents the industry-wise distribution of the rating changes, upgrades and downgrades with their frequency.

Table 3. Summary statisitics

	N	Mean	Standard Deviation	Minimum	Median	Maximum
CAR	647	0,027	0,153	-0,649	0,020	1,080
CAR*	647	0,016	0,116	-0,472	0,014	0,852
RCHANGE	647	0,662	0,474	0,000	1,000	1,000
RATING	647	10,185	2,694	2,000	10,000	18,000
LOGTA	647	3,882	0,517	2,684	3,818	5,085
ROA	647	0,013	0,028	-0,260	0,013	0,179
LOSS	647	0,156	0,363	0,000	0,000	1,000
BTM	647	1,384	0,945	0,079	1,128	4,968
DA	647	-0,031	0,214	-1,962	-0,018	0,741
ABS.DA	647	0,114	0,183	0,000	0,057	1,962
PADTA	647	0,004	0,262	-1,939	0,001	1,874
ABSDA	647	0,130	0,228	0,000	0,060	1,939

Table 3 represents the descriptive statistics of the dependent, independent and control variables. Our sample comprises 647 firm-year observations spanning the period 2010-2017. All continuous variables are winsorised at 1% and 99% levels.

Table 4. Correlation analysis

		(1)	(1)*	(2)	(3)	(4)	(5)	(6)
(1)	CAR	1	1					
(2)	RCHANGE	-0,011	-0,010	1				
(3)	RATING	0,106***	0,063	0,002	1			
(4)	YEAR	0,116***	0,107***	-0,091**	-0,001	1		
(5)	LOGTA	-0,029	0,016	0,001	-0,422***	0,060	1	
(6)	ROA	0,038	0,052	0,117***	-0,119***	-0,097**	-0,018	1
(7)	LOSS	0,045	0,012	-0,106***	0,162***	0,126***	0,026	-0,602***
(8)	INDUSTRY	0,007	0,020	0,032	-0,014	-0,030	0,013	0,072*
(9)	BTM	-0,113***	-0,106***	0,013	0,265***	-0,036	0,163***	-0,282***
(10)	DA	0,025	0,036	0,159***	-0,066*	0,008	0,074*	0,133***
(11)	ABS.DA	0,041	-0,004	-0,053	-0,012	0,006	-0,060	-0,053
(12)	PADTA	0,000	-0,009	-0,062	-0,028	0,000	-0,032	-0,011
(13)	ABSDA	0,051	-0,003	0,021	0,053	-0,018	-0,061	-0,011

		(7)	(8)	(9)	(10)	(11)	(12)	(13)
		1						
(8)	INDUSTRY	-0,097	1					
(9)	BTM	0,181	0,016	1				
(10)	DA	-0,100	0,045	0,019	1			
(11)	ABS.DA	-0,013	0,018	-0,061	-0,356***	1		
(12)	PADTA	-0,005	0,026	-0,054	-0,331***	0,617***	1	
(13)	ABSDA	-0,045	0,039	-0,041	-0,254***	0,616***	-0,088**	1

Table 4 present the Pearson correlation matrix of the dependent, independent and control variables. Our sample comprise 647 firm-year observations spanning the period 2010-2017. All continuous variables are winsorised at 1% and 99% levels. *****, ******, *******, *indicate statistical significance at the 10%; 5%, and 1% level respectively.*

Table 5. Uncontaminated sample ([-30;30] event window)

	(1)	(2)	(3)	(4)
(Intercept)	-0.109 (0.613)	-0.154 (0.484)	-0.153 (0.479)	-0.16 (0.46)
*RCHANGE * DA*	-0.302* (0.097)			
*RCHANGE * ABS.DA*		-0.034 (0.861)		
*RCHANGE * PADTA*			-0.024 (0.843)	
*RCHANGE * ABSDA*				-0.101 (0.64)
DA	0.27* (0.065)			
ABS.DA		0.004 (0.977)		
PADTA			-0.014 (0.873)	
ABSDA				0.029 (0.882)
RCHANGE	-0.054 (0.11)	-0.041 (0.29)	-0.044 (0.206)	0.033 (0.417)
RATING	0.012* (0.064)	0.013** (0.05)	0.013** (0.048)	0.013* (0.042)
ROA	0.528 (0.5)	0.507 (0.523)	0.617 (0.446)	0.323 (0.698)
MTB	0.03** (0.038)	0.03** (0.045)	0.028* (0.06)	0.034** (0.033)
LOSS	0.08 (0.116)	0.076 (0.147)	0.079 (0.126)	0.071 (0.17)
LOGTA	0.022 (0.112)	0.027* (0.054)	0.027* (0.054)	0.027* (0.051)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
R^2	0.225	0.202	0.204	0.206
Adjusted R^2	0.085	0.058	0.06	0.062
VIF	2.306	2.105	1.79	3.29
Num. obs.	122	122	122	122

Table 6. Positive and negative samples ([-30;30] event window)

	(1)	(2)	(3)	(4)
(Intercept)	-0.014 (0.91)	-0.023 (0.846)	0.078 (0.33)	0.073 (0.351)
*RCHANGE * DA*	-0.245 (0.265)		-0.012 (0.87)	
*RCHANGE * PADTA*		-0.134* (0.095)		0.005 (0.936)
DA	0.263 (0.21)		0.013 (0.812)	
PADTA		0.084 (0.141)		0.007 (0.844)
RCHANGE	-0.012 (0.68)	-0.03 (0.204)	0.007 (0.713)	0.008 (0.581)
RATING	0.003 (0.435)	0.004 (0.309)	-0.002 (0.411)	-0.002 (0.436)
ROA	-0.066 (0.886)	-0.167 (0.715)	0.797** (0.041)	0.793** (0.041)
MTB	0.017 (0.188)	0.022* (0.075)	0.012* (0.079)	0.012* (0.079)
LOSS	-0.001 (0.968)	-0.005 (0.903)	0.051** (0.043)	0.051** (0.044)
LOGTA	0 (0.983)	0.002 (0.827)	0.001 (0.844)	0.001 (0.817)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
R^2	0.096	0.102	0.102	0.102
Adjusted R^2	0.008	0.014	0.047	0.047
VIF	3.441	1.451	1.513	1.479
Num. obs.	226	226	374	374

Table 7. Investment grades and speculative grades ([-30;30] event window)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	-0.245* (0.073)	-0.262* (0.055)	-0.262* (0.053)	-0.257* (0.059)	-0.098 (0.327)	-0.098 (0.327)	-0.089 (0.37)	-0.096 (0.334)
*RCHANGE * DA*	-0.142 (0.144)				0.016 (0.781)			
*RCHANGE * ABS.DA*		0.036 (0.732)				-0.018 (0.78)		
*RCHANGE * PADTA*			-0.073 (0.349)				-0.027 (0.617)	
*RCHANGE * ABSDA*				0.019 (0.854)				0.01 (0.877)
DA	0.147 (0.11)				-0.01 (0.8)			
ABS.DA		-0.005 (0.962)				0.02 (0.657)		
PADTA			-0.062 (0.377)				0.003 (0.936)	
ABSDA				-0.011 (0.913)				0.025 (0.581)
RCHANGE	-0.02 (0.34)	-0.013 (0.559)	-0.01 (0.603)	-0.011 (0.616)	0.001 (0.963)	0.003 (0.86)	0 (0.967)	-0.001 (0.964)
RATING	0.012* (0.054)	0.012* (0.053)	0.012* (0.052)	0.012* (0.058)	0.005 (0.294)	0.005 (0.316)	0.005 (0.321)	0.004 (0.363)
ROA	0.414 (0.271)	0.441 (0.243)	0.424 (0.262)	0.442 (0.243)	-0.28 (0.508)	-0.273 (0.52)	-0.31 (0.462)	-0.256 (0.541)
MTB	0.027*** (0.009)	0.025** (0.014)	0.026** (0.011)	0.025** (0.014)	0.022*** (0.001)	0.021*** (0.002)	0.022*** (0.001)	0.021*** (0.021)
LOSS	0.034 (0.242)	0.03 (0.305)	0.029 (0.316)	0.031 (0.3)	-0.021 (0.425)	-0.021 (0.433)	-0.023 (0.392)	-0.021 (0.42)
LOGTA	0.023*** (0.008)	0.024** (0.015)	0.024** (0.015)	0.024** (0.017)	0.005 (0.45)	0.005 (0.453)	0.004 (0.508)	0.005 (0.443)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.146	0.140	0.142	0.14	0.101	0.102	0.102	0.104
Adjusted R^2	0.0932	0.087	0.088	0.086	0.017	0.018	0.018	0.02
VIF	2.135	2.057	2.288	2.922	1.58	1.582	1.577	1.585
Num. obs.	354	354	354	354	246	246	246	246

Table 8. High-level versus low-level discretionary accruals ([-30;30] event window)

	(1)	(2)	(3)	(4)
(Intercept)	0.016 (0.870)	-0.022 (0.819)	0.053 (0.537)	0.059 (0.497)
*RCHANGE * DA*	-0.067 (0.315)		0.182 (0.74)	
*RCHANGE * PADTA*		-0.099 (0.121)		0.007 (0.923)
DA	0.062 (0.254)		-0.303 (0.502)	
PADTA		0.067 (0.123)		0.015 (0.744)
RCHANGE	-0.019 (0.366)	-0.011 (0.59)	0.011 (0.601)	0.006 (0.721)
RATING	0.001 (0.886)	0.001 (0.746)	-0.001 (0.857)	0 (0.918)
ROA	0.001 (0.998)	-0.035 (0.932)	1.139** (0.01)	1.077** (0.015)
MTB	0.015* (0.064)	0.016* (0.052)	0.01 (0.343)	0.01 (0.322)
LOSS	0.016 (0.626)	0.013 (0.693)	0.048* (0.08)	0.047* (0.087)
LOGTA	0.004 (0.638)	0.007 (0.41)	-0.004 (0.571)	-0.004 (0.616)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
R^2	0.089	0.093	0.094	0.093
Adjusted R^2	0.02	0.024	0.027	0.026
VIF	1.831	1.395	1.875	1.449
Num. obs.	302	302	298	298

Appendices

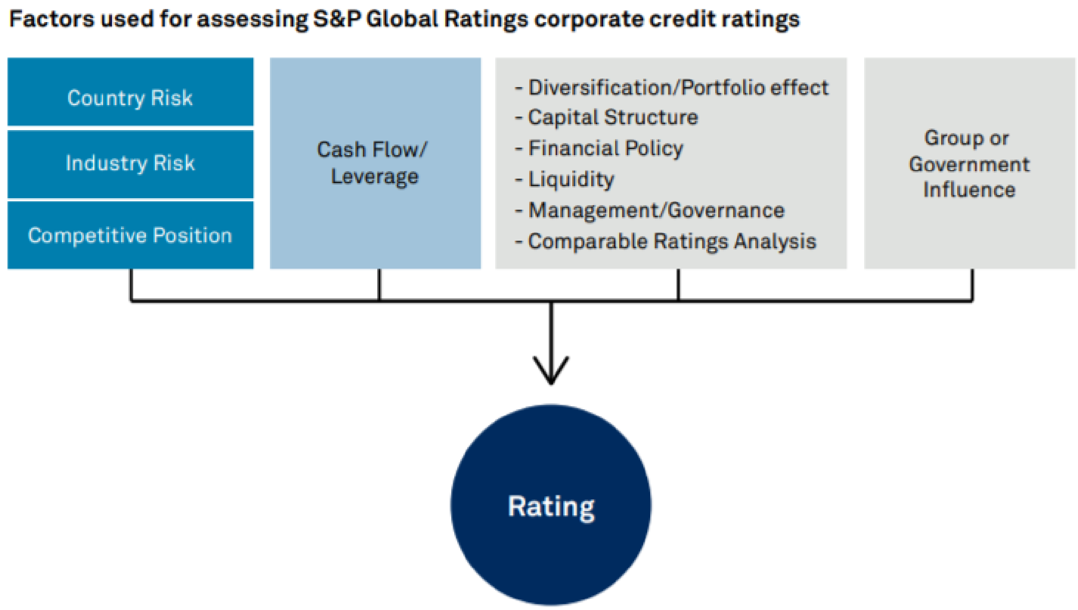
Appendix-A

Long-Term Issue Credit Ratings*

Category	Definition	Cardinal value	Grade
AAA	An obligation rated 'AAA' has the highest rating assigned by S&P Global Ratings. The obligor's capacity to meet its financial commitment on the obligation is extremely strong.	1	Investment grade
AA	An obligation rated 'AA' differs from the highest-rated obligations only to a small degree. The obligor's capacity to meet its financial commitment on the obligation is very strong.	2, 3, 4	
A	An obligation rated 'A' is somewhat more susceptible to the adverse effects of changes in circumstances and economic conditions than obligations in higher-rated categories. However, the obligor's capacity to meet its financial commitment on the obligation is still strong.	5, 6, 7	
BBB	An obligation rated 'BBB' exhibits adequate protection parameters. However, adverse economic conditions or changing circumstances are more likely to lead to a weakened capacity of the obligor to meet its financial commitment on the obligation.	8, 9, 10	
BB; B; CCC; CC; and C	Obligations rated 'BB', 'B', 'CCC', 'CC', and 'C' are regarded as having significant speculative characteristics. 'BB' indicates the least degree of speculation and 'C' the highest. While such obligations will likely have some quality and protective characteristics, these may be outweighed by large uncertainties or major exposures to adverse conditions.		Speculative grade
BB	An obligation rated 'BB' is less vulnerable to nonpayment than other speculative issues. However, it faces major ongoing uncertainties or exposure to adverse business, financial, or economic conditions which could lead to the obligor's inadequate capacity to meet its financial commitment on the obligation.	11, 12, 13	
B	An obligation rated 'B' is more vulnerable to nonpayment than obligations rated 'BB', but the obligor currently has the capacity to meet its financial commitment on the obligation. Adverse business, financial, or economic conditions will likely impair the obligor's capacity or willingness to meet its financial commitment on the obligation.	14, 15, 16	
CCC	An obligation rated 'CCC' is currently vulnerable to nonpayment, and is dependent upon favorable business, financial, and economic conditions for the obligor to meet its financial commitment on the obligation. In the event of adverse business, financial, or economic conditions, the obligor is not likely to have the capacity to meet its financial commitment on the obligation.	17, 18, 19	
CC	An obligation rated 'CC' is currently highly vulnerable to nonpayment. The 'CC' rating is used when a default has not yet occurred, but S&P Global Ratings expects default to be a virtual certainty, regardless of the anticipated time to default.	20	
C	An obligation rated 'C' is currently highly vulnerable to nonpayment, and the obligation is expected to have lower relative seniority or lower ultimate recovery compared to obligations that are rated higher.	21	
D	An obligation rated 'D' is in default or in breach of an imputed promise. For non-hybrid capital instruments, the 'D' rating category is used when payments on an obligation are not made on the date due, unless S&P Global Ratings believes that such payments will be made within five business days in the absence of a stated grace period or within the earlier of the stated grace period or 30 calendar days. The 'D' rating also will be used upon the filing of a bankruptcy petition or the taking of similar action and where default on an obligation is a virtual certainty, for example due to automatic stay provisions. An obligation's rating is lowered to 'D' if it is subject to a distressed exchange offer.	22	
NR	This indicates that no rating has been requested, or that there is insufficient information on which to base a rating, or that S&P Global Ratings does not rate a particular obligation as a matter of policy.		

*The ratings from 'AA' to 'CCC' may be modified by the addition of a plus (+) or minus (-) sign to show relative standing within the major rating categories.

Appendix-B


Factors used for assessing S&P Global Ratings corporate credit ratings
Country Risk
Industry Risk
Competitive Position
Cash Flow/ Leverage
- Diversification/Portfolio effect
- Capital Structure
- Financial Policy
- Liquidity
- Management/Governance
- Comparable Ratings Analysis
Group or Government Influence
Rating

Appendix-C

Full sample ([-30;30] event window)

	(1)	(2)	(3)	(4)
(Intercept)	-0.228*** (0.007)	-0.239*** (0.005)	-0.235*** (0.006)	-0.234*** (0.006)
*RCHANGE * DA*	-0.046 (0.421)			
*RCHANGE * ABS.DA*		0.016 (0.805)		
*RCHANGE * PADTA*			0.032 (0.524)	
*RCHANGE * ABSDA*				0.011 0.853
DA	0.048 (0.309)			
ABS.DA		0.048 (0.309)		
PADTA			-0.029 (0.496)	
ABSDA				0.002 (0.973)
RCHANGE	-0.008 (0.534)	-0.006 (0.644)	-0.006 (0.653)	-0.006 (0.656)
RATING	0.012*** (0.000)	0.012*** (0.000)	0.012*** (0.000)	0.012*** (0.000)
ROA	0.283 (0.317)	0.311 (0.272)	0.293 (0.3)	0.309 (0.276)
MTB	0.025*** (0.000)	0.024*** (0.000)	0.025*** (0.000)	0.024*** (0.000)
LOSS	0.02 (0.325)	0.02 (0.333)	0.019 (0.356)	0.02 (0.333)
LOGTA	0.016** (0.013)	0.016*** (0.01)	0.016** (0.012)	0.016** (0.011)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
R^2	0.105	0.104	0.104	0.104
Adjusted R^2	0.072	0.071	0.071	0.07
VIF	1.744	1.669	1.947	2.072
Number of observations	623	623	623	623

Appendix-D

Full sample ([-20;20] event window)

	(1)	(2)	(3)	(4)
(Intercept)	-0.118* (0.073)	-0.122* (0.066)	-0.120* (0.068)	-0.125* (0.058)
*RCHANGE * DA*	-0.042 (0.346)			
*RCHANGE * ABS.DA*		-0.005 (0.914)		
*RCHANGE * PADTA*			0.006 (0.885)	
*RCHANGE * ABSDA*				-0.013 0.774
DA	0.038 (0.296)			
ABS.DA		-0.005 (0.894)		
PADTA			-0.017 (0.603)	
ABSDA				0.001 (0.976)
RCHANGE	-0.008 (0.426)	-0.005 (0.674)	-0.006 (0.558)	-0.004 (0.743)
RATING	0.006*** (0.006)	0.006*** (0.006)	0.006*** (0.006)	0.006*** (0.005)
ROA	0.228 (0.3)	0.232 (0.292)	0.238 (0.278)	0.229 (0.3)
MTB	0.012** (0.011)	0.012** (0.011)	0.013** (0.01)	0.013** (0.01)
LOSS	0.008 (0.61)	0.007 (0.649)	0.008 (0.639)	0.007 (0.666)
LOGTA	0.006 (0.194)	0.006 (0.184)	0.006 (0.19)	0.007 (0.17)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
R^2	0.064	0.062	0.063	0.062
Adjusted R^2	0.029	0.028	0.028	0.028
VIF	1.744	1.669	1.947	2.072
Number of observations	623	623	623	623

Uncontaminated sample ([-20;20] event window)

	(1)	(2)	(3)	(4)
(Intercept)	-0.056 (0.556)	-0.066 (0.485)	-0.058 (0.536)	-0.072 (0.441)
*RCHANGE * DA*	-0.051 (0.351)			
*RCHANGE * ABS.DA*		0.008 (0.895)		
*RCHANGE * PADTA*			0 (0.991)	
*RCHANGE * ABSDA*				-0.045 (0.41)
DA	0.041 (0.352)			
ABS.DA		0.011 (0.825)		
PADTA			-0.013 (0.747)	
ABSDA				0.044 (0.375)
RCHANGE	-0.021 (0.138)	-0.019 (0.237)	-0.018 (0.193)	-0.012 (0.446)
RATING	0.006** (0.04)	0.006** (0.037)	0.006** (0.04)	0.006** (0.033)
ROA	0.085 (0.8)	0.112 (0.74)	0.095 (0.777)	0.101 (0.766)
MTB	0.013* (0.065)	0.012* (0.089)	0.012* (0.069)	0.012* (0.077)
LOSS	0.016 (0.491)	0.016 (0.505)	0.016 (0.513)	0.015 (0.536)
LOGTA	0.004 (0.555)	0.005 (0.496)	0.004 (0.551)	0.004 (0.513)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
R^2	0.101	0.098	0.098	0.1
Adjusted R^2	0.033	0.03	0.03	0.032
VIF	1.71	1.661	1.9	2.09
Number of observations	290	290	290	290

Positive and negative samples ([-20;20] event window)

	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	-0.032 (0.736)	-0.033 (0.727)	-0.023 (0.804)	0.036 (0.542)	0.034 (0.563)	0.029 (0.61)
*RCHANGE * DA*	-0.147 (0.408)			0.011 (0.851)		
*RCHANGE * PADTA*		-0.069* (0.602)			0.01 (0.807)	
*RCHANGE * ABSDA*			0.108 (0.165)			0.03 (0.535)
DA	0.151 (0.371)			0.017 (0.672)		
PADTA		0.036 (0.776)			-0.024 (0.474)	
ABSDA			-0.03 (0.558)			-0.014 (0.654)
RCHANGE	-0.02 (0.409)	-0.032* (0.09)	-0.046** (0.039)	0.008 (0.519)	0.007 (0.528)	0.004 (0.768)
RATING	0.002 (0.441)	0.003 (0.324)	0.003 (0.377)	-0.002 (0.346)	-0.002 (0.342)	-0.002 (0.369)
ROA	0.055 (0.883)	0.026 (0.945)	0.051 (0.891)	0.4 (0.167)	0.419 (0.145)	0.415 (0.149)
MTB	0.001 (0.948)	0.003 (0.748)	0.002 (0.856)	0.01* (0.07)	0.009* (0.074)	0.009* (0.077)
LOSS	0.021 (0.535)	0.021 (0.544)	0.021 (0.533)	0.011 (0.55)	0.012 (0.535)	0.011 (0.537)
LOGTA	0.001 (0.885)	0.002 (0.829)	0.002 (0.777)	-0.001 (0.837)	-0.001 (0.871)	0 (0.947)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.067	0.067	0.072	0.086	0.087	0.086
Adjusted R^2	-0.024	-0.024	-0.018	0.3	0.031	0.03
VIF	3.441	3.585	1.463	1.513	1.737	1.509
Number of observations	226	226	226	374	374	374

Investment grades and speculative grades ([-20;20] event window)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	−0.122 (0.248)	−0.135 (0.204)	−0.137 (0.193)	−0.145 (0.17)	−0.06 (0.459)	−0.135 (0.204)	−0.137 (0.193)	−0.145 (0.17)
*RCHANGE * DA*	−0.095 (0.209)				0.059 (0.923)			
*RCHANGE * ABS.DA*		0.008 (0.922)				0.008 (0.922)		
*RCHANGE * PADTA*			0.043 (0.472)				0.043 (0.472)	
*RCHANGE * ABSDA*				−0.053 (0.512)				−0.053 (0.512)
DA	0.111 (0.115)				−0.09 (0.568)			
ABS.DA		0.008 (0.922)				0.008 (0.922)		
PADTA			−0.046 (0.399)				−0.046 (0.399)	
ABSDA				0.042 (0.597)				0.042 (0.597)
RCHANGE	−0.007 (0.637)	−0.001 (0.958)	−0.001 (0.954)	0.006 (0.734)	0.005 (0.756)	−0.001 (0.958)	−0.001 (0.954)	0.006 (0.734)
RATING	0.007 (0.156)	0.007 (1.623)	0.007 (0.153)	0.007 (0.15)	0.008 (0.326)	0.007 (1.623)	0.007 (0.153)	0.007 (0.15)
ROA	0.305 (0.297)	0.32 (0.276)	0.322 (0.273)	0.312 (0.289)	−0.279 (0.301)	−0.313 (0.237)	−0.342 (0.213)	−0.299 (0.299)
MTB	0.012 (0.113)	0.012 (0.138)	0.012 (0.13)	0.018 (0.141)	0.014 (0.123)	0.018 (0.145)	0.019 (0.12)	0.011 (0.131)
LOSS	0.011 (0.629)	0.007 (0.743)	0.007 (0.738)	0.005 (0.817)	−0.012 (0.728)	−0.013 (0.793)	−0.015 (0.888)	−0.013 (0.847)
LOGTA	0.008 (0.276)	0.009 (0.216)	0.01 (0.212)	0.01 (0.201)	0.022 (0.398)	0.019 (0.416)	0.024 (0.412)	0.02 (0.379)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.098	0.092	0.094	0.093	0.0	0.092	0.094	0.093
Adjusted R^2	0.042	0.036	0.038	0.037	0.009	0.009	0.007	0.01
VIF	2.135	2.057	2.288	2.922	1.378	1.38	1.775	1.854
Number of observations	354	354	354	354	354	354	354	354