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DECLARATION OF DOCTORAL CANDIDATE

The present doctoral dissertation was submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy of the University of Cyprus. It is a product of original work of my own, unless otherwise mentioned through references, notes, or any other statements.

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Περίληψη

Σε αυτή την διατριβή εξετάζονται οι συμπεριφορικές προκαταλήψεις των επενδυτών. Συγκεκριμένα, εξετάζεται πρώτον, κατά πόσο οι τιμές των εταιρικών ομολόγων μπορεί να επηρεάζονται και να παρεκκλίνουν από τις βασικές αρχές της χρηματοοικονομικής όταν ετεροχρονισμένες πληροφορίες ανακυκλώνονται στα μέσα μαζικής ενημέρωσης (περιορισμένη προσοχή), δεύτερον, κατά πόσο οι ασφαλιστικές εταιρείες προχωρούν σε αγοραπωλησίες εταιρικών ομολόγων όταν ετεροχρονισμένες πληροφορίες ανακυκλώνονται στα μέσα μαζικής ενημέρωσης, και τρίτον, κατά πόσο υπάρχει υπερβολική αντίδραση από επενδυτές όσο αφορά τις αγοραπωλησίες εταιρικών ομολόγων μετά από μια σειρά θετικών/αρνητικών ειδήσεων (προκατάληψη αντιπροσωπευτικότητας).

Λόγω του τεράστιου όγκου πληροφοριών και του αριθμού των κινητών αξιών που διατίθενται για επενδύσεις, οι επενδυτές ενδέχεται να μην επεξεργαστούν κατάλληλα ετεροχρονισμένες πληροφορίες που ανακυκλώνονται στα μέσα μαζικής ενημέρωσης. Στο πρώτο κεφάλαιο διερευνώνται πιθανές επιπτώσεις στις τιμές των εταιρικών ομολόγων λόγω της περιορισμένης προσοχής. Τα αποτελέσματα δείχνουν ότι οι τιμές των εταιρικών ομολόγων επηρεάζονται κυρίως όταν ένας οργανισμός αξιολόγησης πιστοληπτικής ικανότητας υποβαθμίζει μια εταιρεία. Υπάρχει επίσης ένδειξη μιας σχέσης μεταξύ όγκου συναλλαγών και τιμής.

Η μελέτη του δεύτερου κεφαλαίου εστιάζει στον ασφαλιστικό τομέα καθώς είναι από τους μεγαλύτερους θεσμικούς επενδυτές σε εταιρικά ομόλογα. τα αποτελέσματα δείχνουν σημαντικές αυξήσεις στον όγκο συναλλαγών όταν ετεροχρονισμένες πληροφορίες ανακυκλώνονται στα μέσα μαζικής ενημέρωσης. Τα στοιχεία αυτά δεν συνάδουν με τις προβλέψεις της ημι-ισχυρής αποδοτικής αγοράς, αλλά υποστηρίζουν την ύπαρξη περιορισμένης προσοχής στις θεσμικές συναλλαγές.

Τέλος, η υπάρχουσα βιβλιογραφία όσον αφορά τη προκατάληψη της αντιπροσωπευτικότητας εγείρει το ερώτημα εάν υπάρχει υπερβολική αντίδραση της συνολικής αντίδρασης στην αγορά. Η μελέτη προσεγγίζει αυτού του τύπου συμπεριφοράς χρησιμοποιώντας ανακοινώσεις αξιολόγησης πιστοληπτικής ικανότητας. Τα αποτελέσματα δείχνουν ότι μετά από μια σειρά αρνητικών ειδήσεων, υπάρχει υπερβολικής αντίδρασης της

συνολικής αγοράς με αποτέλεσμα να παρατηρείται στατιστικά σημαντική αύξηση τιμών μέχρι και ένα χρόνο μετά από μια σειρά αρνητικών ειδήσεων.

Abstract

The growing body of literature on the existence of market inconsistencies has led in the evolvement of behavioral finance, an area of research which investigates whether market anomalies could be explained by several plausible behavioral biases. The aim of this dissertation is to analyze the extent to which investors' behavior is consistent with two behavioral biases in the US corporate bond market; namely limited attention and representativeness bias.

Using the relative timeliness of rating actions in the same direction, the late mover is used as a proxy for limited attention, after controlling for the informativeness of the rating action using a news analytics database. What the evidence suggests is that there is an abnormal reaction towards the direction of the signal in a set of uninformative rating actions. Results are consistent with investors being prone to the limited attention bias. Furthermore, there seems to be an observable price pressure from institutional investors as the abnormal reaction is positively correlated with their buy-sell imbalance.

The work on limited attention bias is extended by concentrating on insurance companies (PC, Life and Health insurance companies) as they are the largest domestic bondholders in the US corporate bond market. With availability of bond transaction data on a daily basis and by comparing a group of institutional investors with a homogeneous regulatory framework, the second chapter investigates the trading behavior of insurance companies around uninformative rating actions. There is evidence of abnormal trading in insurance companies when credit rating announcements contain no new information, lending the support of the limited attention hypothesis.

The last chapter of the thesis evaluates the mispricing effects in the US corporate bond market and whether these could be explained by the representativeness bias. By constructing sequences of upgrades and downgrades, the future performance is tested up to a year after formation period. The results show that following a sequence of downgrades (negative news), a price reversal is observed up to one year after formation period. There is an asymmetry between sequences of negative and positive news; the strong significance of the reversal is not observed in sequences of upgrades, which is consistent with the results documented in existing literature.

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Introduction

Behavioral Finance (BF) has gained recognition among academics in recent years, mostly as a complement to traditional finance theories (TFT). Asset pricing models of TFT are based on the efficient market hypothesis (Fama, 1965; 1970), which assumes that market prices incorporate all available information (however the efficient market hypothesis does not necessarily assume that all investors are rational).

BF relaxes investors' rationality assumption and is motivated by empirical anomalies not fully addressed by the efficient market hypothesis. Even though investors try to optimize their decisions, they do not always do so which could also be due to inexperience or lack of training. Although intuitively behavior may have always played a part in analysis, it wasn't until the late 1970s, early 1980s where concepts of behavior were being studied. The most common behavioral traits referenced in empirical and theoretical BF studies include: (a) limited attention; (b) framing (investor's perceptions); (c) overconfidence (overestimating personal ranking relative to others); (d) disposition effect (selling winning investments too quickly but keeping losing investments too long); (e) home bias; (f) herding behavior (following others' trades); (g) representativeness (discover trends and overweigh new information) (h) conservatism (give a higher weight to initial beliefs); and (i) heuristics (rule of thumb, common sense, intuition). In my thesis, I focus on two BF biases: (a) limited attention (chapters one and two) and (b) representativeness (chapter three).

Chapter one contributes to the literature by providing evidence consistent with limited attention, at the institutional setting. In psychology terms, attention is a cognitive ability, and limited attention is an inevitable outcome to the vast amount of information and securities available (Hirshleifer and Teoh (2003)). The study concentrates on one strand of literature of limited attention; the ability of investors identifying the staleness of news and whether there is abnormal price reaction when news are being recycled in the public domain. There is currently extant literature when it comes to institutional investors; particularly, only one paper (Tetlock, 2011) empirically tests whether institutional investors react to old information and provides no evidence of abnormal reaction. On the contrary, a recent paper (Fedyk and Hodson 2019) experimentally tests how finance professionals perceive two types of old news (reprints and recombination of old information) and provides evidence of professionals not fully realizing the staleness of news when these are given as a recombination of old information. While they develop their idea further and empirically test and provide evidence of market reaction at the aggregate level, they do not investigate whether market reaction is correlated with institutional investors' actual trading.

Using the universe of credit rating and outlook/watchlist announcements, we construct pairs of same sign signals and identify announcements that do not provide new information. The work draws from the credit rating agencies (CRAs) literature, specifically the timeliness of credit rating announcements (Beaver et al., 2006, Berwart et al., 2016). While CRAs may not all rate at the same day, there is evidence of a bi-directional relationship between issuer-paid and investor-paid rating agencies. What this implies is that a rating that comes first is expected to contain more information compared to subsequent ones that follow (late movers – LM). By using the Thomson Rheuters Marketpsych Indices (TRMI) overall market sentiment, we are able to distinguish between LMs that provide new information in the public domain and those that do not.

The results indicate an overall price impact towards the direction of the rating signal in the corporate bond market when news are being recycled in the market, lending the support to a limited attention hypothesis, i.e., that investors cannot disentangle the true informativeness of a credit rating announcement. Furthermore, there seems to be an observable price pressure from institutional investors as the abnormal reaction is positively correlated with their buy-sell imbalance.

Chapter two extends the work done on limited attention in chapter one, by focusing on one type of institutional investors, that is insurance companies (IC). The availability of daily individual bond trading activity of ICs allows us to fully explore their trading behavior when stale news are being released in the public domain. Furthermore, ICs are currently the largest domestic holders in the US corporate bond market (around 25% of total size), suggesting that it is important to investigate whether abnormal trading and price impact due to limited attention could be affected by the behavior of ICs. By constructing a sample of uninformative LM (as described above), the study concentrates on the trading volume of all PC/Life/Health insurance companies. Of importance is to note the fact that they are highly regulated by the National

Association of Insurance Commissioners (NAIC), specifically, as to the percentage of non-investment grade bonds that they could hold in their portfolio; therefore, an overall market reaction could be due to regulatory constraints rather than institutional investors not realizing the true informativeness of a credit rating announcement per se.

The NAIC has its own designation system when it comes bond ratings. ICs are required to follow all Nationally Recognized Statistical Research Organizations (NRSROs) and convert the combination of all available ratings into a NAIC rating. This is particularly essential when deciding whether a bond is considered as having an investment grade or junk rating. Following the NAIC designation rule, for companies that are being rated by three or more rating agencies, there should be at least two CRAs, which rate bonds as non-investment grade. Therefore, if LM results in a bond rating being considered as non-investment grade, the ICs may need to rebalance their portfolios without necessarily implying that the do not fully realize the true informativeness of credit rating announcements. We control for this by excluding events that result in a change in the NAIC rating as well as controlling for the probability of a NAIC rating change. By running panel regressions with fixed effects at the issuer CUSIP and year level, there is evidence of abnormal trading in ICs when credit rating announcements contain no new information, lending the support of the limited attention hypothesis; without however exerting price pressure in the bond corporate market.

The last chapter of the thesis explores whether any mispricing effects could be attributed to the representativeness bias. The representativeness bias, introduced by Kahneman and Tversky (1972), refers to the process of making judgments about the probability of an event without appropriately incorporating the probability of such an event actually occurring (ignoring base rates). The authors defined representativeness as "the degree to which (an event) (i) is similar in essential characteristics to its parent population, and (ii) reflects the salient features of the process by which it is generated". In the context of finance, investors may try to predict future performance of a company by extrapolating a short history of good/bad past performance. They may assume that a company will keep on performing in the same direction (i.e., forming trends) without taking into account the probability of a company carry on trending in the same direction. This ultimately leads to price overreaction, which reverses when in the future investors realize that their expectations are not met.

The literature empirically tests future performance of good and bad performance companies by looking at several profitability measures. The contribution of this chapter lies on the fact that credit default risk is observed in past performance of bond-issuing companies as opposed to profitability measures. CRAs act as information intermediaries and consolidate all available information into a single letter rating, which is easily comprehensible by market participants, with the aim of reducing information asymmetries. By looking at a more illiquid market, i.e., US corporate bond market (compared to the equity market investigated so far), sequences of past performance are formed by constructing samples of same sign credit rating announcements (negative and positive news). Future performance is tested by looking at whether there is evidence of any overreaction effects following trends of good/bad performance, i.e., whether there is a mean reversal in future performance.

The results show that following a sequence of downgrades (negative news), a price reversal is observed up to one year after formation period. There is an asymmetry between sequences of negative and positive news; the strong significance of the reversal is not observed in sequences of upgrades, which is consistent with the results documented by De Bondt and Thaler (1985). Further analysis indicates that the higher the number of negative credit rating signals, the higher the magnitude of the reversal.

Chapter 1: Price impact of bonds due to limited attention.

Abstract

Using the universe of bond investment transactions from 2002 to 2014, we examine whether institutional investors are affected by limited attention in their trading activities. To capture limited attention, we condition on the credit quality of investment targets (i.e. corporate bonds) using actions in credit quality signals (rating and outlook actions by credit rating agencies). Using the relative timeliness of rating actions in the same direction (e.g. two consecutive negative signals), we use the late mover rating action as a proxy for limited attention. To control for new information potentially present in a late rating action, we use a unique news-analytics database. What the results suggest is that investors cannot distinguish between informative and uninformative rating actions and react abnormally towards the direction of the signal (negative for downgrades). Furthermore, we find that there exists a contemporaneous relationship between the institutional investors' buy-sell imbalance and abnormal bond returns. This is an indication of institutional investors exerting a price pressure when news are being recycled in the public domain.

1.1 Introduction

In this empirical chapter, we contribute to the literature by focusing on limited attention for institutional investors, an area of behavioral finance that has not been extensively explored. We proxy for institutional investor behavior using TRACE enhanced (TRACE thereafter), which reports individual bond transactions since July 2002, including data such as transaction date and time, par value volume, transaction price and the direction of the trade. TRACE individual corporate bond transaction data has not been used to research behavioral traits in institutional trading[1]. Only very few studies have studied the potential of limited attention bias for institutional investors using individual transactions of institutional investors, with little evidence of limited attention at the institutional setting[2].

Since institutional investors are predominant players in the corporate bond market, and since a strong signal of change in credit quality is largely provided by actions in corporate debt ratings and outlooks, we focus this study on the investing behavior of institutional investors around actions in bond ratings and outlooks. Pivotal to our study is the timeliness of bond rating and outlook actions, the amount and content of news coverage related to actions in credit quality of a corporate bond, and most importantly the attention (or lack of attention) paid by institutional investors.

To measure attention, we use actions in bond ratings and outlooks by the two types of credit rating companies; issuer-paid (Fitch, Moody's, Standard & Poor's – S&P, Dominion Bond Rating Services – DBRS, AM Best – AMB, Kroll Bond Rating Agency - KBR) and

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[1] When it comes to investigating behavioral traits in institutional trading using corporate bond transactions/portfolio holdings, Broeders et al. (2016) use Dutch pension funds investment bond holdings, Cai et al. (2018) use institutional investors' holdings from Thomson Rheuters Lipper eMAXX.

[2] Barber and Odean (2008) use daily trading records of individual and institutional money managers. The authors find no evidence of net buying behavior for institutional investors. Yuan (2015) distinguishes between individual and institutional investors using trade size (as a proxy for institutional investor trading) and provides no evidence of increased trading activity by institutional investors. Tetlock (2011) uses individual and institutional trading orders through a large market center and provides no evidence of increased trading activity with stale news in stocks which are largely composed of institutional investors. Akepanidtaworn et al. (2018) look at daily trading activity of institutional investors and provide evidence of consistent underperformance when it comes to selling decisions. They attribute this to the allocation of limited attentional resources in selling decisions as opposed to buying decisions. Cohen and Frazzini (2008) investigate economically linked firms (customer-supplier linked firms) and provide evidence of mutual funds being more likely to trade on supplier (mutual funds that own shares for both supplier and customer) when there are news about customer linked firms that affect suppliers performance as well, compared to mutual funds that own shares of the supplier firm only.

investor-paid agencies (Egan-Jones Rating Agency - EJR) [3]. The difference in the compensation structure of rating agencies is associated with a difference in the timeliness of their rating changes (Beaver et al., 2006; Milidonis, 2013; Bruno et al., 2016), which has changed over the past fifteen years (Berwart et al., 2016)[4]. Hence, we construct a "first mover" (FM) filter based on the union of all rating actions[5] relevant to a corporate bond (i.e. the investment target), which identifies the first rating action across all seven rating agencies. We use the FM rating actions as an early signal of credit quality of a corporate bond and the "late mover" (LM) rating actions as a late signal of credit quality[6]. According to the semi-strong efficient market hypothesis, we would expect that institutional investors will not be reacting to LM actions, if these do not provide any new information to the market.

To control for the amount of information present in the news around rating actions, we use a unique news analytics database, namely Thomson Reuters Marketpsych Indices (TRMI). TRMI is an advancement over news' textual analysis typically used in the literature (e.g. Tetlock, 2007); it goes beyond counting positive and negative words in news articles by also incorporating tone and emotions inherent on news readers, and has been used and validated in the finance literature for the first time by Michaelides et al. (2015) using sovereign data. TRMI sentiment is an index constructed by an algorithm that reads and transforms news articles related to a bond issuing company, into a normalized index. We validate the sentiment index at the issuer CUSIP level by computing the cumulative abnormal sentiment (CAS) around credit rating announcements which are "clean" from other types of events. Consistent with our expectations, the CAS is statistically significant for upgrades and downgrades in the positive and negative direction respectively; an indication that overall, the public domain perceives upgrades (downgrades) positively (negatively).

We use TRMI (abnormal) sentiment to categorize our LM sample in portfolios of "No News" (interquartile range), "Positive News" (fourth quartile) and "Negative News" (first

[3] All seven CRAs are the ones out of the Nationally Recognized Statistical Rating Organizations (NRSROs) which rate US corporate bonds.
[4] An announcement that comes first is expected to include more information than an announcement that follows in the next few days. According to Berwart et al. (2016), even though differences in timeliness between issuer-paid and investor-paid credit rating agencies existed before 2002, these differences weakened after this time period.
[5] Throughout the paper, rating actions will refer to both rating and outlook actions.
[6] The FM is free from other rating actions in the previous 60 trading days. The LM follows immediately the FM (in the same direction) within 60 trading days. In addition, we require that there are no other rating actions between the FM and LM.

quartile). Focusing on uninformative LM actions, we provide evidence of an overall abnormal reaction in the negative direction for downgrades, which seems to lend the support of limited attention bias since these LM do not provide any new information in the market. Furthermore, we test whether buy-sell imbalance from institutional investors is correlated with abnormal bond returns. We find that there exists a contemporaneous relationship between the institutional investors' buy-sell imbalance and abnormal bond returns. Since these events do not provide new information to the market, a price pressure from institutional investors is not expected. This seems to lend the support to the hypothesis of limited attention bias, since the LM rating actions are categorized as non-informative.

The remainder of the paper is organized as follows. Section 1.2 provides a literature review and motivates the study. Section 1.3 presents the empirical set-up constructed to test the hypothesis of limited attention. Section 1.4 describes the methodology and section 1.5 the sample selection. Section 1.6 presents the results. Section 1.7 concludes.

1.2 Literature review and motivation

Hirshleifer and Teoh (2003) refer to limited attention as an inevitable outcome due to the vast amount of public information and number of securities available for investment. Investors therefore may fail to process appropriately the true informativeness of news available. This cognitive bias has been studied in several settings when it comes to investigating the effect on financial markets at the institutional setting.

The first refers to how investors allocate their resources when it comes to investment decisions. A recent working paper by Akepanidtaworn et al. (2018) looks at daily trading activity of institutional investors and provides evidence of consistent underperformance when it comes to selling decisions. They attribute this to the allocation of limited attentional resources in selling decisions as opposed to buying decisions. Furthermore, Cohen and Frazzini (2008) investigate economically linked firms (customer-supplier linked firms) and provide evidence of mutual funds being more likely to trade on supplier (mutual funds that own shares for both supplier and customer) when there are news about customer linked firms that affect suppliers performance as well, compared to mutual funds that own shares of the supplier firm only.

Secondly, researchers have studied the effect of trading activity of investors when it comes to attention grabbing events. Attention grabbing news is a possible effect of a net buying behavior mostly by individuals instead of institutional investors when looking at the time period between 1993 and 1996, according to Barber and Odean (2008). Lastly, Yuan (2015) uses a proxy when distinguishing between individual and institutional investors, i.e. trade size. The author argues that attention-grabbing events lead to individual investors being more active.

Lastly, an area of research concentrates on the ability of investors to realize the true informativeness of publicly available information and how they react to news that is being repeated in the news domain (stale news). An interesting paper by Huberman and Regev (2001) describes in detail a case about EntreMed that has occurred in the late 1990s. While news was released about this company on November 1997; an article on May 1998 which consisted of no new information in addition to the article in November 1997, resulted in a permanent stock price change. Gilbert et al. (2012) look at the aggregate market effect of stocks and bonds and suggest that investors' inattention to the staleness of news result in a short-term mispricing. Tetlock (2011) presents results for both individual and institutional investors and provides evidence that in stocks where the investor trading activity is largely composed of individual (instead of institutional) investors, there is a tendency to overreact more to stale information. A more recent paper by Fedyk and Hodson (2019), examines experimentally how finance professionals perceive stale news and whether they can differentiate news articles as providing old information. They provide evidence of investors not being able to disentangle the true informativeness of news when it consists of recombination of stale information rather than simple reprints; however, the authors test this empirically at the aggregate market level only providing evidence of temporary mispricing in the stock market.

Whilst institutional investors are expected to trade based on the principles of traditional finance theories (TFT) without being affected as much by behavioral biases, there have been several articles providing evidence of possible price effects due to behavioral biases by institutional investors[7]. Our work focuses on stale news at the institutional setting. So far, there has only been one paper which empirically tests the reaction of institutional investors to stale news (Tetlock, 2011), providing no evidence of abnormal reaction. The research question we aim to answer in this paper is:

Does limited attention affect institutional trading?

To answer this question we need an empirical set-up where we can examine how institutional investors trade when they receive "No News"; that is, an announcement that does not marginally add new positive or negative information to the existing set of publicly available information about an investment target[8]. Put differently, the semi-strong efficient market hypothesis predicts that prices should reflect all publicly available information, hence in the case of "No News", we should not observe any trading which exerts price pressure towards creating abnormal returns. On the contrary, behavioral finance predicts that in the case that investors experience limited attention, there could be abnormal reaction (trading) when old information is repeated in the news domain. In the next section, we describe how we empirically construct a setting of "No News" and test whether there is a price impact in corporate bonds.

1.3 <u>Empirical set-up</u>

1.3.1 Institutional investors

To empirically answer the research question, we focus on all institutional investors using TRACE database as the corporate bond market is predominantly traded by institutional

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[7] The majority of empirical literature testing attention effects is based on indirect proxies of attention, namely, extreme returns (Barber and Odean, 2008), trading volume (Barber and Odean, 2008), news and headlines (Barber and Odean, 2008 and Yuan, 2015), advertising expense (Grullon et al., 2004 and Lou, 2014) and price limits (Seasholes and Wu, 2007). Da et al. (2011) suggest a new direct measure which is suitable for individual investors using the search volume index. Ben-Raphael et al. (2017) propose a new direct measure for institutional investors, namely the abnormal institutional investor attention (AIA). While the authors in the paper about AIA argue that investors' reaction to news is more prominent with higher AIA values, we investigate the ability of investors to distinguish between old and new news in the market.

[8] Henceforth we use the phrase "No News" portfolio and uninformative rating announcements interchangeably.

investors. TRACE bond transactions dataset consists of all corporate and agency bond transactions reported by brokers/dealers since July 2002 (we concentrate on US corporate medium term notes, US corporate debentures and US corporate convertibles). The aim of the creation of TRACE was to increase price transparency. The database reports individual bond transactions including data such as transaction date and time, par value volume, transaction price and the direction of the trade. TRACE does not provide information on who buys or sells a bond, therefore we use trades with a size volume of at least $100,000[9] as a proxy for institutional trades (Bessembinder et al., 2009).

We follow Asquith et al. (2013) and Dick-Nielsen (2014)[10] to delete the following observations from the original sample: (a) unavailable 9-digit CUSIP and par value volume of transaction; (b) chain of observations that resulted in a cancellation; (c) chain of observations that resulted in a correction (kept only latest observation); (d) reversals (with matched initial trades); (e) delayed reversals and delayed dissemination; (f) transactions where date occurred before offering or after maturity date of the bond[11].

1.3.2 Credit rating agencies as information intermediaries

To be able to measure and assess the amount and content of information related to an investment target (i.e. corporate bonds) we focus on the respective announcements of credit rating agencies (CRAs). CRAs are information intermediaries that help transform a large volume of typically complicated data into a letter (credit) rating, which is easily comprehensible by market participants (e.g. investors). To capture as much as possible from the universe of credit rating actions, we follow Berwart et al. (2016) and obtain ratings from both types of CRAs operating in the US bond market: issuer-paid and investor-paid CRAs.

[9] TRACE reports the par value volume of the trade. We refer to volume of transaction as the actual volume of transaction given the price at which the bond was bought/sold. Reported price is given as a percentage of par value and par value volume assumes a $1,000 par value. Therefore, the actual volume of transaction was computed as (reported price/100)*par value*(par value volume/1,000).

[10] Data structure of TRACE has changed since February 2012. Asquith et al. (2013) use data up until December 2006. In order to incorporate all data cleaning procedures for our sample, it was deemed appropriate to follow data cleaning process from both authors.

[11] Data for offering and maturity date were obtained from Mergent Fixed Income Securities Database (MFISD).

Since we use both types of CRAs, it is important to identify that there are cross-sectional differences in the content of CRAs' announcements. Issuer-paid CRAs receive compensation from the companies whose corporate bonds they rate. During the rating process, they meet with the companies they rate, hence their ratings are expected to include private in addition to public information. On the contrary, investor-paid CRAs are paid by investors to rate investment targets, while their ratings are based entirely on public information. We control for the cross-sectional differences in rating actions of CRAs using the TMRI sentiment variable (section 1.3.3).

In addition to cross-sectional differences in credit ratings of issuer-paid versus investor-paid CRAs, another strand of literature shows that there exist differences in the timeliness of their announcements, where these differences vary over the past twenty years (e.g. Beaver et al., 2006; Berwart et al., 2016; Bruno et al., 2016; Milidonis, 2013). In the most recent study, Berwart et al. (2016) find that while investor-paid CRAs used to be faster before 2002 with respect to their rating changes, differences in timeliness have disappeared after 2002, while when outlook changes are taken into consideration, differences in timeliness are virtually non-existent. These conclusions do not imply that all rating agencies announce at the same time, but that on average there seem to be bi-directional relationships between the FM and the follower. Timeliness is important because an announcement that comes first is expected to include more information than an announcement that follows in the next few days, ceteris paribus.

We use actions in ratings for corporate bonds (senior unsecured), by six issuer-paid CRAs (Fitch, Moody's, S&P, DBRS, AMB, KBRS), and the most widely used investor-paid CRA (EJR)[12], as a signal of the announcement in credit quality. When providing additional information, announcements in credit quality are expected to be associated with changes in expected future returns on the underlying corporate bond, hence institutional investors are expected to engage in portfolio rebalancing around changes in ratings, to achieve their investment target returns and risk.

[12] Rating announcements for Fitch, Moody's, S&P, EJR are available since the beginning of our sample period. Data for DBRS are available since 27/02/2003, for AMB since 03/03/2005, and KBR since 11/02/2008, which are the dates in which each CRA has become a NRSRO.

1.3.3 Controlling for the information content in rating actions (TRMI)

The literature has identified links between information transmitted through newswires and market reactions. Specifically, Tetlock (2007) shows that when there is negative tone in news articles, a decline in market prices follows, which is then followed by a return to the basic principles affecting prices. Furthermore, Tetlock (2010) finds that public news is associated with stock return reversals while Michaelides et al. (2015) find a reversal in international stock markets when there is rumor in the news about a forthcoming sovereign downgrade and also momentum in trading. In addition, according to Antweiler and Frank (2004), when there is disagreement in the news, this creates uncertainty, which increases the underlying trading volume. In a more recent paper, the impact of news on trading becomes evident since Engelberg and Parsons (2011) find that when local media discuss a market-related event, there is subsequent trading from local investors.

To control for the amount and content of information present in the public domain related to each rated corporate bond, we use the TRMI published through the collaboration of Thomson Reuters Corporation and Marketpsych LLC[13]. TRMI are an improvement over traditional, news' textual analysis in the literature (e.g. Tetlock et al., 2008), as they cover a much larger group of news sources, and they improve existing methods (e.g. counting positive and negative articles) by also considering the tone and extracting emotions inflicted on the reader (such as fear, joy, conflict, gloom, stress, anger, and optimism), macroeconomic indices (such as earnings expectations and interest rate forecasts) and buzz indices (such as litigation, mergers and volatility) from news articles and social media. TRMI combine the abundance of news articles (such as - but not limited to - The New York Times, The Wall Street Journal, Financial Times and Seeking Alpha) distributed through the Thomson Reuters News Feed Direct, Factiva News, and other sources, and the proprietary algorithm of MarketPsych LLC to produce daily indices related to about 8000 companies worldwide, 119 countries and about 30 currencies (about 3 million articles are scored on a daily basis).

TRMI are computed by analyzing news, social media and at the integrated level (i.e. both news and social media) and were first published in mid-2012. These indices can be broadly

[13] For more information see https://www.marketpsych.com/.

summarized into the frequency of news articles (non-negative integer) related to a reference entity (e.g. a bond issuing company) and the overall associated investor sentiment[14,15] (normalized from -1 to 1). Michaelides et al. (2015) were the first to use and validate in the finance literature the TRMI by showing that sovereign downgrade announcements were associated with an abnormal negative effect on TRMI sentiment. This validation is important to our study because it allows us to measure if rating action announcements create abnormal sentiment reaction (in either a positive or a negative direction). In addition to the validation in Michaelides et al. (2015), the sentiment variable has been validated at the issuer company level for the purposes of this study. A description of the validation process is provided in the next two subsections.

1.3.3.1 Validation of TRMI sentiment at the issuer company level – Cumulative abnormal sentiment (CAS)

To validate the TRMI sentiment variable at the company level, short-term event studies have been conducted to measure the abnormal sentiment at the day and the day after the event (as credit rating announcements could occur at the end of the day) for several estimation windows (estimation windows [-20,-3], [-30,-3], [-40,-3]). The universe of credit rating announcements (all upgrades, downgrades, affirmations for ratings, outlooks and watchlist inclusions/exclusions) from seven credit rating agencies (Fitch, Moody's, S&P, EJR, DBRS, AMB, KBR) have been used to define the FM as the rating action in which there haven't been any other rating actions in any direction 60 trading days (approximately 3 calendar months)[16] prior to the event[17]. To ensure that the TRMI sentiment is "clean" from other type of events that could potentially distort the sentiment level, FM have been excluded where other credit rating

[14] The most widely used sentiment index in academic research is the monthly Baker-Wurgler sentiment index (Baker and Wurgler, 2006) which combines several characteristics of market data (closed-end fund discount, NYSE share turnover, number and average first-day returns on IPOs, equity share in new issues and dividend premium). The daily sentiment constructed variable in TRMI (Peterson, 2016) mirrors the net of positive and negative content of companies captured by news and/or social media. Thomson Reuters Corporation provided the dataset (up to and including November 2015), free of charge for additional research related to company-specific research.

[15] We are using the sentiment computed by analyzing news only.

[16] As a robustness check, FM have also been constructed where no other rating actions occur in any direction 40 days prior to the event (approximately two calendar months) and LM occur within the next 40 days. Results were qualitatively the same and are thus not reported.

[17] Cases where there have been rating announcements from more than one credit rating agency on the same day in different directions have been excluded from the sample (e.g both an upgrade and an affirmation on the same day).

announcements have occurred within [1,5] relative to the event, as well as earnings announcements and mergers and acquisitions that have occurred within [-5,5] relative to the event[18].

The CAS has been computed by using a short-term event study method. First the average sentiment in the time period [-20,-3], [-30,-3] and [-40,-3] relative to the credit rating announcement is estimated for each bond issuing company using the 6-digit issuer CUSIP with at least one observation available during the estimation window (and event window). Abnormal sentiment at the day and the day after the event is calculated as

$$Ab\_Sent\ (t)\ =\ Sent(t) - Av\_Sent\ (estimation\ period) \tag{1}$$

where *Ab_Sent(t)* is the abnormal sentiment at day *t*, where $t \in [0,1]$; *Sent(t)* is the actual sentiment at day *t*; and *Av_Sent (estimation period)* is the average sentiment over the estimation windows [-20,-3], [-30,-3] and [-40,-3]. We then calculate the CAS (for US companies) over the event window [0,1] to capture the full impact of the rating action announcement on news sentiment, as captured through TRMI:

$$CA\_Sent =\ Ab\_Sent\ (t = 0)\ +\ Ab\_Sent\ (t = 1) \tag{2}$$

The significance of the CAS is tested using a t-test, i.e. whether the CAS is significantly different from zero. The results of event studies are presented in table 1.1, separately for upgrades, downgrades and affirmations. The results are consistent over the three different estimation windows used. The sample size used (for the time period July 2002 to September 2014[19]) for each direction of credit rating announcement varies across estimation windows, ranging between 1,187 to 1,230 for downgrades, 2,746 to 2,804 for affirmations and 1,241 to 1,274 for upgrades. The reason for the differences in the sample sizes lies in the fact that the number of companies with at least one observation available during estimation period increases as the estimation window increases. The CAS is statistically significant at the 1% level for all three estimation windows for both upgrades and downgrades in the positive and negative direction respectively, with the effect for downgrades being more pronounced compared to upgrades. This implies that overall, upgrades (downgrades) are perceived positively (negatively)

[18] Chae (2005) states that there is documented evidence in the literature on four types of events that affect trading volume; earnings announcements, credit rating announcements, mergers and acquisitions. Earnings announcements have been downloaded from COMPUSTAT fundamentals quarterly. Mergers and acquisitions announcements have been downloaded from Thomson Rheuters Eikon.

[19] This is the common time period between all data sources used in this study.

in the public domain. For affirmations, there seems to be a non-significant change in sentiment across all three estimation windows.

[Insert Table 1.1]

Another sample was tested for the three estimation windows, indicated as random sample in table 1.1. Stratified random sampling (simple random sample, seed=1950) was used to choose five random dates for each company in the universe of US companies in TRMI database. Following the same process as with credit rating actions, dates have been excluded where there have been credit rating announcements, earnings announcements or mergers and acquisitions [-5,5] relative to the date chosen for each company. The aim of testing a random sample is to observe whether in time periods where there are no important companies' announcements in the media result in any abnormal sentiment. The results confirm the expectation of a non-significant abnormal sentiment in time periods of no events.

1.3.3.2 Validation of TRMI sentiment at the issuer company level – Cumulative abnormal bond returns (CARs)

For the sample of events used in the TRMI validation of news sentiment[20], CARs (where bond price data available) for several event windows have also been computed to investigate the extent to which upgrades, affirmations, downgrades and a random sample of no event dates result in positive, none, negative and no abnormal reaction respectively.

Abnormal bond returns are calculated following the method suggested by Bessembinder et al. (2009) for daily bond price data (trade-weighted price, trades>=100,000, firm level approach[21] for companies with multiple bonds). Data are obtained from TRACE (as described in section 1.3.1). Daily abnormal return[22] is defined as

$$AR_t = return\ of\ bond\ of\ interest_t - expected\ return\ of\ matching\ portfolio_t$$

[20] The sample of events for the estimation window [-20,-3].
[21] For events in which there have been transactions for more than one bond within the same company, a market value weighted average abnormal return was computed.
[22] Following Bessembinder et al. (2009), we exclude cases where absolute value of return is greater than 20%.

$$AR_t = \frac{(P_{t+1}+AI_{t+1})-(P_t+AI_t)}{(P_t+AI_t)} - \ expected\ return\ of\ matching\ portfolio_t \tag{3}$$

where P_t= price at time t

AI_t= accrued interest at time t

$expected\ return\ of\ matching\ portfolio_t$= average return of bonds within the same rating/maturity group[23]

It is well known in the literature that when it comes to bonds, risk factors such as default risk and time-to-maturity result in differing variability in bond return reactions. Thus, we adjust for this by using a matching portfolio when computing the average expected return of matching portfolio based on seven rating groups (S&P rating categories AAA, AA, A, BBB, BB, B, CCC and below and the corresponding rating categories for the rest of credit rating agencies[24]) and three time-to maturity groups (0 up to but excluding 5 years, 5 up to but excluding 10 years, 10 years and above).

The results are depicted in table 1.2[25] for three event windows; [0,1], [0,2] and [0,3].The mean CARs are reported in basis points for all events with available bond price data ("All" under "Bonds" column) and for all events that were not a result of a new bond being issued by the company of interest[26] ("No new bonds" under "Bonds" column). When looking at downgrades, we observe statistically significant negative CARs for all event windows. More specifically, for the event the event window [0,1], the mean CAR (statistically significant at the 1% level) is -39.874 and -41.954 bps for all bonds with available price data and for events where ratings were not a result of a new bond being issued in the market respectively. Overall, results are negative and statistically significant at the 5% and 1% level for all three event windows reported. For the sample of all events with available price data, the mean CAR ranges between

[23] Bonds have been excluded from matching portfolio if there has been a credit rating announcement during the period of interest.

[24] To account for the fact that bonds may be rated by more than one credit rating agency, the average rating was used across all NRSROs which rate the company of interest, i.e. for NRSROs that have rated companies within a year of the date of interest.

[25] Results are qualitatively the same when defining a FM to be a rating announcement with no prior rating announcements 40 days prior to the event and LM occur within the next 40 days and are thus not reported.

[26] When a new bond is being issued by a company, there is a press release from a credit rating agency which rates the new bond. We would like therefore to test the robustness of our results by excluding any possible effects to the cumulative abnormal returns due to this.

-39.874 and -29.037 bps (depending on event window)[27]. When excluding events which were a result of a new bond being issued in the market, the mean CAR ranges between -41.954 and -32.429 bps.

[Insert Table 1.2]

Next, we observe weak significance for upgrades for the event window [0,2]. Consistent with the literature on asymmetrical market reactions between upgrades and downgrades, a smaller reaction is observed for upgrades, while for many studies there is no evidence of abnormal reaction (Dichev and Piotroski, 2001)). For the event window [0,2], the mean CAR is 13.487 bps for all bonds with available price data (at the 10% level).

Lastly, affirmations and the random sample[28] do not result in any statistically significant mean CARs for neither of event windows tested. When CRAs announce an affirmation for a company, they confirm the company's existing rating. Therefore, we would not expect a significant response to price when a CRA reviews the credit quality of a company with no change in rating. Similarly, for the random sample, we provide a test to confirm that there is no abnormal reaction at any point with no important news announcements. Consistent with the findings in table 1.1 for CAS, affirmations and the random sample do not result in neither an abnormal sentiment, nor an abnormal price reaction.

1.3.4 Limited attention: late rating action

We use the relative timeliness of rating actions to propose our proxy for limited attention. Berwart et al. (2016) use Fitch, Moody's, S&P and EJR to find that there is bi-directional predictability between rating actions of investor-paid and issuer-paid CRAs when ratings, outlooks and watchlist revisions are taken into consideration. Since the TRMI can control for

[27] The number of events in each window differ due to the fact that for greater event windows there is price availability for more events.
[28] The percentage of events with available price data (compared to events for CAS) in the random sample is much smaller compared to upgrades, downgrades and affirmations. This is because not all companies covered in TRMI have a credit rating available.

the informational value of rating actions by any CRA, we construct pairs of rating actions (by any CRA) as described below[29].

Figure 1.1 depicts the methodology used in constructing late rating actions. We define a FM to be a rating action which is not preceded by any other rating action (in any direction) in the previous 60 trading days (approximately 3 calendar months). Hence, the FM has potentially some new information to offer to market participants. Next, we define the LM to be the next rating action in the 60 days following the FM rating action; where both rating actions have to be in the same direction[30]. Therefore, we use the LM as a proxy of limited attention in the sense that rating action is provided up to 60 days later than the first credit signal in the same direction. From the sample of LM, we delete all those observations that had a rating action in the 10 trading days immediately before the LM action, in order to avoid contamination of the abnormal sentiment estimation.

[Insert Figure 1.1]

A skeptic could ask: Is it possible that the LM provides additional useful information to market participants? Yes it is, but such additional information would be captured by an abnormal impact on the CA_Sent (as described in section 1.3.3.1). For example, if an upgrade provides additional positive news to the market, we expect that the CA_Sent for the rated corporate bond to be abnormally positive[31]. But if the upgrade does not provide any new information relative to what the FM has provided, then the limited attention hypothesis could justify trading at or after the LM rating action. The same rationale applies to rating actions in a negative direction (negative outlook or downgrade) or an affirmation. CA_Sent will inform us whether a negative rating action or affirmation has provided additional negative, positive or no new information.

[29] By "pair", we mean that there have to be at least two rating actions in the same direction for the same bond issuing company within 60 trading days by any CRA.

[30] Cases where there has been a rating action in a different direction in between FM and LM have been excluded from analysis.

[31] It is also possible for an upgrade to provide negative news to the market. For example, if there was anticipation in the market (which is captured by the average sentiment in the estimation period) for a multi-notch upgrade, while the actual upgrade was only for a single notch.

1.3.5 Limited attention: informative versus uninformative late rating actions

Figure 1.2 shows the histogram of CAS (CA_Sent) estimated using the union of LM rating actions as described in section 1.3.4. The average and median values are both very close to zero: -0.024 and -0.023 respectively. In addition, the standard deviation is 0.441 with a minimum value of -2.622 and a maximum value of 2.182. Intuitively, a value in the left (right) tail of the distribution would indicate that the LM rating action was associated with a negative (positive) change in TRMI sentiment, relative to the average TRMI sentiment present in the 20 to 3 trading days before the announcement.

[Insert Figure 1.2]

As shown, the overall sentiment has a mean and median value very close to zero. Hence, we construct the three portfolios, namely "Negative News", "No News" and "Positive News" by separating the distribution in three mutually exclusive parts. "Negative News" comprises all observations ranging from the distribution's 1st quartile ($-2.622 \leq CA_{Sent} < -0.258$); "No News" is the distribution's interquartile range ($-0.258 \leq CA_{Sent} < +0.220$); "Positive News" is the distribution's 4th quartile ($+0.220 \leq CA_{Sent} \leq +2.182$). The same cut-off points are used for all rating actions.

1.4 <u>Methodology</u>

To analyse the trading behaviour of institutional investors around LM we use the overall institutional trading buy-sell imbalance volume (following Barber and Odean, 2008)[32] over the event window of interest defined as

$$IMB_i^{[j,k]} = \frac{B_i^{[j,k]} - S_i^{[j,k]}}{B_i^{[j,k]} + S_i^{[j,k]}} \tag{4}$$

where $B_i^{[j,k]}$ = total volume[33] of bonds bought over the event window [j,k]

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[32] The buy-sell imbalance was also calculated using the number of trades instead of the volume of trades. The results were qualitatively the same and are thus not reported.

[33] Volume is defined in footnote 9.

$S_i^{[j,k]}$ = total volume of bonds sold over the event window [j,k]

We then estimate OLS regressions with robust standard errors (controlling for bond characteristics). The cross-sectional regressions are

$$CAR_i^{[j,k]} = IMB_i^{[j,k]} + age_i + maturity_i + debt_i + rating_i + liquidity_i^{[j,k]} + Upgrade_i + Downgrade_i \tag{5}$$

where $CAR_i^{[j,k]}$ = cumulative abnormal return (see section 1.3.3.2) over the event window [j,k]

$IMB_i^{[j,k]}$ = buy-sell imbalance over the event window [j,k]

age_i = age of the bond (in years)

$maturity_i$ = time to maturity of the bond (in years)

$debt_i$ = amount outstanding of the bond[34]

$rating_i$ = rating of the bond

$liquidity_i^{[j,k]}$ = liquidity[35] of the bond over the event window [j,k]

$Upgrade_i$ = Dummy variable indicating whether the event is an upgrade

$Downgrade_i$ = Dummy variable indicating whether the event is a downgrade

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[34] The definition of amount outstanding given in MFISD is "The amount of the issue remaining outstanding".

[35] We use the high-low spread estimator proxy for liquidity, which is the measure suggested by Schestag et al. (2016) for bonds.

1.5 Sample selection

1.5.1 Rating actions

We obtain actions in ratings, outlooks and watchlist inclusions/exclusions from various sources; for the big three issuer-paid CRAs (Fitch, Moody's and S&P) we obtain data from MFISD, for the rest CRAs (EJR, DBRS, AMB, and KBRS) from the CRAs' websites[36]. Our sample period starts from July 2002 and ends in September 2014. As explained in section 1.3.4, we then produce pairs of rating actions (for the common 6-digit CUSIPs between sources used) for each rated bond to identify the FM and LM rating action. Our rating sample comprises 6,055 pairs of events (i.e. 6,055 FM and 6,055 LM, comprised of 1,010 upgrade pairs, 1,145 downgrade pairs and 3,900 affirmation pairs). From the sample of LM, we delete all those observations (a) that had a rating action in the 10 trading days immediately before the LM action, in order to avoid contamination of the abnormal sentiment, (b) where other rating actions occurred between the FM and LM in a different direction, (c) where multiple rating actions on the same day in different directions occurred, (d) if rating action occurred during a weekend. These filters reduce our LM sample to 3,343 (542 upgrades, 621 downgrades and 2,180 affirmations).

1.5.2 Matching with TRMI sentiment

Our next step in the sample selection process is to match the sample with TRMI sentiment data. As previously mentioned, TRMI publishes the sentiment index specific to each publicly traded firm (in our case which also has corporate debt) on a daily basis since 1998. The LM sample with available TRMI data is 2,993 (454 upgrades, 524 downgrades and 2,015 affirmations). When looking at informativeness' portfolios constructed, the "Negative News" portfolio comprises 749 events (95 upgrades, 195 downgrades and 459 affirmations), the "No News" portfolio 1,496 (202 upgrades, 239 downgrades and 1,055 affirmations) and the "Positive News" portfolio 748 (157 upgrades, 90 downgrades and 501 affirmations).

[36] We would like to acknowledge the support of Egan-Jones Ratings for providing us access to their website thus retrieving data since 1999.

1.5.3 Matching LM rating actions with TRACE

Our final step is to match the sample data with TRACE volume data for the days of interest. The LM rating actions are matched with TRACE at the issuer (6-digit) CUSIP level. Hence, we match the daily volume of transactions for each rated bond over the period of interest, where an event is defined as a LM rating action for each bond. Events are also excluded where there have been other types of announcements around the event window, i.e, a credit rating announcement during [1,5] relative to the event and earnings announcements or mergers and acquisitions during [-5,5] relative to the event.

One argument of why institutional investors would react in rating announcements that do not provide any new information is due to regulatory constraints that they face. Certain institutional investors have restrictions as to the percentage of non-investment grade bonds that they could hold in their portfolios (e.g. insurance companies). For example, when a company is rated by three or more CRAs, a company is considered as non-investment grade when it is rated by at least two CRAs as non-investment grade. The implications of this would be that a CRA downgrading a company as non-investment grade for the first time (i.e. FM in our sample) would not affect institutional investors regulatory constraints until a second CRA (i.e. LM in our sample) announces a downgrade from investment to non-investment grade. Given this information, even though a LM may not provide any new information to the public domain, a market reaction could occur due to the fact that institutional investors may need to rebalance their portfolios due to regulatory constraints. As such, LM events that resulted in a company being considered as non-investment grade by two CRAs were deleted from the sample. The final sample of LM actions with available transaction volume data in the period around the event is 743[37]. More specifically, when looking at informativeness' portfolios constructed, the "Negative News" portfolio comprises 174 events (14 upgrades, 54 downgrades and 106 affirmations), the "No News" portfolio 392 (42 upgrades, 64 downgrades and 286 affirmations) and the "Positive News" portfolio 177 (42 upgrades, 16 downgrades and 119 affirmations).

[37] The sample size varies depending on event window used, i.e. the number of available transaction data for the event window [0,3] is higher compared to the event window [0,1]. The sample of 743 events comprises events in the event window [0,1].

1.6 Results

1.6.1 Descriptive statistics

Table 1.3 reports the distribution of bond ratings[38] split by the three portfolios. The "Positive News" portfolio has the lowest percentage of investment grade bonds (57%) across the three portfolios, followed by the "Negative News" portfolio (60%) and "No News" portfolio (69%). The BBB rating category comprises the highest percentage of bonds for all the three portfolios; 32%, 34% and 37% for the "Positive News", "No News" and "Negative News" respectively.

[Insert Table 1.3]

Summary statistics of the bond characteristics[39] in the sample are presented in Table 1.4. The distribution of age and maturity of the bonds are very similar across the three portfolios with a mean (median) of around 3 (3) years and 9 (7) years for age and maturity respectively. The mean (median) debt (in amount outstanding) is around 600,000 (500,000) for the "Positive News" and "Negative News" portfolios, and around 700,000 (500,000) for the "No News" portfolio. The total trading volume around the events is also presented for all investors as well as for institutional investors (using a cut-off of $100,000). The majority of transactions come from institutional investors as observed in all three portfolios[40]. The mean (median) institutional trading volume at the day and the day after the event is around 53 (11), 109 (17) and 111 (13) million dollars for the "Positive News", "No News" and "Negative News" portfolios respectively. Lastly, the mean trading imbalance for institutional investors is 0.008, 0.070 and 0.036 for the "Positive News", "No News" and "Negative News" portfolios respectively.

[Insert Table 1.4]

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[38] To account for the fact that bonds may be rated by more than one credit rating agency, the average rating was used across all NRSROs which rate the company of interest, i.e. for NRSROs that have rated companies within a year of the dates of interest.
[39] In our sample, there are events with trades from more than one bond for a specific company. In such cases, the average age, debt and maturity was computed.
[40] There are less events in the "Positive News" and "Negative News" portfolios when presenting the total trading volume for institutional investors. This is because when computing volume of trades (footnote 9), there are could occur trades where par value volume is greater than $100,000 but the actual volume of transaction is less.

1.6.2 Overall price impact

Table 1.5 reports the overall CARs for three event windows for the LM in our sample by portfolio, along with their t-statistic and statistical significance[41]. The mean CARs are given in basis points for all events ("All" under "Bonds" column) and for all events that were not a result of a new bond being issued by the company of interest[42] ("No new bonds" under "Bonds" column). The results are similar across event windows for each subgroup tested.

Specifically, the portfolio of events for which we can observe both a statistical and economic significance is for the "Negative News" portfolio. When looking at the whole sample, the mean CAR is statistically significant for all event windows ranging between -28.128 and -25.244 bps. When excluding events which were a result of a new bond being issued by the company that is being rated, the mean CAR is higher across all event windows. The mean CAR ranges between -32.126 and -28.132 bps depending on the event window tested, with results being statistically significant at the 5% level.

[Insert Table 1.5]

We now concentrate on the "No News" portfolio and investigate further the overall price impact effect. Due to the fact that the portfolio consists of upgrades, downgrades and affirmations, the sample is not heterogeneous and the reaction from investors for each direction of the signal may differ. We therefore observe the overall price effect for uninformative rating actions split by the direction of the signal. Results are presented in table 1.6. Out of the 392 uninformative events ("No News" portfolio in table 1.5), there are 64 downgrades, 286 affirmations and 42 upgrades. The mean CARs and t-test results are reported for the whole sample as well for the events which were not due to a new sample being issued by the company of interest. We notice here that the reaction within this group of events differs since the overall significance is not the same across the three sets of signals. First, for downgrades, we notice that there is an overall statistically significant negative reaction across the three event windows for

[41] For the interest of the reader, the possibility of a drift effect from the FM to LM was tested separately for upgrades, downgrades and affirmations. Specifically when mean CARs were tested (using a t-test) for the event window [4,10] relative to the event date of the FM, results were not statistically significant.
[42] As explained in footnote 26.

both samples tested. The highest effect occurs in the event window [0,1] where the mean CAR is -67.642 bps for the sample of events when excluding new bonds being issued by the company of interest (at the 5% level). The statistical significance ranges between -63.975 and -50.919 bps for the whole sample and between -67.642 and -51.018 bps after excluding events which were due to a new bond issue for the company[43]. For upgrades, we notice that the significant positive effect at event window [0,2]. Results are statistically significant at the 10% level with an effect of 30.736 bps for the whole sample. For affirmations, there are no statistically significant changes for any event window.

[Insert Table 1.6]

1.6.3 Could other biases be affecting our results?

The existence of market anomalies and how much the behavior of investors deviates from the expected one under traditional finance theories has led to the evolvement of behavioral finance, which relaxes the assumption of investor rationality. There are several behavioral biases that have been documented over the past few decades. In this section we address any other possible biases that could affect our results.

The most researched bias when it comes to institutional investors is herding. Herding is defined as the tendency to follow each other's trades. There is an overall consensus of herding at the institutional setting with contradicting evidence as to whether it pushes prices away from fundamentals. We control for the possibility of herding by including a measurement of weekly herding (following Puckett and Yan, 2008) in the regressions discussed in section 1.6.4 when looking at the relationship between imbalance and CARs. We employ a measure used in Oehler and Chao (2000) which uses information on the volume of trades[44] as shown below

[43] The sample of downgrades where an abnormal reaction is observed was tested for subsequent reversals. After testing several post event windows up to 2 weeks after the events, the results indicate that there is no statistically significant reversal.

[44] The most common measures of herding used in the literature use the number of institutions who buy and sell securities. Since we do not have information on who buys/sells a bond, we make use of the herding measure which takes into account the volume of transactions.

$$Weekly\ herding_t = \frac{|Volume\ bought_t - Volume\ sold_t|}{Volume\ bought_t + Volume\ sold_t}$$

(6)

Another possible bias which has been studied in the literature is the disposition effect. The disposition effect refers to investors who tend to sell winners too soon and keep losers for too long. One would argue that should institutional investors be prone to the disposition effect, then there could be an effect from the FM to the LM that would cause a price drift effect (i.e., investors keep losers for too long after a FM announcement). As discussed in footnote 41 in section 1.6.2, a possible drift effect was tested from FM to LM for days [4,10] relative to FM without finding statistically significant results.

In the next subsection, we investigate whether there is price pressure from institutional investors by looking at the contemporaneous relationship between abnormal returns and buy-sell imbalance after controlling for other factors.

1.6.4 Institutional trading around events

It is important to investigate whether the trading of institutional investors is correlated with the abnormal reaction of bonds. This is done by looking at the total institutional buy-sell imbalance for the event window [0,1]. As a proxy, we define institutional trades to be the ones with a volume of at least $100,000 (Bessembinder et al., 2009). The results are reported in table 1.7 for the sample of uninformative rating announcements. The models control for the age, maturity, size of debt, rating, and liquidity of the bond during the event window, the direction of the signal (i.e., dummy variable for upgrades and downgrades) and previous week's institutional herding. Results are reported for the whole sample and the sample of events which were not due to a new bond being issued by the company.

[Insert Table 1.7]

In Table 1.7 we can observe a correlation between the buy-sell imbalance and the cumulative abnormal returns for the event window [0,1][45]. There is an overall contemporaneous correlation between institutional buy-sell imbalance and abnormal returns for both the whole sample (Model 1, coefficient= 22.655, significant at the 1% level) and the sample after excluding events in which there has been a new issue at the day of the event (Model 3, coefficient 19.916, significant at the 5% level). The coefficient of the whole sample (model 1) is 22.655 indicating that a one standard deviation increase in the buy-sell imbalance results on average in an increase of abnormal return of 12.26 bps. Additionally, regressions are presented for the two samples by controlling for the year of the events as well. Results are qualitatively the same, as shown in models 2 and 4 for the whole sample and the sample after excluding events in which there has been a new issue at the day of the event respectively.

1.7 Conclusions

In this first empirical study, we test for limited attention bias in the US corporate bond market. Our work draws from the literature on the timeliness of changes in corporate bond ratings and outlooks by constructing pairs of rating actions that arrive later than others. We control for the amount of information present in late rating actions, using a novel news analytics database. Thus, we are able to categorize rating actions as informative and uninformative. Using a sample of uninformative rating actions during the sample period July 2002 to September 2014, we test whether there is an overall abnormal market reaction in corporate bond prices. We provide evidence of an abnormal reaction mainly in the negative direction for downgrades, which seems to lend the support of limited attention bias since investors cannot distinguish between informative and uninformative rating actions and react abnormally towards the direction of the signal.

Furthermore, using the universe of institutional investors‘ trading (by using a proxy for trade size), we test for a contemporaneous relationship between trading activity and CARs on our proxy for “stale information” in the market place, to observe whether there is a price pressure

[45] Due to the fact that for some events there has not been any trading in the week before the event, there was no herding measure available resulting in a smaller sample compared to the overall price impact results presented in section 1.6.2. As a robustness check, a herding measure of 0 was set for those events, resulting in the same qualitative results (not reported).

from institutional investors. We find statistically significant contemporaneous correlations between institutional trading and CARs associated with announcements of uninformative rating actions. This evidence is not consistent with the predictions of the semi-strong efficient market hypothesis, but lends support to the existence of limited attention bias at the institutional trading which results in an overall price pressure in the corporate bond market.

Figure 1.1: Construction of late mover (LM)

This diagram depicts the method used to construct the sample of LM. The first mover (FM) is defined as a rating action which is not preceded by any other rating action (in any direction) in the previous 60 trading days (t). The LM is defined as the next rating action (in the same direction) in the following 60 trading days (no other rating actions between FM and LM). Any LM within 10 trading days of FM have been excluded from analysis.

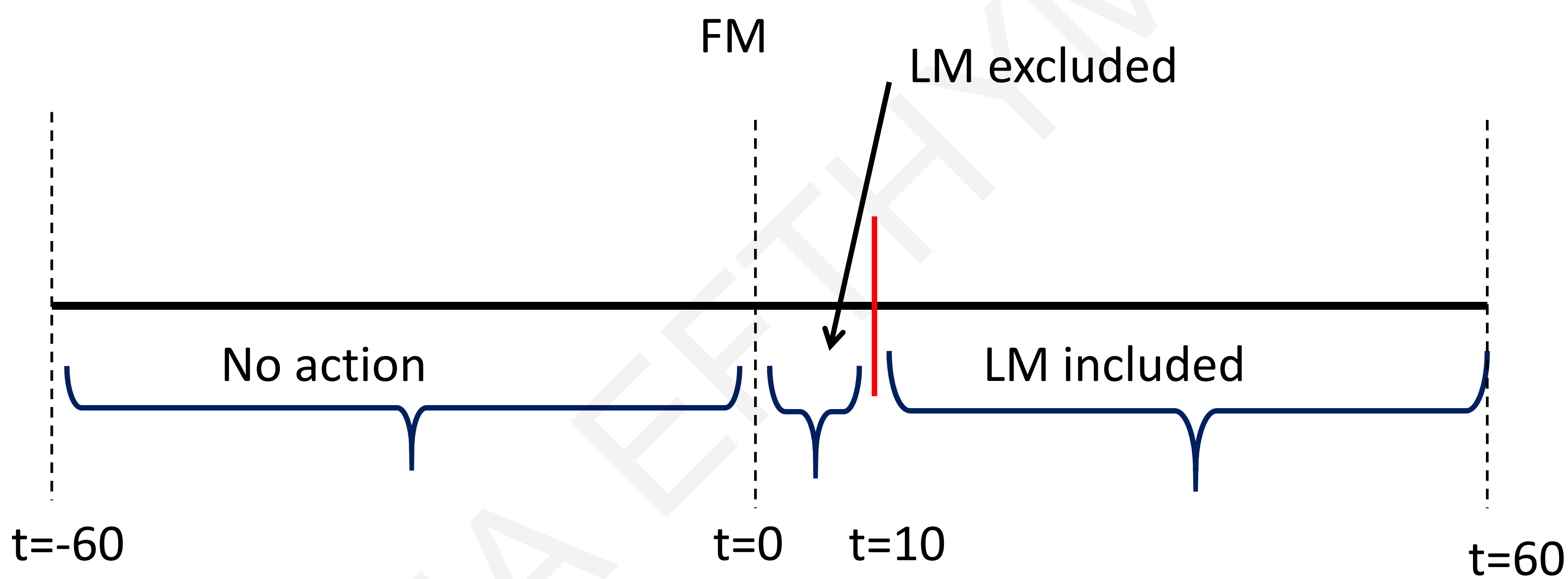

Figure 1.2: Histogram of Abnormal TRMI Sentiment

This graph shows the distribution of the CAS for the period [0,1] of the event for the union of LM upgrade, downgrade and affirmation events. The dotted filled bars indicate the 25th and 75th percentile.

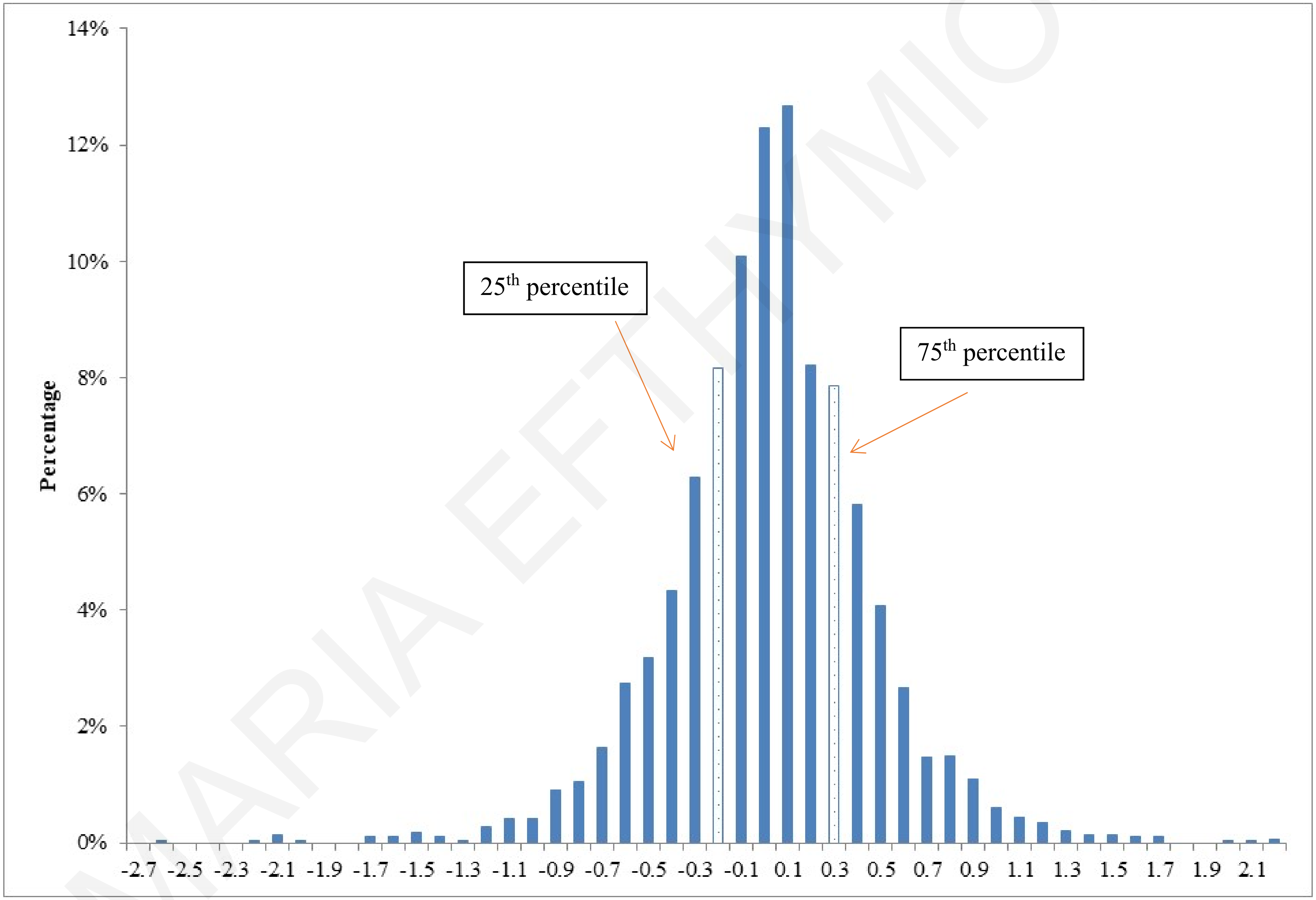

Table 1.1: Cumulative abnormal sentiment (CAS) for upgrades, downgrades, affirmations and a random sample over the event window [0,1].

This table presents t-test results for CAS for upgrades, downgrades, affirmations and a random sample over three estimation windows; [-20,-3], [-30,-3] and [-40,-3] relative to the event (for the time period July 2002 to September 2014). The sample comprises rating announcements in which there have not been any other credit rating announcements (in any direction) 60 trading days prior to the event. Cases where other type of announcements have occurred during the time period [-5,5] relative to the event have been excluded from the analysis (earnings announcements and mergers and acquisitions) or other credit rating announcements [1,5] relative to the event. *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively.

	Estimation Window [-20,-3]				**Estimation Window [-30,-3]**				**Estimation Window [-40,-3]**			
Action	**N**	**Mean**	**t-statistic**	**Sig**	**N**	**Mean**	**t-statistic**	**Sig**	**N**	**Mean**	**t-statistic**	**Sig**
Downgrade	1,187	-0.152	-10.363	***	1,213	-0.160	-11.253	***	1,230	-0.154	-11.059	***
Affirmation	2,746	0.013	1.393		2,783	0.007	0.839		2,804	0.010	1.200	
Upgrade	1,241	0.047	3.257	***	1,260	0.053	3.826	***	1,274	0.056	4.125	***
Random	4,067	-0.001	-0.082		4,191	-0.002	-0.170		4,253	0.003	0.271	

Table 1.2: Cumulative abnormal returns (CARs) for upgrades, downgrades, affirmations and a random sample over the event windows [0,1], [0,2] and [0,3].

This table presents t-test results for CARs (in basis points) for upgrades, downgrades, affirmations and a random sample over three event windows; [0,1], [0,2] and [0,3] relative to the event (for the time period July 2002 to September 2014). The sample comprises rating announcements in which there have not been any other credit rating announcements (in any direction) 60 trading days prior to the event. Cases where other type of announcements have occurred during the time period [-5,5] relative to the event have been excluded from the analysis (earnings announcements and mergers and acquisitions) or other credit rating announcements [1,5] relative to the event. "All" under bonds column refers to the whole sample; "No new bonds" refers to events that were not a result of a new bond being issued by the company of interest. *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively.

		Event Window [0,1]				Event Window [0,2]				Event Window [0,3]			
Action	**Bonds**	**N**	**Mean**	**t-statistic**	**Sig**	**N**	**Mean**	**t-statistic**	**Sig**	**N**	**Mean**	**t-statistic**	**Sig**
Downgrade	All	311	-39.874	-3.281	***	359	-29.037	-2.245	**	395	-29.527	-2.285	**
Downgrade	No new bonds	298	-41.954	-3.346	***	343	-32.429	-2.428	**	377	-33.020	-2.470	**
Affirmation	All	714	-1.621	-0.292		799	-1.845	-0.362		852	0.305	0.055	
Affirmation	No new bonds	647	0.155	0.026		727	-2.560	-0.475		779	-0.509	-0.087	
Upgrade	All	277	13.340	1.473		344	13.487	1.700	*	383	8.086	1.075	
Upgrade	No new bonds	259	12.627	1.323		321	11.301	1.373		359	4.792	0.617	
Random	All	226	3.538	0.384		284	8.413	1.015		321	12.267	1.417	

Table 1.3: Distribution of bond ratings by portfolio

Frequency and percentage distribution of ratings for LM, split by portfolio, for the time period July 2002 to September 2014. The sample comprises rating announcements which have occurred within 60 trading days of the FM (ratings within the first 10 trading days of the FM have been excluded). Cases where other type of announcements have occurred during the time period [-5,5] relative to the event have been excluded from the analysis (earnings announcements and mergers and acquisitions) or other credit rating announcements [1,5] relative to the event. To account for the fact that companies may be rated by more than one credit rating agency, the average rating was used across all NRSROs which rate the company of interest.

	Positive News	**No News**	**Negative News**
Rating group	**N (%)**	**N (%)**	**N (%)**
AAA	2(1.1%)	3(0.8%)	0(0%)
AA	6(3.4%)	17(4.3%)	5(2.9%)
A	35(19.8%)	115(29.3%)	36(20.7%)
BBB	57(32.2%)	135(34.4%)	64(36.8%)
BB	42(23.7%)	59(15.1%)	45(25.9%)
B	22(12.4%)	44(11.2%)	13(7.5%)
CCC (& below)	13(7.3%)	19(4.8%)	11(6.3%)
Total	**177**	**392**	**174**

Table 1.4: Summary statistics of bond characteristics and trading volume around events

This table reports summary statistics for the bonds used in the LM sample, split by portfolio, for the time period July 2002 to September 2014. The sample comprises rating announcements which have occurred within 60 trading days of the FM (ratings within the first 10 trading days of the FM have been excluded). Cases where other type of announcements have occurred during the time period [-5,5] relative to the event have been excluded from the analysis (earnings announcements and mergers and acquisitions) or other credit rating announcements [1,5] relative to the event. Age and maturity are reported in years. Amount outstanding (provided by MFISD) assumes a par value of $1,000. For events where trades from more than one bond for a specific company occur, the average age, debt and maturity is reported. Volume is computed as (reported price/100)*par value*(par value volume/1,000).

Action	Portfolio	N	Minimum	P25	P50	Mean	P75	Maximum
Age (years)	Positive News	177	0.003	1.400	2.661	3.425	4.422	19.545
	No News	392	0.003	1.450	2.649	3.462	4.553	15.786
	Negative News	174	0.003	1.405	2.718	3.261	4.227	15.244
Debt (amount outstanding)	Positive News	177	28,243	305,350	500,000	560,017	700,000	2,124,765
	No News	392	50,641	350,000	519,868	678,984	818,008	4,500,000
	Negative News	174	76,050	350,000	500,000	607,224	700,000	2,750,000
Maturity (years)	Positive News	177	0.173	4.718	7.281	8.867	10.225	43.386
	No News	392	0.170	4.503	6.985	9.124	11.541	56.195
	Negative News	174	0.153	4.367	6.982	9.129	12.258	33.030
Total trading volume ($)	Positive News	177	163,585	3,614,781	11,065,000	52,262,416	28,224,592	1,317,893,449
	No News	392	161,960	5,367,641	17,417,377	109,629,658	49,201,095	8,845,595,614
	Negative News	174	70,158	4,369,376	12,836,350	110,969,536	35,809,950	5,800,965,402
Total institutional trading volume ($)	Positive News	174	106,150	3,630,370	11,305,189	52,762,730	28,485,742	1,314,711,279
	No News	392	102,610	5,247,542	16,993,006	108,942,271	47,681,737	8,840,682,803
	Negative News	173	104,280	3,855,534	12,578,886	111,229,207	35,295,400	5,795,784,387
Trading imbalance	Positive News	174	-1.000	-0.347	-0.013	0.008	0.451	1.000
	No News	392	-1.000	-0.272	0.051	0.070	0.423	1.000
	Negative News	173	-1.000	-0.281	0.020	0.036	0.392	1.000

Table 1.5: Cumulative abnormal returns (CARs) for LM by portfolio

This table presents t-test results for CARs (in basis points) for "Positive News", "No News" and "Negative News" portfolios over three event windows; [0,1], [0,2] and [0,3] relative to the event (for the time period July 2002 to September 2014). The sample comprises rating announcements which have occurred within 60 trading days of the FM (ratings within the first 10 trading days of the FM have been excluded). Cases where other type of announcements have occurred during the time period [-5,5] relative to the event have been excluded from the analysis (earnings announcements and mergers and acquisitions) or other credit rating announcements [1,5] relative to the event. "All" under bonds column refers to the whole sample; "No new bonds" refers to events that were not a result of a new bond being issued by the company of interest. *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively.

		Event Window [0,1]				**Event Window [0,2]**				**Event Window [0,3]**			
Portfolio	**Bonds**	**N**	**Mean**	**t-statistic**	**Sig**	**N**	**Mean**	**t-statistic**	**Sig**	**N**	**Mean**	**t-statistic**	**Sig**
Positive News	All	177	-5.878	-0.447		207	4.106	0.234		224	13.575	0.773	
Positive News	No new bonds	166	-7.430	-0.531		195	2.567	0.138		212	12.426	0.672	
No News	All	392	-6.396	-0.900		454	-3.027	-0.465		481	-2.263	-0.316	
No News	No new bonds	365	-6.882	-0.908		424	-4.227	-0.613		451	-3.649	-0.482	
Negative News	All	174	-25.244	-1.941	*	194	-28.128	-1.987	**	213	-26.174	-1.917	*
Negative News	No new bonds	164	-28.132	-2.047	**	184	-32.126	-2.167	**	203	-29.189	-2.048	**

Table 1.6: Cumulative abnormal returns (CARs) for the "No News" portfolio split by direction of rating announcement
This table presents t-test results for CARs (in basis points) for the "No News" portfolio, split by upgrades, downgrades and affirmations over three event windows; [0,1], [0,2] and [0,3] relative to the event (for the time period July 2002 to September 2014). The sample comprises rating announcements which have occurred within 60 trading days of the FM (ratings within the first 10 trading days of the FM have been excluded). Cases where other type of announcements have occurred during the time period [-5,5] relative to the event have been excluded from the analysis (earnings announcements and mergers and acquisitions) or other credit rating announcements [1,5] relative to the event. "All" under bonds column refers to the whole sample; "No new bonds" refers to events that were not a result of a new bond being issued by the company of interest. *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively.

		Event Window [0,1]				Event Window [0,2]				Event Window [0,3]			
Action	**Bonds**	**N**	**Mean**	**t-statistic**	**Sig**	**N**	**Mean**	**t-statistic**	**Sig**	**N**	**Mean**	**t-statistic**	**Sig**
Downgrade	All	64	-63.975	-2.036	**	75	-54.323	-1.876	*	82	-50.919	-1.728	*
Downgrade	No new bonds	61	-67.642	-2.056	**	72	-55.379	-1.836	*	79	-51.018	-1.668	*
Affirmation	All	286	3.845	0.663		331	3.700	0.684		346	7.973	1.299	
Affirmation	No new bonds	266	4.496	0.732		308	3.397	0.599		323	6.719	1.043	
Upgrade	All	42	11.604	0.555		48	30.736	1.863	*	53	6.191	0.280	
Upgrade	No new bonds	38	11.008	0.481		44	26.100	1.469		49	4.382	0.184	

Table 1.7: OLS regressions for CARs for the "No News" portfolio

This table reports coefficient estimates of OLS regressions (with robust standard errors) for the institutional trading imbalance variable ("No News" portfolio) for the event window [0,1]. In the regressions, we control for the age, maturity, debt size, rating, liquidity of the bond, whether event was an upgrade or downgrade and herding. Model 1 refers to the whole sample. Model 2 refers to the whole sample controlling for year. Model 3 refers to events that were not a result of a new bond being issued by the company of interest. Model 4 refers to events that were not a result of a new bond being issued by the company of interest, controlling for year. *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively.

	Whole sample		Excluding new bonds	
VARIABLES	**Model 1 Coefficient (SE)**	**Model 2 Coefficient (SE)**	**Model 3 Coefficient (SE)**	**Model 4 Coefficient (SE)**
Buy-sell imbalance	**22.655*** **	**23.070*** **	**19.916** **	**20.580** **
	(7.566)	(7.495)	(7.996)	(8.156)
Rating	-3.103	-3.389	-3.330	-3.613
	(2.390)	(2.333)	(2.557)	(2.545)
Maturity (years)	0.073	0.374	0.049	0.333
	(0.815)	(0.849)	(0.825)	(0.860)
Age (years)	-2.219	-2.789	-2.186	-2.745
	(3.094)	(3.076)	(3.198)	(3.253)
Liquidity	-4,600.942	-4,098.992	-4,758.913	-4,303.946
	(6,073.867)	(5,856.649)	(6,192.157)	(6,013.428)
Amount of debt outstanding	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Upgrade	22.640	29.768	21.488	31.586
	(19.424)	(19.417)	(21.374)	(21.398)
Downgrade	-27.467	-20.046	-28.276	-23.230
	(18.688)	(19.541)	(19.493)	(20.599)
Herding	5.691	10.213	8.280	11.112
	(17.091)	(17.934)	(18.446)	(19.467)
Constant	31.545	26.975	34.968	31.857
	(31.303)	(40.214)	(33.655)	(42.089)
Control for year	No	Yes	No	Yes
Observations	372	372	350	350
Adjusted R-squared	0.044	0.049	0.042	0.044

Chapter 2: Does limited attention affect trading of insurance companies?

Abstract

Using the US insurance investment transactions from 2002 to 2014, we examine whether insurance companies are affected by limited attention in their trading activities. To capture limited attention, we condition on the credit quality of investment targets (i.e. corporate bonds) using actions in credit quality signals (rating and outlook actions by credit rating agencies). Using the relative timeliness of rating actions in the same direction, we use the late mover rating action as a proxy for limited attention. To control for new information potentially present in a late rating action, we use a unique news-analytics database. Results show that institutional trading volume increases abnormally in subsamples of rating actions that do not provide any new information to the market place, thus lending support to a limited attention bias hypothesis that could affect institutional investor trading behavior.

2.1 **Introduction**

The evidence consistent with the limited attention bias amongst institutional investors (chapter 1 of thesis) has led to the curiosity of whether there are any specific types of institutional investors who are more prone to this bias. There is a difficulty in obtaining daily trading data for all types of investors and this is because most institutional investors report their portfolio holdings at a quarterly level (unless data are obtained from a brokerage house). Furthermore, although TRACE enhanced (TRACE thereafter) provides detailed transactions at a daily level, there is no information on who buys/sells a bond. In this chapter, we focus on US insurance individual bond transaction data reported through the National Association of Insurance Commissioners (NAIC) statutory statements (2002-2014) for all three insurance sectors: health, life and property-casualty. Through the NAIC Schedule D parts 3, 4 and 5, US insurance companies report individual bond investment transactions at a quarterly basis, thus being able to link the investing behavior of one of the largest bondholders in the US corporate bond market around credit rating announcements. To the best of our knowledge, the US insurance transaction data has not been used to research behavioral traits in institutional trading. There is currently no extensive literature on the limited attention bias when it comes to institutional investors[46].

Since US insurance companies are among the largest institutional investors for US corporate bonds[47], and since the decision on what bonds they include in their portfolio is largely determined by the debt ratings and outlooks provided by credit rating agencies, we focus this study on the investing behavior of US insurance companies around actions in bond ratings and

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[46] Barber and Odean (2008) use daily trading records of individual and institutional money managers. The authors find no evidence of net buying behavior for institutional investors. Yuan (2015) distinguishes between individual and institutional investors using trade size (as a proxy for institutional investor trading) and provides no evidence of increased trading activity by institutional investors. Tetlock (2011) uses individual and institutional trading orders through a large market center and provides no evidence of increased trading activity with stale news in stocks which are largely composed of institutional investors. Akepanidtaworn et al. (2018) look at daily trading activity of institutional investors and provide evidence of consistent underperformance when it comes to selling decisions. They attribute this to the allocation of limited attentional resources in selling decisions as opposed to buying decisions. Cohen and Frazzini (2008) investigate economically linked firms (customer-supplier linked firms) and provide evidence of mutual funds being more likely to trade on supplier (mutual funds that own shares for both supplier and customer) when there are news about customer linked firms that affect suppliers performance as well, compared to mutual funds that own shares of the supplier firm only.

[47] According to US Federal Reserve's flow of funds, during the first quarter of 2018, life insurance companies were the largest domestic corporate bond holders with 20.7% of a total size of $13.1 trillion. P&C companies hold 3.5% (for more information see https://global-macro-monitor.com/2018/06/12/major-holders-of-the-u-s-corporate-bond-market/).

outlooks. Crucial to our study is the informational value (in both amount and content of news coverage terms), the timeliness of a credit rating/outlook action and how investors perceive (attention) and react to the content of such an announcement.

We focus on credit rating announcements as our proxy for attention. The relative timeliness of credit rating outlook announcements between issuer and investor paid credit rating agencies has been investigated over the past few years (Beaver et al., 2006; Milidonis, 2013; Bruno et al., 2016), with the difference between them being almost non-existent after 2002 (Berwart et al., 2016)[48]. We build on this by constructing pairs of rating announcements where a rating that comes first is expected to provide more information compared to subsequent ones. We first use the union of all rating actions[49] (upgrades, downgrades and affirmations) from all Nationally Recognized Statistical Research Organizations (NRSROs)[50], namely issuer-paid (Fitch, Moody's, Standard & Poor's – S&P, Dominion Bond Rating Services – DBRS, AM Best – AMB, Kroll Bond Rating Agency - KBR) and investor-paid agencies (Egan-Jones Rating Agency - EJR), to construct our "first mover" (FM)[51]. We then define the "late mover" (LM) to be a rating action, which follows the FM in the same direction, within 60 trading days and use this a late signal of credit quality[52]. Provided that these LM do not provide any additional information to the market, under the semi-strong efficient market hypothesis we would not expect insurance companies to react on the these signals. Stated differently, if insurance companies can recognize the non-informativeness of these LM (i.e. are not affected by the limited attention bias), then they will not trade abnormally around such events.

We control for the informativeness of a LM by using the Thomson Reuters Marketpsych Indices (TRMI), a database which carries out extensive textual analysis on news and social media on a daily (and higher frequency) basis. The uniqueness of the TRMI lies in the fact that it does not only count the net positive and negative articles (the textual analysis technique used by the majority of the literature until recently, e.g. Tetlock, 2007), but also extracts emotions inflicted on the reader. The TRMI news sentiment measure at the issuer CUSIP level has been

48 According to Berwart et al. 2016, even though differences in timeliness between issuer-paid and investor-paid credit rating agencies existed before 2002, these differences weakened after this time period.
49 Throughout the paper, rating actions will refer to both rating and outlook actions.
50 The National Association of Insurance Commissioners (NAIC) requires insurance companies to use the credit rating quality of bonds from all NRSROs that rate a specific company. See section 2.5 for more details on this.
51 The first mover is free from other rating actions in the previous 60 trading days.
52 We require that there are no other rating actions between the FM and LM.

validated in chapter one of the thesis. Through the TRMI's algorithm of textual analysis, the news sentiment index is constructed by analyzing news content on media, and convert all information related to a bond issuing company into a normalized index which reflects the overall market sentiment. The abnormal TRMI sentiment is then used to split our LM sample in portfolios of "No News", "Positive News" and "Negative News". For each of the three portfolios, we conduct panel regressions for the logarithmic volume return with fixed effects at the company and year level.

Focusing on LM actions and on the portfolios of "Positive News" and "Negative News", we find that insurance companies trade more when: (a) rating actions provide additional positive news to the market place and (b) rating actions provide additional negative news respectively. Since these two portfolios provide new information to the market, increased trading volume provides early evidence consistent with the semi-strong efficient market hypothesis (given the documented link between changes in volume and price, (Karpoff, 1987)), which assumes that if new information enters the public domain, market prices will adjust to reflect the new information.

We also find however, that institutional investors' trading volume increases abnormally when rating actions (upgrades, downgrades and affirmations) do not provide additional information to the market (i.e., the "No News" portfolio). This evidence is not consistent with the semi-strong efficient market hypothesis, as we would not expect more trading to occur when no new information is available. On the contrary, this result provides support to a behavioral finance hypothesis that institutional investors' trading could be affected by limited attention[53] bias.

A possible price pressure from insurance companies was tested by looking at the correlation of their buy-sell imbalance with abnormal returns. Even though there seems to be abnormal trading, this does not seem to be on average correlated with abnormal returns of

[53] Sims (2003) introduced the idea of rational inattention as an effect of limited attention. Due to the time and cost constraints, investors choose to allocate their attention in as optimal way as possible which may lead in a delayed reaction. Models developed in this area of literature focus on slow price adjustments in various settings (i.e. prices, consumption, portfolio choice and wages) due to rational inattention (Wiederholt (2010)). The possibility of rational attention would result in a slower adjustment in prices.

overall bond prices, suggesting that insurance companies are not one of the type of institutional investors which exert price pressure on uninformative rating actions.

The importance of empirically identifying behavioral biases in institutional investors lies in the large percentage of market transactions (as measured by volume of transactions) conducted by institutional investors and the potential of driving prices away from fundamentals. Our paper contributes to the debate between traditional finance and behavioral finance theories by providing evidence consistent with insurance companies' trading volume affected by limited attention bias.

The remainder of the paper is organized as follows. Section 2.2 provides a literature review and develops the motivation. Section 2.3 presents the methodology used to test the hypothesis of limited attention. Section 2.4 describes the data. Section 2.5 discusses the regulatory constraints that US insurance companies face when making decisions about their portfolio holdings. Section 2.6 presents the results. Section 2.7 describes several robustness checks. Section 2.8 looks at the relationship between buy-sell imbalance of insurance companies and bond abnormal returns and section 2.9 concludes.

2.2 Literature review and motivation

Hirshleifer and Teoh (2003) refer to limited attention as an inevitable outcome due the vast amount of public information and number of securities available for investment. Investors therefore may fail to process appropriately the true informativeness of news available. This cognitive bias has been studied in several settings when it comes to investigating the effect on financial markets at the institutional setting.

The first refers to how investors allocate their resources when it comes to investment decisions. A recent working paper by Akepanidtaworn et al. (2018) look at daily trading activity of institutional investors and provide evidence of consistent underperformance when it comes to selling decisions. They attribute this to the allocation of limited attentional resources in selling decisions as opposed to buying decisions. Furthermore, Cohen and Frazzini (2008) investigate economically linked firms (customer-supplier linked firms) and provide evidence of mutual funds being more likely to trade on supplier (mutual funds that own shares for both supplier and customer) when there are news about customer linked firms that affect suppliers performance as well, compared to mutual funds that own shares of the supplier firm only.

Secondly, researchers have studied the effect of trading activity of investors when it comes to attention grabbing events. Attention grabbing news is a possible effect of a net buying behavior mostly by individuals instead of institutional investors when looking at the time period between 1993 and 1996, according to Barber and Odean (2008). Lastly, Yuan (2015) uses a proxy when distinguishing between individual and institutional investors, i.e. trade size. The author argues that attention-grabbing events leads to individual investors being more active.

Lastly, an area of research concentrates on the ability of investors to realize the true informativeness of publicly available information and how they react to news that is being repeated in the news domain (stale news). An interesting paper by Huberman and Regev (2001) describes in detail a case about EntreMed that has occurred in the late 1990s. While news was released about this company on November 1997, an article on May 1998, which consisted of no new information compared to the earlier article, resulted in a permanent stock price change. Gilbert et al. (2012) look at the aggregate market effect of stocks and bonds and suggest that investors' inattention to the staleness of news result in a short-term mispricing. Tetlock (2011) presents results for both individual and institutional investors and provides evidence that in stocks where the investor trading activity is largely composed of individual (instead of institutional) investors, there is a tendency to overreact more to stale information. A more recent paper by Fedyk and Hodson (2019) experimentally examines how finance professionals perceive stale news and when they can differentiate news articles as providing old information. They provide evidence of investors not being able to disentangle the true informativeness of news when it consists of recombination of stale information rather than simple reprints; however, the authors test this empirically at the aggregate market level only.

Our work focuses on stale news at the institutional setting. So far, there has only been one paper which empirically tests the reaction of institutional investors (Tetlock, 2001), providing no evidence of abnormal reaction. Under traditional finance theories, investors are expected to act rationally and not be affected by behavioral biases as such, especially when it comes to institutional investors. The growing literature on possible behavioral biases by institutional investors which could affect trading and pricing of equity and bonds leads to a controversial debate on whether behavioral biases could explain any of the market anomalies that exist. The research question we aim to answer in this paper is:

Does limited attention affect trading of insurance companies?

We shed light on this question by empirically examining whether insurance companies trade abnormally when they receive uninformative news ("No News" portfolio), that is, when a rating action does not provide any incremental information (either in the positive or negative direction) compared to the already publicly available information. Under the semi-strong efficient market hypothesis, new information would be rapidly incorporated in prices, therefore in the case of uninformative rating actions, we would not expect any abnormal trading. On the other hand, abnormal trading resulting from news that are being repeated in the news domain could be a result of investors experiencing limited attention bias. A description on how we empirically construct a setting of "No News" and test for abnormal trading volume by insurance companies is given in the next section.

2.3 Methodology

2.3.1 Insurance industry

To empirically answer the research question, we focus on the insurance industry as they are among the largest institutional investors in bonds (portfolio holdings worth USD 3.78 trillion as of 2015)[54]. We do this because US insurance companies have to report individual bond investment transactions at a quarterly basis; hence, we are able to link the investing behavior at the individual bond transaction level in close connection to the TRMI variables and credit rating actions.

[54] Authors' calculation from www.snl.com.

2.3.2 Credit rating and outlook/watchlist announcements

The significant role that CRAs play in the capital markets lies in the fact that they act as information intermediaries and they consolidate all publicly available information (and private for issuer-paid credit rating agencies) into a single letter rating which is more easily comprehensible by market participants. Furthermore, credit ratings are also used for regulatory purposes. Specifically, for insurance companies, the NAIC uses credit ratings as a way of monitoring insurance companies' portfolio holdings[55]. We follow Berwart et al. (2016) and use credit rating actions of US corporate bonds (senior unsecured) from two types of rating agencies; issuer-paid CRAs (Fitch, Moody's, S&P, DBRS, AMB, KBRS), and the most widely used investor-paid CRA (EJR). When providing additional information, announcements in credit quality are expected to be associated with changes in expected future returns on the underlying corporate bond, hence insurance companies are expected to engage in portfolio rebalancing around changes in ratings, to achieve their investment target returns and risk.

The compensation structure between issuer-paid and investor paid CRAs may result in cross-sectional differences in their content of information. Issuer-paid CRAs get paid by the bond-issuer company whereas investor-paid CRAs get paid by investors to rate investment targets. Issuer-paid CRAs meet with their clients before the rating announcement, therefore their rating is expected to include private information in addition to public information; whereas investor-paid CRAs base their rating solely on publicly available information. These possible cross-sectional differences in their ratings are controlled for by using the TRMI sentiment (section 2.3.3).

Furthermore, the relative timeliness of credit rating actions between issuer and investor paid credit rating agencies has been investigated over the past few years (Beaver et al., 2006; Berwart et al., 2016; Milidonis, 2013; Bruno et al., 2016). While there is documented evidence of a difference in the relative timeliness between the two types of CRAs before 2002, when looking at rating and outlook actions, these cease to exist after 2002[56]. What this means is that CRAs do not always necessarily rate at the same day, but there is evidence of a bi-directional

[55] For more information, see section 2.5.
[56] Our sample time period starts in July 2002.

relationship between CRAs, therefore a rating announcement that comes first is expected to include more information compared to subsequent ones over the next few days.

2.3.3 Thomson Reuters Marketpsych Indices (TRMI)

To control for the informational content of credit rating announcements, i.e. how it is perceived in the public domain, we use the Thomson Reuters Marketpsych Indices (TRMI), a database which carries out extensive textual analysis on news and social media on a daily (and higher frequency) basis (first published in mid-2012). The uniqueness of the TRMI lies in the fact that it does not only count the net positive and negative articles (the textual analysis technique used by the majority of the literature until recently, e.g. Tetlock, 2007), but also extracts emotions inflicted on the reader. The TRMI news sentiment measure at the issuer CUSIP level has been validated in chapter one of the thesis. Through the TRMI's algorithm of textual analysis, the news sentiment index is constructed by analyzing news content on media, and convert all information related to a bond issuing company into a normalized index which reflects the overall market sentiment[57,58] (normalized from -1 to 1).

To measure abnormal sentiment we use a short-term event study method. First we estimate the average sentiment in the 20 to 3 trading days before the rating action announcement of each rated bond issuing company using the 6-digit issuer CUSIP (i.e. in the event window [-20,-3]). Then we estimate abnormal sentiment at the day of (and the following day of) the rating action announcement using the following equation:

$$Ab\_Sent\ (t) \ = \ Sent(t) - Av\_Sent\ (-20, -3) \qquad (1)$$

where *Ab_Sent(t)* is the abnormal sentiment at day *t,* where $t \in [0,1]$; *Sent(t)* is the actual sentiment at day *t*; and *Av_Sent (-20,-3)* is the average sentiment over the estimation window [-20,-3]. We estimate the abnormal sentiment at day 0 (announcement day) and day +1, as some

[57] The most widely used sentiment index in academic research is the monthly Baker-Wurgler sentiment index (Baker and Wurgler, 2006) which combines several characteristics of market data (closed-end fund discount, NYSE share turnover, number and average first-day returns on IPOs, equity share in new issues and dividend premium). The daily sentiment constructed variable in TRMI (Peterson, 2016) mirrors the net of positive and negative content of companies captured by news and/or social media. Thomson Reuters Corporation provided the dataset (up to and including November 2015), free of charge for additional research related to company-specific research.

[58] We are using the sentiment computed by analyzing news only.

rating actions may have taken place at the end of day 0. We then calculate the cumulative abnormal sentiment (CAS) over the event window [0,1] to capture the full impact of the rating action announcement on news sentiment as captured through TRMI:

$$CA\_Sent = Ab\_Sent\ (t = 0) + Ab\_Sent\ (t = 1) \tag{2}$$

In section 2.3.5 we plot the distribution of CA_Sent and explain how we construct the portfolios of "Positive News", "Negative News" and "No News".

2.3.4 Late movers: proxy for limited attention

We draw from the literature of the relative timeliness of CRAs to create our proxy of limited attention[59]. There is documented evidence (Berwart et al., 2016) of a bi-directional relationship between credit rating announcements (ratings, outlooks and watchlist inclusions) of issuer-paid and investor-paid rating agencies. We build on this by constructing pairs of rating actions where a rating action that comes first is expected to provide more information compared to subsequent ones[60]. The methodology used to construct pairs of events is shown in figure 2.1. We first use the union of all rating actions (upgrades, downgrades and affirmations) from all NRSROs[61], namely issuer-paid (Fitch, Moody's, S&P, DBRS, AMB, KBR) and investor-paid agencies (EJR), to construct our FM which is free from other types of announcements, 60 trading days prior to the event. We then define the LM to be a rating action, which follows the FM, in the same direction[62] within 60 trading days and use this a late signal of credit quality. From the sample of LM, we delete all those observations that had a rating action in the 10 trading days

[59] The majority of empirical literature testing attention effects is based on indirect proxies of attention, namely, extreme returns (Barber and Odean, 2008), trading volume (Barber and Odean, 2008), news and headlines (Barber and Odean, 2008 and Yuan, 2015), advertising expense (Grullon et al., 2004 and Lou, 2014) and price limits (Seasholes and Wu, 2007). Da et al. (2011) suggest a new direct measure which is suitable for individual investors using the search volume index. Ben-Raphael et al. (2017) propose a new direct measure for institutional investors, namely the abnormal institutional investor attention (AIA). While the authors in this paper argue that investors' reaction to news is more prominent with higher AIA values, we investigate the ability of investors to distinguish between old and new news in the market.

[60] By "pair", we mean that there have to be at least two rating actions in the same direction for the same bond issuing company within 60 trading days by any CRA.

[61] The National Association of Insurance Commissioners (NAIC) requires insurance companies to use the credit rating quality of bonds from all NRSROs that rate a specific company. See section 2.5 for more details on this.

[62] Cases where there has been a rating action in a different direction in between FM and LM have been excluded from analysis.

immediately before the LM action, in order to avoid contamination of the abnormal sentiment estimation.

[Insert Figure 2.1]

Our sample of LM is not restrictive in their informational content. A rating action that follows a few trading days of the FM does not necessarily imply that it does not provide any new information to the public domain. We control for the informational content of rating actions by using the abnormal TRMI sentiment (CA_Sent). If a rating action provides additional positive (negative) information to market participants, then this would be captured by an abnormal positive (negative) overall sentiment. Similarly, if the overall market sentiment is approximately the same before and during a rating action, then this would imply that the rating action does not provide any new information relative to what the FM has already provided and any abnormal trading would not be justified under the semi-strong efficient market hypothesis.

2.3.5 Informativeness of late rating actions

The distribution of the CAS for the union of all LM rating actions is shown in figure 2.2. As expected (since the sentiment is a normalized index), CAS is approximately normally distributed with a mean (median) of -0.012 (-0.014). The CAS values range between -2.973 and 2.687 with a standard deviation of 0.476. CAS values to the right (left) tail of the distribution indicate that events are associated with a positive (negative) abnormal change when compared to the estimation window -20 to -3 trading days before the event.

[Insert Figure 2.2]

We use the CAS to split LM rating actions into ones which contain new information and uninformative ones. We construct three portfolios, namely "Negative News", "No News" and "Positive News". The "Negative News" portfolio consists of all events in which their CAS lies within the first quartile ($-2.973 \leq CA_{Sent} < -0.279$), the "No News" includes all events within the interquartile range ($-0.279 \leq CA_{Sent} < +0.263$)[63] and the "Negative News" portfolio comprises of events within the fourth quartile of CAS distribution ($+0.263 \leq CA_{Sent} \leq +2.687$).

2.3.6 Abnormal volume

To estimate (logarithmic) volume return around rating actions for the rated corporate bond, we first estimate the average volume of transaction (Av_Vol) for the rated bond issuing company, over a period of [-40,-3] before the rating action announcement. Since the volume measure is not normalized (like the TRMI sentiment), we normalize $Vol(t)$ by computing the logarithmic volume return at day *t* for each rated bond:

$$Ab\_Vol\_ret(t) = \log(Vol(t) \, / \, Av\_Vol) \quad (3)$$

We then test whether there are significant differences around the event by running panel regressions with fixed effects (with robust clustered standard errors at the event level) at the company (i.e. the company who issued the rated bond) and year level, where the dependent variable is the logarithmic return of daily transaction volume for the relative time period [-40,+2] of each event[64]. Equation (3) is used to compute the logarithmic volume return for each of the days within the [-40,+2] time period. Panel regressions are conducted separately for sub-samples of rating action events with "Positive News", "Negative News" and "No News", as measured using the TRMI sentiment variable.

2.4 Data

2.4.1 Rating announcements

The history of rating actions for each bond issuer company are obtained from several sources; Fitch, Moody's and S&P from MFISD; EJR, DBRS, AMB and KBRS from their

[63] A smaller interval of the "No News" portfolio was also used as a robustness check.
[64] Panel regressions were also run by using logarithmic volume as the dependent variable. The results were qualitatively the same and are thus not reported.

respective websites[65,66]. Our sample covers the period from July 2002 to September 2014[67]. Initially, FM rating actions are defined as the ones in which no other rating actions have occurred 60 trading days prior to the event (6-digit issuer CUSIPs). Subsequently, we construct pairs of FM and LM by obtaining the next rating action in the same direction to FM within the next 60 trading days. This results in 6,231 pairs of rating actions (6,231 FM and 6,231 LM) out of which 1,038 are upgrades, 1,176 are downgrades and 4,017 are affirmations[68]. Events are excluded if (a) a rating action occurred within 10 trading days of the FM in order to avoid contamination of the abnormal sentiment, (b) more than one rating action occurred at the same day with at least one of those being in a different direction (e.g. both an upgrade and a downgrade), (c) other rating announcements in a different direction occurred between FM and LM. After filtering out the pairs of rating actions using these criteria, the samples comprises 3,449 (558 upgrades, 642 downgrades and 2,249 affirmations) events.

2.4.2 Insurance transaction data

Insurance companies are required to report acquisitions and disposals of bonds in NAIC schedule D, parts 3, 4 and 5, where transactions include equity (common and preferred stock) and fixed income securities, such as corporate bonds, state bonds, and sovereign bonds. Parts 3 (4) are filled in on a calendar quarterly and yearly basis and include acquisitions (disposals) within a quarter/year. Part 5 is filled in on a yearly basis only and includes equity and fixed income securities that have been acquired and disposed of within the same year. Companies fill in their forms for the first 3 quarters of the calendar year and then at the 4th quarter, annual forms are reported. Insurance companies report transactions either at an aggregate quarterly/yearly level or at a transaction level basis for each bond.

[65] We would like to acknowledge the support of Egan-Jones Ratings for providing us access to their website thus retrieving data since 1999.

[66] Rating announcements for Fitch, Moody's, S&P, EJR are available since the beginning of our sample period. Data for DBRS are available since 27/02/2003, for AMB since 03/03/2005, and KBR since 11/02/2008, which are the dates in which each CRA has become a NRSRO.

[67] This time period covers data availability between all data sources used.

[68] The number of pairs differs between chapters one and two. This is due to the way that the samples were constructed at each stage of the study. In this case, pairs of actions comprise of events in which there was availability of data in SNL. In chapter one, since we are using returns in prices from TRACE, the common 6-digit issuer CUSIP differs at this stage of the design.

Data on insurance bond transactions (US corporate medium term notes, US corporate debentures and US corporate convertible) were downloaded from SNL financial database for all insurance sectors (health, life and property-casualty). Observations were deleted from the original sample because of the following reasons: (a) unavailable 9-digit CUSIPs; (b) unavailable transaction date; (c) reported transaction dates were outside the filing period range (as insurance companies are required to report their transactions within the same quarter/year of the filing date); (d) transaction dates occurring in the future or before offering date or after maturity date of bond; (e) unavailable transaction volume data[69]; (f) volume of transaction less than $1,000, (g) not considered as buy or sell transactions (with the following codes: call, cancel, convert, exchange, issue, mature, put, redeem, sinking fund, tax-free exchange, tender, transfer, paydown, replace)[70].

The next issue we had to address was an aggregation reporting issue. Specifically, insurance companies have the option to report their transactions at an individual or aggregate level for each bond. For instance, if an insurance company acquired an amount of bonds on January 10th, 2013 and February 20th, 2013, it has the option to report either two individual transactions on the same bond (with the respective dates mentioned), or a single transaction of the total amount of the bond bought/sold using the most recent transaction date (i.e. February 20th 2013).

To address this issue, we matched the final sample of insurance bond transactions from SNL with the TRACE bond transactions database. TRACE bond transactions data consists of all bond transactions reported by brokers. Hence, by matching SNL transactions with TRACE bond transactions by 9-digit CUSIP, transaction date, buy/sell and aggregate par value volume, we create a proxy of individual transaction data, which is free from the aggregation issue that some insurance companies are using when they report their transaction data.

[69] Volume of transaction is defined by SNL as "Cost of acquiring the bond including broker commission and other related fees, excluding accrued interest and dividends" for acquisitions and "Total proceeds received at time of sale, including broker commission and delivery expense, but excluding accrued interest and dividends" for disposals.
[70] Same codes used as in Asquith et al. (2013).

2.4.3 Matching with TRMI abnormal sentiment

In the next phase of the sample construction, we match the LM rating actions with available daily TRMI sentiment data around the event [71]. As described in more detail in section 2.3.3, using a complex algorithm of textual analysis, TRMI creates an overall normalized sentiment index specific to each bond issuer company on a daily basis. When matching the sample with TRMI data, we end up with 2,752 LM (394 upgrades, 462 downgrades and 1,896 affirmations). More specifically, at this stage of our sample selection, the "Negative News" portfolio comprises 732 events (101 upgrades, 163 downgrades and 468 affirmations), the "No News" portfolio 1,340 (159 upgrades, 223 downgrades and 958 affirmations) and the "Positive News" portfolio 680 (134 upgrades, 76 downgrades and 470 affirmations) [72].

2.4.4 Matching bond rating actions with insurance bond transactions

Lastly, LM are matched with transaction volume data for insurance companies. The LM rating actions are matched with the transaction volume data at the issuer (6-digit) CUSIP level. Hence, we match the daily volume of transactions for each rated bond over the period [-40,2] relative to the event date, where an event is defined as a LM rating action for each bond. As implied, the window [-40,2] refers to 40 trading days before and 2 days after the rating action day (i.e. relative day 0). The number of LM actions with available transaction volume data in the [-40,2][73] period is 561 (41 upgrades, 57 downgrades and 463 affirmations). More specifically, the final sample comprises 119 events (11 upgrades, 20 downgrades and 88 affirmations) in the "Negative News" portfolio, 322 (19 upgrades, 30 downgrades and 273 affirmations) in the "No News" portfolio and 120 (11 upgrades, 7 downgrades and 102 affirmations) in the "Positive News" portfolio.

[71] Not all companies of interest were included in the TRMI database. The distribution of ratings for each sub-sample (companies included versus companies not included in the TRMI sample) were checked and the distributions of the two samples were almost identical.
[72] Cases were excluded if they resulted in a change in the NAIC designation (described in detail in section 2.5).
[73] Sample used included rating actions with at least one observation available in the time period [-40, -3], which is the time period used to compute average volume before event, and one in time period [0, 2]. At a later stage, robustness checks have been conducted for samples that included more observations in the time period before the event, i.e. [-40, -3].

2.5 NAIC designation

Insurance companies have certain restrictions when it comes to forming their portfolios. They are regulated by the NAIC at the state level and can hold up to an amount of non-investment grade bonds depending on the bond rating level[74]. The NAIC has its own definition of a bond rating which is divided into six categories; investment grade bonds have an NAIC rating of 1 or 2, while non-investment grade bonds take values between 3 and 6[75]. Since bonds can be rated by more than one CRA, an insurance company must use the ratings assigned by all NRSROs and convert the information to a NAIC designation[76].

Since a bond may be rated by more than one NRSRO, a rule is used to designate a rating. There has been a change in rating designation through time, for bonds rated by three or more NRSROs. If a bond is rated by one NRSRO, then that rating is used to convert to a NAIC designation. If a bond is rated by two NRSROs, then the worse of the two is used. For bonds rated by three or more NRSROs, then, for years up until 2006[77], the second best rating was used. Ratings were ordered according to credit quality and the second best rating was chosen. Since 2007, the second worst rating is used. Ratings are ordered according to credit quality and the second worse is used as a NAIC designation[78]. Furthermore, there are currently ten NRSROs, eight of which rate corporate bonds, namely; S&P, Moody's, Fitch, DBRS, AMB, Japan credit rating agency (non-US corporate bonds), EJR and KBR. All these are currently used by insurance companies to convert a bond rating to an equivalent NAIC designation[79].

As such, one could argue that insurance companies may react to a rating action according to the NAIC regulation; that is, they may choose to rebalance their portfolios when more than

[74] For more information on investment restrictions, see http://www.naic.org/store/free/MDL-280.pdf and http://www.naic.org/store/free/MDL-283.pdf.

[75] For more details on NAIC designation see http://www.naic.org/documents/svo_naic_aro.pdf

[76] http://www.naic.org/documents/cipr_events_impact_rating_overview_svo.pdf

[77] The NAIC filing exemption rule states that insurance companies do not have to file for a NAIC designation of a bond that is rated by NRSROs through the Securities Valuation Office (http://www.naic.org/documents/svo_FE_FAQ.pdf). This rule was effective as of 01/01/2004. For our purposes, for the time period before 2004 of our sample, we convert to a NAIC designation using the same rule as for years 2004-2006.

[78] http://www.naic.org/documents/SVO_FE-2nd_Lowest_Notice.pdf

[79] Not all CRAs were recognized as NRSROs throughout the time period of our sample (since beginning of sample period for Fitch, Moody's, S&P, since 27/02/2003 for DBRS, since 03/03/2005 for AMB, since 21/12/2007 for EJR, since 11/02/2008 for KBR). This was taken into account in the NAIC designation for each bond.

one CRA has upgraded/downgraded a specific bond and not when the first CRA does so. This could also imply that even in the case of no additional useful information being provided by a rating action, there could be abnormal trading volume due to the fact that insurance companies follow the NAIC regulation as to when a bond is considered to have been upgraded/downgraded. For this reason, any rating actions that resulted in a change in the NAIC designation were excluded from our sample to avoid any possible bias in our results.

In addition to this, a rating action may provide additional information for insurance companies which is not captured by the TRMI[80]. If for example, there has been an upgrade for a specific bond, then this could increase the probability of a change in the NAIC designation in the near future with other subsequent upgrades from other CRAs (or the same one). Given this, an insurance company may decide to react at a non-informative LM depending on the probability of a change in the NAIC designation of a bond instead of waiting until there has been an actual change in the NAIC designation. This was controlled for in the panel regression models by using the probabilities of a NAIC change in designation given the direction of a rating action (i.e. upgrade, downgrade or affirmation) and how many notches away the bond is from a change in the NAIC designation (independent variable named as NAIC (probability)). A detailed account of the calculation of these probabilities as well as the probabilities used is given in the appendix.

2.6 <u>Descriptive statistics and results</u>

2.6.1 Descriptive statistics

Summary statistics of the quarterly volume of transactions (in billions of dollars) for TRACE (overall trading) and SNL (insurance companies' trading) for the time period 2002Q3 to 2014Q3 are depicted in table 2.1. The overall trading of during the time period of interest ranges between 576 and 1,742 billion dollars; while for insurance companies the overall trading volume ranges between 68 and 149 billion dollars. The mean trading volume is around 114 (951) billion dollars for insurance companies (all investors) respectively. Insurance companies on average account for around 12% of the total trading volume.

[80] This was tested in the predictability models as described in appendix.

[Insert Table 2.1]

Table 2.3 reports descriptive statistics for the bonds used in our sample. There are in total 561 events (119 in "Negative News", 322 in "No News" and 120 in "Positive News" portfolios)[81]. In Panel A we observe the frequency distribution of the ratings of LM rating actions. The majority of bonds are at investment grade level (around 87%) with the highest number of rating actions taking place at rating category BBB (226 events). The sample comprises of around 13% non-investment grade bonds. In panel B, summary statistics of bond characteristics are reported for the 561 rating actions. The average mean (median) for age and maturity of the bonds traded are 3.65 (3.40) and 9.62 (8.77) years respectively. The amount of debt outstanding ranges between 86,500 and 5,000,000 with a mean (median) of 654,476 (516,667)[82].

[Insert Table 2.2]

[Insert Table 2.3]

There are in total 2,101 insurance companies that have bought and/or sold at least once a bond during the time period [-40,2] of the events; out of which 1,187 are P&C, 596 are life and 321 are health insurance companies. Out the total, 1,626 are affiliated (belong in a group of companies) while 195 are listed. Summary statistics for the insurance companies that trade around the LM rating actions are depicted in table 2.4[83] (the definitions as provided by SNL for each variable are shown in table 2.2). The average mean (median) total assets is 3,661,942 (246,236) thousands. Return on average assets has a mean (median) of 2.06% (1.97%) and investment yield varies between 0.00% and 34.30%.

[Insert Table 2.4]

[81] Descriptive statistics are similar between three portfolios.
[82] For cases where insurance companies have traded in more than one bond of the same company around a rating action, the average age, debt and maturity were computed.
[83] If an insurance company buys/sells a bond in more than one event then the average company characteristics are computed (for all variables in table 2.4).

2.6.2 Results

We now focus on the sample selected using the procedure described in section 2.4. Hence, our focus is on 561 late mover rating actions (41 upgrades, 57 downgrades and 463 affirmations) with available insurance transaction level data at the daily level and corresponding TRMI sentiment data. We conduct panel regressions separately for the three portfolios. There are 119 in "Negative News", 322 in "No News" and 120 in "Positive News" portfolios.

Table 2.5 presents panel regression results where the dependent variable is the logarithmic volume return for the time period [-40,2][84]. All upgrades, downgrades and affirmations are included in each of the models run for each of the three portfolios ("Negative News", "No News" and "Positive News" portfolio). It is of interest here to observe that after controlling for the variability within each company and year (issuer 6-digit CUSIP and year fixed effects) the results show that, there is an overall significant increase in the trading volume around the events for all three portfolios.

[Insert Table 2.5]

More specifically, when looking at the "Negative News" portfolio (table 2.5, Panel A), models 1 and 2 show results for the whole sample, i.e. 119 events; model 1 when excluding the NAIC (probability) variable (as described in section 2.5) and model 2 when including this variable. By looking at these two models, we observe a statistically significant increase in the trading volume for days 0 to 2 relative to the event.

When considering the possibility of other type of events influencing the trading behavior of insurance companies, we further examine whether there is abnormal trading after excluding cases where other types of events for the same company have occurred around the LM. Chae (2005) states that there is documented evidence in the literature on four types of events that affect trading volume, namely earnings announcements, credit rating announcements, mergers and acquisitions. We therefore compare results of the full sample with results obtained after excluding other types of announcements[85]. In models 3 (excluding NAIC probability variable)

[84] The logarithmic volume was also used as a dependent variable for robustness. The results are qualitatively the same and are thus not reported.
[85] Earnings announcements have been downloaded from COMPUSTAT fundamentals quarterly. Mergers and acquisitions announcements have been downloaded from Thomson Rheuters Eikon.

and 4 (including NAIC probability variable) (table 2.5, panel A) we exclude events where other credit rating announcements have occurred during the time period [1,5] relative to the event as well as events where earnings announcements or mergers and acquisitions (for the same company) have occurred during the time period [-5,5] relative to the event. The results are consistent with the semi-strong efficient market hypothesis in the sense that this sample of LM rating actions provide additional negative information to markets and as such, result in abnormal trading volume.

Moving on now to the "No News" portfolio, the results are indicative of a contradiction to the semi-strong efficient market hypothesis. Table 2.5 (Panel B1) presents results where the dependent variable is the logarithmic volume return. Even though the "No News" portfolio contains uninformative LM credit rating/outlook announcements, we can still observe a significant increase in trading volume for the whole sample as well as for the LM rating actions, which are "clean" from other type of announcements around the event. More specifically, when looking at the whole sample (models 1 and 2) and after excluding other events in the time period [-5,5] (models 3 and 4) relative to the event, insurance companies seem to trade abnormally at days 0 to 1 and 0 respectively relative to the event. These results seem to lend the support to the hypothesis of limited attention bias, since one would not expect to observe abnormal trading when no new information is available in the public domain. The sample of "No News" portfolio was further partitioned into three sub-groups; downgrades, affirmations and upgrades (panel B2). All three signals of rating actions indicate that there is an increase in the trading volume of insurance companies, mainly at day 0 of the events[86].

Finally, the "Positive News" (table 2.5, Panel C) portfolio provides similar qualitatively results as in the other two portfolios. In all regressions run, there is a general consensus of an increased trading behavior at day -2 relative to the event, while when all events are included, there is a statistically significant increase in trading volume at days -2 to 0 relative to the event. Likewise, as in the "Negative News" portfolio, results are justified by the fact that this sample provides new information to the public, thus resulting in an increased trading behavior.

[86] The negative coefficient for the sample of downgrades at day -1 relative to the event disappears when events are excluded if there have been other types of announcements [-5,5] relative to the event.

2.7 Robustness checks

2.7.1 Additional robustness checks

Additional robustness checks have been conducted for the three portfolios ("Negative News", "No News" and "Positive News" portfolios) to test the validity of results presented. For the analysis of the "No News" portfolio, the interquartile range of CAS was used to construct the sample of uninformative LM. As a robustness check, a narrower "No news" portfolio was tested by including LM in which their CAS lies between the 37.5th and 62.5th quartile for the logarithmic volume return (i.e., +/-12.5% around median CAS). The results are presented in table 2.6 and are robust for the narrower portfolio; we can still observe a significant increase in trading volume, at days 0 and 1 of the event. Results remain statistically significant even after the exclusion of events where other types of announcements have occurred around LM rating actions.

[Insert Table 2.6]

A second robustness check used different cut-offs when forming the three portfolios. Instead of splitting the three portfolios into the first quartile, the interquartile range and the fourth quartile, the sample was split into three equal quartiles of CAS. Similarly, as in the results presented so far, in table 2.7, there is evidence of increased trading volume for days 0 to 2 relative to the event when it comes to the "Negative News" , days 0 and 1 for the "No News" portfolio and days -2 to 0 for the "Positive News" portfolio.

[Insert Table 2.7]

Finally, another set of robustness checks have been conducted. Specifically, panel regressions have been run for events where there has been more volume data available during the time period [-40,-3] of event (at least 2 values and at least 3) and excluding corporate convertible bonds. All robustness checks conducted produced qualitatively the same results and are thus not reported[87].

[87] Panel regressions were also run using the total trading volume around events by all investors (using TRACE enhanced). Results were qualitatively the same for all three portfolios constructed (not reported).

2.7.2 Could the aggregation in reporting transactions bias our results?

We next investigate whether the aggregation reporting issue (as described in section 2.4.2) of insurance companies could bias the results of abnormal trading during uninformative rating actions. As mentioned before, insurance companies have the option of reporting their transactions at an individual or aggregate level[88]. However, since we do not have information on when an insurance company reports an individual or aggregate transaction when acquisitions and disposals are reported, we match the database with TRACE bond transactions database to distinguish between individual and aggregate transactions. The matching process allows us to indicate for each transaction whether it is an individual or an aggregate one. What we would like to explore is whether the reporting tendency depends on certain characteristics and/or past performance of insurance companies.

Due to the complexity of our dataset (multiple transactions by more than one insurance company and bond on a specific day, as well as a non-consistent tendency on their choice of reporting individual versus aggregate transactions), it is difficult to address fully the possible endogeneity issues that arise due to the sample selection. Therefore, we use an approximation of the probability of insurance companies reporting individual versus aggregate transactions and proceed along the logic followed in the Heckman two stage procedure.

We make a start by identifying whether an insurance company is inclined towards reporting individual transactions or not at the yearly level. For each insurance company, we calculate the percentage of individual transactions out of the total number of transactions within a year. If a company reports individual transactions greater or equal to a threshold level (in percentage out of the total), then that company is given a value of one indicating a tendency to report individual transactions. As a first step, we estimate a probit model (with robust clustered standard errors at the insurance company level) which predicts the likelihood that a company reports individual transactions as given below

$$\begin{aligned} Ind_{i,t} = {} & affiliated_{i,t} + age_{i,t} + ta_{i,t-1} + rbc_{i,t-1} + inv\_yield_{i,t-1} + pc_i + life_i \\ & + listed_{i,t} + ownership_{i,t} \end{aligned}$$

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88 This information was provided by the SNL support group (snl.com).

(4)

where $Ind_{i,t}$ = 1 if a large percentage of transactions are reported by an insurance company (i) at an individual level (at least 70%, 80%, 90%) within a year (t) and 0 otherwise

$affiliated_{i,t}$ = 1 if the company is affiliated (belongs to a group of companies) and 0 otherwise

$age_{i,t}$ = age (in years) of the insurance company

$ta_{i,t-1}$ = total assets at year t-1

$rbc_{i,t-1}$ = ACL Risk Based Capital[89] at year t-1

$inv\_yield_{i,t-1}$ = investment yield at year t-1

pc_i = 1 if company is a P&C insurance company, 0 otherwise

$life_i$ = 1 if company is a life insurance company, 0 otherwise

$listed_{i,t}$ = 1 if company is listed, 0 otherwise

$ownership_{i,t}$ = NAIC ownership structure; 1 if mutual company, 0 if stock company[90]

The results of the probit models are depicted in table 2.8. Three different models are run with the difference being in the independent variable; that is, at what percentage level of individual transactions reported is defined as a company having the tendency of reporting individual transactions within a year. The results are consistent at all percentage levels tested. Almost all variables used are strongly significant (at the 1% level). Overall, large (by looking at total assets) and affiliated insurance companies reduce the tendency of reporting individual transactions (negative coefficient). In terms of last year's performance, companies with higher

[89] The CAL RBA was also used as a robustness check which resulted in the same qualitative results and are thus not reported. Definition of both variables are provided in table 2.2.

[90] Stock companies are owned by shareholders. Mutual companies are owned by policyholders. Due to the differences in ownership structure of insurance companies, there are also differences in governance so we control for this in the model.

ACL RBC and investment yield also increase the probability of reporting aggregate transactions at the yearly level, which can be seen by the negative coefficient of these two variables.

[Insert Table 2.8]

The type and ownership structure of insurance companies also seem to differ in terms of their tendency to report individual versus aggregate transactions (positive coefficients). P&C and life insurance companies tend to report more individual transactions compared to health companies. If a company is listed or is a mutual company, then again it increases the probability of reporting individual transactions.

The inverse Mills ratio was computed for these models which was included subsequently in the panel regressions when looking at whether insurance companies trade abnormally in uninformative rating actions. Therefore, for each insurance company-year combination we compute the inverse mills ratio which is defined as the ratio of the standard normal density to the standard cumulative distribution function. As panel regressions look at daily data, i.e. total volume of transactions, this means that more than one insurance company can buy or sell a bond during a day, leading in several inverse mills ratios depending on the insurance company. As a proxy, we use the volume weighted average inverse mills ratio for each day depending on which insurance companies have bought/sold a bond. The results for the "No News" portfolio are reported in table 2.9.

[Insert Table 2.9]

Overall, the results remain qualitatively the same. Even after controlling for possible sample selection bias, we still obtain statistically significant results, meaning that there is an indication of abnormal trading by insurance companies for the sample of stale news. The positive statistically significant coefficient of the inverse mills ratio indicates that there is a selection bias in our sample with results being biased upwards. By including this variable in the model, we control for the bias and still obtain the same qualitative results as the ones reported in section 2.6. This holds for any of the three probit models used when defining the dependent variable.

2.8 Trading behavior of insurance companies and cumulative abnormal returns

The statistically significant abnormal trading in uninformative credit rating announcements seems to lend the support of limited attention bias amongst one specific type of institutional investors, namely insurance companies. What we would next like to explore is the extent to which insurance companies create a price pressure in bonds. To do this, we would like to test whether there is a correlation between insurance companies' buy-sell imbalance and cumulative abnormal returns. First, abnormal bond returns are calculated following the method suggested by Bessembinder et al. (2009) for daily bond price data (trade-weighted price, trades>=100,000, firm level approach[91] for companies with multiple bonds). Data are obtained from TRACE. Daily abnormal return[92] is defined as

$$AR_t = return\ of\ bond\ of\ interest_t - expected\ return\ of\ matching\ portfolio_t$$

$$AR_t = \frac{(P_{t+1}+AI_{t+1})-(P_t+AI_t)}{(P_t+AI_t)} - expected\ return\ of\ matching\ portfolio_t \tag{5}$$

where P_t= price at time *t*

AI_t= accrued interest at time *t*

$expected\ return\ of\ matching\ portfolio_t$= average return of bonds within the same rating/maturity group[93]

It is well known in the literature that when it comes to bonds, risk factors such as default risk and time-to-maturity result in differing variability in bond return reactions. Thus, we adjust for this by using a matching portfolio when computing the average expected return of matching portfolio based on seven rating groups (S&P rating categories AAA, AA, A, BBB, BB, B, CCC and below and the corresponding rating categories for the rest of credit rating agencies[94]) and

[91] For events in which there have been transactions for more than one bond within the same company, a market value weighted average abnormal return was computed.
[92] Following Bessembinder et al. (2009), we exclude cases where absolute value of return is greater than 20%.
[93] Bonds have been excluded from matching portfolio if there has been a credit rating announcement during the period of interest.
[94] To account for the fact that bonds may be rated by more than one credit rating agency, the average rating was used across all NRSROs which rate the company of interest, i.e. for NRSROs that have rated companies within a year of the date of interest.

three time-to maturity groups (0 up to but excluding 5 years, 5 up to but excluding 10 years, 10 years and above).

Table 2.10 reports the overall price effect of uninformative rating actions split by the direction of the signal (where price data available). Out of the 203 events (event window [0,1]), there are 22 downgrades, 170 affirmations and 11 upgrades. The overall significance differs across the three groups of events, with downgrades resulting in a statistically and economically significant negative abnormal effect. The mean CAR ranges between -78.9 and -61.2 bps. While there is a weak significance of positive abnormal reaction for upgrades, the sample size is small to make any inferences. For affirmations, there is a statistically significant positive abnormal reaction at the event window [0,3] (at the 10% level). However the mean CAR (8.9 bps) is not economically significant.

[Insert Table 2.10]

To analyse the trading behaviour of insurance companies around LM we use the overall institutional trading buy-sell imbalance volume (following Barber and Odean, 2008) over the event window of interest defined as

$$IMB_i^{[j,k]} = \frac{B_i^{[j,k]} - S_i^{[j,k]}}{B_i^{[j,k]} + S_i^{[j,k]}} \tag{6}$$

where $B_i^{[j,k]}$ = total volume of bonds bought over the event window [j,k]

$S_i^{[j,k]}$ = total volume of bonds sold over the event window [j,k]

We then estimate OLS regressions with robust standard errors (controlling for bond characteristics). The cross-sectional regressions are

$$CAR_i^{[j,k]} = IMB_i^{[j,k]} + age_i + maturity_i + debt_i + rating_i + liquidity_i^{[j,k]} + Upgrade_i + Downgrade_i + prob_i \tag{7}$$

where $CAR_i^{[j,k]}$ = cumulative abnormal return over the event window [j,k]

$IMB_i^{[j,k]}$ = buy-sell imbalance over the event window [j,k]

age_i = age of the bond (in years)

$maturity_i$ = time to maturity of the bond (in years)

$debt_i$ = amount outstanding of the bond

$rating_i$ = rating of the bond

$liquidity_i^{[j,k]}$ = liquidity[95] of the bond over the event window [j,k]

$Upgrade_i$ = Dummy variable indicating whether the event is an upgrade

$Downgrade_i$ = Dummy variable indicating whether the event is a downgrade

$prob_i$ = probability of a change in NAIC designation as described in the appendix.

The results are shown in table 2.11. Even though there is evidence of abnormal trading around uninformative credit rating announcements, insurance companies do not seem to create a price pressure when it comes to bond pricing. The buy-sell imbalance variable is not statistically significant for any of the three event windows tested for neither the whole sample nor the sample after excluding other type of events around the credit rating announcements.

[Insert Table 2.11]

[95] We use the high-low spread estimator proxy for liquidity, which is the measure suggested by Schestag et al. (2016) for bonds.

2.9 Conclusions

Behavioral biases have been documented to affect individual investor trading behavior more than institutional trading behavior. Documenting that institutional investors trade based on behavioral biases is important. This is because asset prices are largely determined by institutional investor trading, since they comprise the largest percentage of transaction volume.

In this paper, we test for limited attention bias in insurance companies' trading. Using the reported US insurance investment transactions, we test for abnormal trading activity on our proxy for "stale information" in the market place. Our work draws from the literature on the timeliness of changes in corporate bond ratings and outlooks by constructing pairs of rating actions that arrive later than others. We control for the amount of information present in late rating actions, using a novel news analytics database. Thus, we are able to categorize rating actions as informative and uninformative.

We find statistically significant increases in trading volume associated with announcements of uninformative rating actions. The results are robust to several models run as well as when events were "clean" from other types of announcements that occurred around the LM. This evidence is not consistent with the predictions of the semi-strong efficient market hypothesis, but lends support to the existence of limited attention bias in institutional trading. Even though there seems to be abnormal trading, it does not seem to be on average correlated with abnormal returns of overall bond prices, suggesting that insurance companies are not one of the type of institutional investors which exert price pressure on uninformative rating actions.

Figure 2.1: Construction of late mover (LM)

This diagram depicts the method used to construct the sample of LM. The first mover (FM) is defined as a rating action which is not preceded by any other rating action (in any direction) in the previous 60 trading days (t). The LM is defined as the next rating action (in the same direction) in the following 60 trading days (no other rating actions between FM and LM). Any LM within 10 trading days of FM have been excluded from analysis.

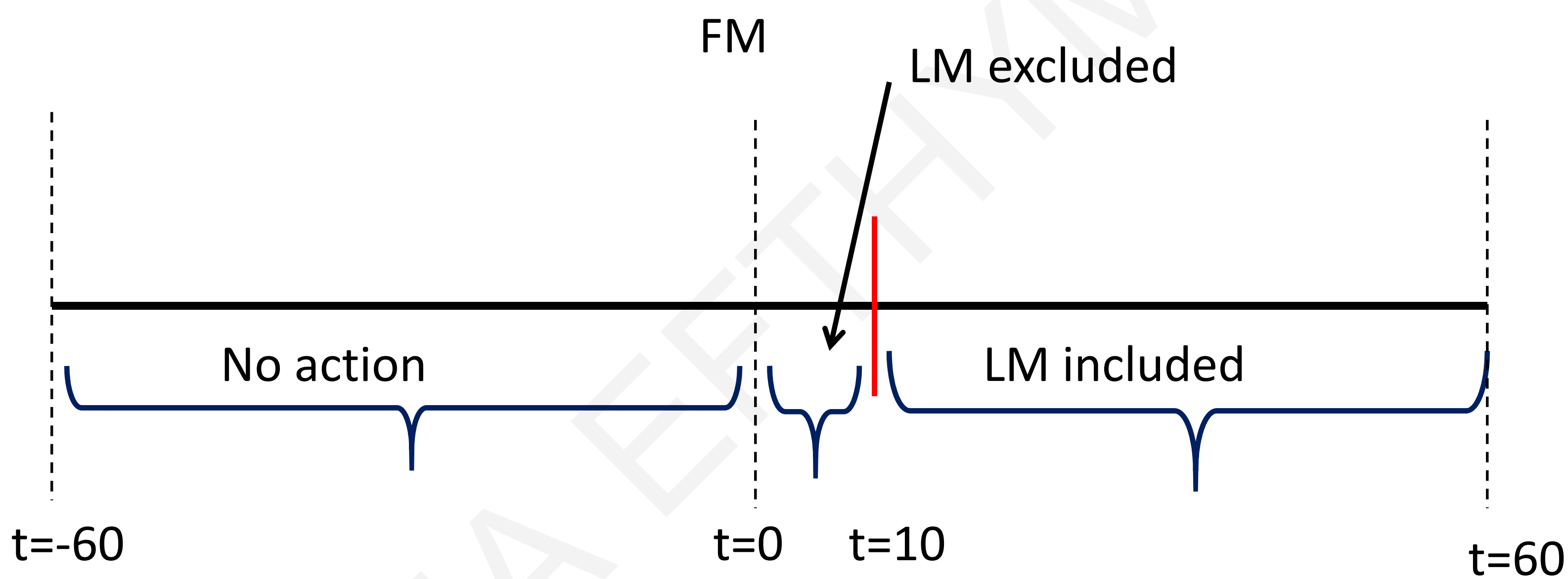

Figure 2.2: Histogram of Abnormal TRMI Sentiment

This graph shows the distribution of the CAS for the period [0,1] of the event for the union of late mover upgrade, downgrade and affirmation events. The dotted filled bars indicate the 25th and 75th percentile.

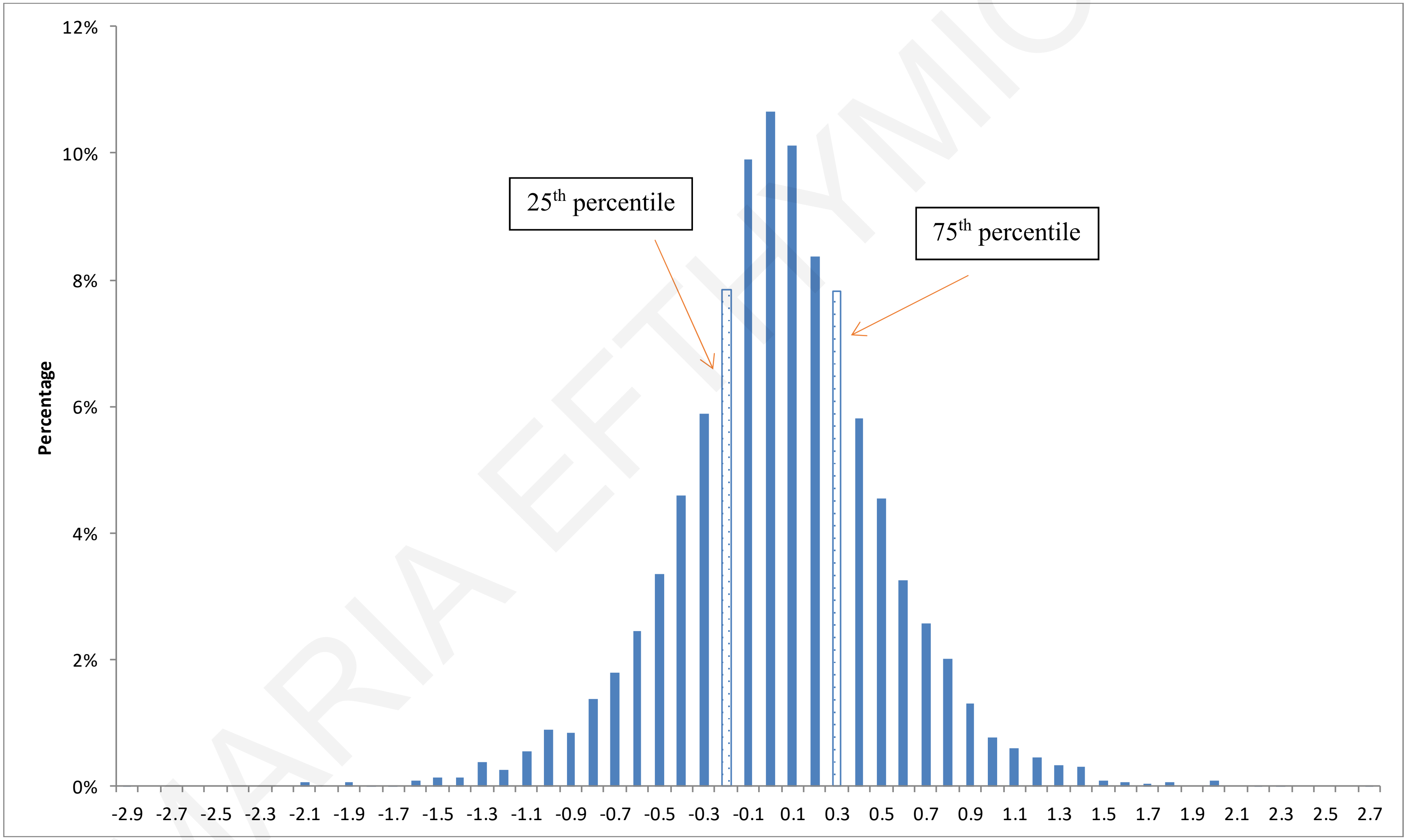

Table 2.1 – Summary statistics of quarterly volume transactions during the time period 2002Q3 and 2014Q3 (in billions of dollars)

This table reports summary statistics for the quarterly volume transactions for TRACE and SNL during the time period 2002Q3 and 2014Q3 (in billions). For TRACE, volume is computed as (reported price/100)*par value*(par value volume/1,000). For SNL, transaction volume is provided by SNL.

Quarterly Volume	N	Minimum	P25	P50	Mean	P75	Maximum
TRACE	49	575.72	717.95	905.84	951.22	1,047.42	1,741.65
SNL	49	68.06	104.09	113.68	114.44	128.31	149.24

Table 2.2: Definitions of insurance companies' characteristics variables
This table provides the definition of variables used for insurance companies' characteristics as given by SNL.

Variable	SNL definition
Investment yield (%)	Investment yield is net investment income earned as a percent of the average amount of cash and invested assets during the year. Cash and invested assets represent the amount in the subtotal line on the assets page of the annual financial statement plus investment income minus borrowed money. In addition to measuring one important element in profitability, the investment yield also provides an indication of the general quality of the insurer's investment portfolio. A ratio result that is outside the usual range is not necessarily considered adverse. Ratios and trends are valuable in identifying insurers who might experience financial difficulties. The typical range for this ratio includes results greater than 3.0 percent and less than 6.5 percent.
NAIC ownership structure	NAIC ownership structure; mutual and stock companies
Net investment income earned (000s)	Net investment income earned. Includes investment income earned from all forms of investment, including investment fees earned relating to uninsured accident and health plans, dividends from subsidiary controlled affiliated entities, joint ventures, partnership, and limited liability companies: minus investment expenses, taxes (excluding federal income taxes), licenses, fees, depreciation on real estate and other invested assets. Also includes investment income credited to uninsured accident and health plans and interest on borrowed money. Excludes capital gains on investments and equity in undistributed income or loss of subsidiary controlled affiliated entities, joint ventures, partnerships, and limited liability companies.
Net total assets (000s)	Net admitted totals includes the sum of all assets in all lines reported. Excludes any valuation allowance. Net admitted assets exclude assets for which the state does not allow the company to take credit.
Total assets (000s)	Admitted and nonadmitted totals includes the sum of all assets in all lines reported. Excludes any valuation allowance.
Total liabilities (000s)	Total liabilities is the sum of all previous lines involving liabilities.

Table 2.2 (continued): Definitions of insurance companies' characteristics variables

Variable	SNL definition
Risk based capital (RBC)-ACL (%)	The RBC ratio shown is the "Authorized Control Level" standard which equates to total adjusted capital (TAC) as a percent of authorized control level risk-based capital (TAC)/(ACL RBC). For individual entities this ratio calculation uses TAC and ACL RBC as reported by the company. For groups, SNL adjusts the company level reported TAC and ACL RBC for inter-company ownership and then calculates the RBC ratio using the adjusted figures.
Risk based capital (RBC)-CAL (%)	The RBC ratio shown is the "Company Action Level" standard which doubles ACL RBC in the ratio's denominator (TAC)/(2*ACL RBC); this equates to half the amount of the "Authorized Control Level" standard. For individual entities this ratio calculation uses TAC and ACL RBC as reported by the company. For groups, SNL adjusts the company level reported TAC and ACL RBC for inter-company ownership and then calculates the RBC ratio using the adjusted figures.
Return on average assets (ROAA) (%)	Income after taxes as a percent of average net admitted assets.
Return on average equity (ROAE) (%)	Annualized income after taxes as a percent of average capital and surplus.

Table 2.3 – Panel A: Distribution of bond ratings

Frequency and percentage distribution of ratings for LM, for the time period July 2002 to September 2014. The sample comprises rating announcements which have occurred within 60 trading days of the FM (ratings within the first 10 trading days of the FM have been excluded). To account for the fact that companies may be rated by more than one credit rating agency, the average rating was used across all NRSROs which rate the company of interest.

Rating group	**Frequency**
AAA	6(1.1%)
AA	42(7.5%)
A	216(38.5%)
BBB	226(40.3%)
BB	53(9.4%)
B	16(2.9%)
CCC (& below)	2(0.4%)
Total	**561**

Table 2.3 – Panel B: Summary statistics of bond characteristics

This table reports summary statistics for the bonds used in the LM sample, for the time period July 2002 to September 2014. The sample comprises rating announcements which have occurred within 60 trading days of the FM (ratings within the first 10 trading days of the FM have been excluded). Age and maturity are reported in years, debt is reported in amount outstanding. Amount outstanding (provided by MFISD) assumes a par value of $1,000. For events where trades from more than one bond for a specific company occur, the average age, debt and maturity is reported.

Variable	N	Minimum	P25	P50	Mean	P75	Maximum
Age	561	0.00	2.01	3.40	3.65	4.82	14.06
Debt	561	86,500	390,000	516,667	654,476	767,987	5,000,000
Maturity	561	0.08	6.02	8.77	9.62	12.39	45.47

Table 2.4: Summary statistics of insurance companies

This table reports summary statistics for insurance companies' characteristics used [-40,2] relative to the LM events, for the time period July 2002 to September 2014. The sample comprises rating announcements which have occurred within 60 trading days of the FM (ratings within the first 10 trading days of the FM have been excluded). Age is reported in years. Total assets, total liabilities, net total assets, and net investment income are reported in thousands. Return on average assets, return on average equity, risk based capital (CAL and ACL) and investment yield are reported in percentages. If an insurance company buys/sells a bond in more than one event then the average company characteristics are computed.

Variable	N	Minimum	P25	P50	Mean	P75	Maximum
Age	2101	0.28	20.27	34.04	45.76	60.50	217.09
Total assets	2087	848	61,599	246,236	3,661,942	1,110,062	330,187,328
Total liabilities	2085	0	30,564	133,266	3,093,654	701,097	313,583,423
Net total assets	2085	848	58,956	236,237	3,602,161	1,077,989	325,806,269
Return on average assets	2078	-79.70	0.26	1.97	2.06	4.37	43.50
Return on average equity	2071	-833	1	6	4	12	173
Risk based capital (CAL)	2034	-240	259	408	899	640	30412
Risk based capital (ACL)	2034	-480	518	816	1,798	1,281	60,825
Net investment income	2085	-6,581	1,171	5,493	114,332	30,328	10,985,658
Investment yield	2085	0.00	2.25	3.36	3.52	4.60	34.30

Table 2.5 – Panel A: Panel regressions for logarithmic volume return for the "Negative News" portfolio

This table presents panel regressions for logarithmic volume return for the "Negative News" portfolio. Logarithmic volume return is defined as log (volume at day of interest / (average volume before announcement)). Referring to the CAS (Figure 2.2), the "Negative News" portfolio comprises all events (upgrades, downgrades and affirmations) whose CAS falls in the 1st quartile. *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively. SE stands for standard error. The NAIC (probability) variable provides information on the probability of a NAIC designation change given the direction of a rating action and how many notches away it is from a NAIC designation change over the next 60 trading days. Models 3 and 4 are "clean" from other type of announcements in the period [-5,5] relative to the event.

	Whole sample		Excluding other events in period [-5,5]	
VARIABLES	**Model 1 Coefficient (SE)**	**Model 2 Coefficient (SE)**	**Model 3 Coefficient (SE)**	**Model 4 Coefficient (SE)**
Relative day: -2	0.365	0.365	-0.005	-0.007
	(0.384)	(0.384)	(0.521)	(0.522)
Relative day: -1	0.413	0.414	-0.346	-0.348
	(0.461)	(0.461)	(0.852)	(0.850)
Relative day: 0	**1.154*** **	**1.168*** **	**1.055** **	**1.071** **
	(0.303)	(0.302)	(0.491)	(0.473)
Relative day: +1	**0.626** **	**0.666** **	**0.871** **	**0.891** **
	(0.278)	(0.271)	(0.378)	(0.370)
Relative day: +2	**0.447* **	**0.473* **	**1.091*** **	**1.098*** **
	(0.266)	(0.276)	(0.375)	(0.378)
NAIC (probability)		-7.273		-8.304
		(13.963)		(62.672)
Constant	-0.899***	-0.831***	-1.009***	-0.931
	(0.034)	(0.138)	(0.057)	(0.602)
Observations	1,106	1,106	471	471
R-squared (within)	0.035	0.035	0.043	0.043
Number of company-year FE	118	118	48	48
Company FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 2.5 – Panel B1: Panel regressions for logarithmic volume return for the "No News" portfolio

This table presents panel regressions for logarithmic volume return for the "No News" portfolio. Logarithmic volume return is defined as log (volume at day of interest / (average volume before announcement)). Referring to the CAS (Figure 2.2), the "No News" portfolio comprises all events (upgrades, downgrades and affirmations) whose CAS falls in the interquartile range. *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively. SE stands for standard error. The NAIC (probability) variable provides information on the probability of a NAIC designation change given the direction of a rating action and how many notches away it is from a NAIC designation change over the next 60 trading days. Models 3 and 4 are "clean" from other type of announcements in the period [-5,5] relative to the event.

	Whole sample		**Excluding other events in period [-5,5]**	
VARIABLES	**Model 1 Coefficient (SE)**	**Model 2 Coefficient (SE)**	**Model 3 Coefficient (SE)**	**Model 4 Coefficient (SE)**
Relative day: -2	0.237	0.242	0.113	0.120
	(0.206)	(0.206)	(0.265)	(0.259)
Relative day: -1	0.201	0.204	0.362	0.367
	(0.239)	(0.239)	(0.339)	(0.339)
Relative day: 0	**1.478*** **	**1.458*** **	**1.155*** **	**1.139*** **
	(0.188)	(0.190)	(0.259)	(0.259)
Relative day: +1	**0.544*** **	**0.518*** **	0.297	0.274
	(0.158)	(0.162)	(0.252)	(0.262)
Relative day: +2	0.094	0.078	-0.070	-0.082
	(0.170)	(0.171)	(0.236)	(0.238)
NAIC (probability)		10.098		7.310
		(7.843)		(15.355)
Constant	-0.892***	-0.946***	-0.920***	-0.954***
	(0.019)	(0.043)	(0.028)	(0.073)
Observations	3,293	3,293	1,638	1,638
R-squared (within)	0.041	0.042	0.024	0.024
Number of company-year FE	303	303	163	163
Company FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 2.5 – Panel B2: Panel regressions for logarithmic volume return for the "No News" portfolio split by downgrades, affirmations and upgrades

This table presents panel regressions for logarithmic volume return for the "No News" portfolio split by direction of rating action. Logarithmic volume return is defined as log (volume at day of interest / (average volume before announcement)). Referring to the CAS (Figure 2.2), the "No News" portfolio comprises all events whose CAS falls in the interquartile range. *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively. SE stands for standard error. The NAIC (probability) variable provides information on the probability of a NAIC designation change given the direction of a rating action and how many notches away it is from a NAIC designation change over the next 60 trading days.

	Downgrades		**Affirmations**		**Upgrades**	
VARIABLES	**Model 1 Coefficient (SE)**	**Model 2 Coefficient (SE)**	**Model 3 Coefficient (SE)**	**Model 4 Coefficient (SE)**	**Model 5 Coefficient (SE)**	**Model 6 Coefficient (SE)**
Relative day: -2	0.494	0.525	0.161	0.167	0.938	0.966
	(0.499)	(0.477)	(0.230)	(0.231)	(0.928)	(0.966)
Relative day: -1	**-1.665***	**-1.635***	0.345	0.350	**1.220*****	**1.196*****
	(0.844)	(0.859)	(0.245)	(0.245)	(0.151)	(0.157)
Relative day: 0	**1.602*****	**1.381*****	**1.453*****	**1.288*****	**1.612****	**1.594****
	(0.432)	(0.478)	(0.213)	(0.254)	(0.629)	(0.605)
Relative day: +1	**0.673***	0.392	**0.523*****	**0.365***	0.501	0.479
	(0.381)	(0.491)	(0.177)	(0.208)	(0.398)	(0.532)
Relative day: +2	-0.360	-0.587	0.187	-0.006	-0.352	-0.101
	(0.525)	(0.559)	(0.186)	(0.229)	(0.673)	(0.616)
NAIC (probability)		11.466		3,093.496		53.073
		(11.357)		(1,896.719)		(46.486)
Constant	-0.862***	-1.453**	-0.899***	-0.967***	-0.796***	-2.082*
	(0.058)	(0.571)	(0.021)	(0.042)	(0.067)	(1.132)
Observations	263	263	2,874	2,874	156	156
R-squared (within)	0.098	0.103	0.039	0.040	0.079	0.087
Number of company-year FE	28	28	255	255	20	20
Company-Year FE	YES	YES	YES	YES	YES	YES

Table 2.5 – Panel C: Panel regressions for logarithmic volume return for the "Positive News" portfolio

This table presents panel regressions for logarithmic volume return for the "Positive News" portfolio. Logarithmic volume return is defined as log (volume at day of interest / (average volume before announcement)). Referring to the CAS (Figure 2.2), the "Positive News" portfolio comprises all events (upgrades, downgrades and affirmations) whose CAS falls in the 4th quartile. *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively. SE stands for standard error. The NAIC (probability) variable provides information on the probability of a NAIC designation change given the direction of a rating action and how many notches away it is from a NAIC designation change over the next 60 trading days. Models 3 and 4 are "clean" from other type of announcements in the period [-5,5] relative to the event.

	Whole sample		**Excluding other events in period [-5,5]**	
VARIABLES	**Model 1 Coefficient (SE)**	**Model 2 Coefficient (SE)**	**Model 3 Coefficient (SE)**	**Model 4 Coefficient (SE)**
Relative day: -2	**0.772*** **	**0.770*** **	**0.744** **	**0.752** **
	(0.265)	(0.264)	(0.334)	(0.333)
Relative day: -1	**1.034** **	**1.036** **	0.753	0.766
	(0.452)	(0.450)	(0.642)	(0.633)
Relative day: 0	**0.740** **	**0.720** **	0.230	0.189
	(0.284)	(0.288)	(0.382)	(0.395)
Relative day: +1	0.347	0.337	-0.272	-0.304
	(0.258)	(0.258)	(0.347)	(0.350)
Relative day: +2	-0.491	**-0.513***	**-0.761***	**-0.770** **
	(0.307)	(0.298)	(0.390)	(0.382)
NAIC (probability)		29.969		34.790
		(34.549)		(47.510)
Constant	-0.778***	-0.922***	-0.865***	-1.049***
	(0.036)	(0.167)	(0.042)	(0.250)
Observations	971	971	572	572
R-squared (within)	0.031	0.032	0.021	0.022
Number of company-year FE	118	118	64	64
Company FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 2.6: Panel regressions for logarithmic volume return for a narrower (between 37.5th and 62.5th CAS quartile) "No News" portfolio.

This table presents panel regressions for logarithmic volume return for a narrower "No News" portfolio. Logarithmic volume return is defined as log (volume at day of interest / (average volume before announcement)). Referring to the CAS, the narrower "No News" portfolio comprises all events (upgrades, downgrades and affirmations) whose CAS falls in between 37.5th and 62.5th quartile. *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively. SE stands for standard error. The NAIC (probability) variable provides information on the probability of a NAIC designation change given the direction of a rating action and how many notches away it is from a NAIC designation change over the next 60 trading days. Models 3 and 4 are "clean" from other type of announcements in the period [-5,5] relative to the event.

	Whole sample		Excluding other events in period [-5,5]	
VARIABLES	**Model 1 Coefficient (SE)**	**Model 2 Coefficient (SE)**	**Model 3 Coefficient (SE)**	**Model 4 Coefficient (SE)**
Relative day: -2	0.052	0.051	0.132	0.130
	(0.247)	(0.247)	(0.343)	(0.342)
Relative day: -1	-0.090	-0.103	-0.079	-0.099
	(0.286)	(0.286)	(0.385)	(0.384)
Relative day: 0	**1.567*** **	**1.596*** **	**0.993*** **	**1.013*** **
	(0.250)	(0.255)	(0.316)	(0.319)
Relative day: +1	**0.516** **	**0.562** **	0.225	0.274
	(0.225)	(0.232)	(0.342)	(0.354)
Relative day: +2	0.003	0.023	-0.307	-0.278
	(0.219)	(0.217)	(0.308)	(0.307)
NAIC (probability)		-19.211		-16.429
		(12.278)		(13.744)
Constant	-0.905***	-0.801***	-0.957***	-0.863***
	(0.025)	(0.066)	(0.032)	(0.082)
Observations	1,924	1,924	1,047	1,047
R-squared (within)	0.044	0.045	0.018	0.019
Number of company-year FE	177	177	95	95
Company FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 2.7: Panel regressions for logarithmic volume return when portfolios are split into three equal quartiles of CAS.
This table presents panel regressions for logarithmic volume return when portfolios are split into three equal quartiles of CAS. Logarithmic volume return is defined as log (volume at day of interest / (average volume before announcement)). *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively. SE stands for standard error. The NAIC (probability) variable provides information on the probability of a NAIC designation change given the direction of a rating action and how many notches away it is from a NAIC designation change over the next 60 trading days. Models 2, 4 and 6 are "clean" from other type of announcements in the period [-5,+5] relative to the event.

	"Negative News"		"No News"		"Positive News"	
VARIABLES	**Model 1 Coefficient (SE)**	**Model 2 Coefficient (SE)**	**Model 3 Coefficient (SE)**	**Model 4 Coefficient (SE)**	**Model 5 Coefficient (SE)**	**Model 6 Coefficient (SE)**
Relative day: -2	0.328	-0.043	0.106	0.113	**0.673*** **	**0.499** **
	(0.270)	(0.396)	(0.221)	(0.282)	(0.175)	(0.229)
Relative day: -1	0.347	-0.049	0.123	0.241	**0.749** **	**0.782***
	(0.335)	(0.662)	(0.281)	(0.379)	(0.308)	(0.439)
Relative day: 0	**1.221*** **	**1.113** **	**1.502*** **	**1.183*** **	**0.916*** **	0.347
	(0.266)	(0.447)	(0.219)	(0.284)	(0.249)	(0.351)
Relative day: +1	**0.834*** **	**1.002*** **	**0.473** **	0.310	0.245	-0.375
	(0.222)	(0.352)	(0.189)	(0.306)	(0.217)	(0.297)
Relative day: +2	**0.669*** **	**0.869*** **	-0.111	-0.269	-0.282	-0.419
	(0.217)	(0.321)	(0.200)	(0.295)	(0.250)	(0.324)
NAIC (probability)	-10.998	-20.066	11.006	13.686	16.232	17.618
	(11.610)	(28.918)	(8.175)	(15.919)	(26.782)	(32.883)
Constant	-0.804***	-0.792***	-0.971***	-1.029***	-0.872***	-0.941***
	(0.098)	(0.252)	(0.051)	(0.100)	(0.110)	(0.157)
Observations	1,686	651	2,599	1,335	1,626	898
R-squared (within)	0.039	0.041	0.042	0.026	0.027	0.016
Number of company-year FE	177	74	240	125	177	98
Company-Year FE	YES	YES	YES	YES	YES	YES

Table 2.8: Probit models for probability of insurance companies reporting individual versus aggregate transactions

This table presents probit models for probability of insurance companies reporting individual versus aggregate transactions for the universe of insurance companies (July 2002 to September 2014). The dependent variable takes the value of 1 if a large percentage of transactions are reported by an insurance company at an individual level (at least 70%, 80%, 90%) within a year and 0 otherwise. Z-statistics are reported in parentheses. *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively.

VARIABLES	**Dependent (70%)**	**Dependent (80%)**	**Dependent (90%)**
Affiliated	**-0.250*****	**-0.222*****	**-0.174*****
	(-6.232)	(-5.376)	(-4.122)
Age (years)	0.001	0.001	**0.001***
	(1.516)	(1.277)	(1.948)
Lag Total Assets (ln)	**-0.143*****	**-0.180*****	**-0.229*****
	(-16.416)	(-19.274)	(-22.186)
Lag Risk Based Capital (ACL)	**-0.000*****	**-0.000*****	**-0.000***
	(-3.844)	(-2.796)	(-1.849)
Lag Investment Yield	**-0.020*****	**-0.019****	**-0.016***
	(-2.660)	(-2.230)	(-1.663)
P&C	**0.166*****	**0.108****	0.031
	(3.099)	(1.971)	(0.552)
Life	**0.232*****	**0.147****	-0.005
	(3.835)	(2.362)	(-0.070)
Listed	**0.139****	**0.160*****	**0.159*****
	(2.534)	(2.780)	(2.737)
Mutual Company	**0.167*****	**0.144*****	**0.108***
	(3.126)	(2.623)	(1.877)
Constant	0.655***	0.880***	1.249***
	(6.127)	(7.749)	(10.223)
Observations	31,153	31,153	31,153
Pseudo R-squared	0.0571	0.0752	0.100

Table 2.9: Panel regressions for logarithmic volume return for the "No News" portfolio – including "Inverse Mills ratio"
This table presents panel regressions for logarithmic volume return for the "No News" portfolio, controlling for selection bias ("Inverse Mills ratio") due to the tendency of insurance companies reporting individual versus aggregate bond trades. Logarithmic volume return is defined as log (volume at day of interest / (average volume before announcement)). Referring to the CAS (Figure 2.2), the "No News" portfolio comprises all events (upgrades, downgrades and affirmations) whose CAS falls in the interquartile range. *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively. SE stands for standard error. The NAIC (probability) variable provides information on the probability of a NAIC designation change given the direction of a rating action and how many notches away it is from a NAIC designation change over the next 60 trading days. Models 2, 4 and 6 are "clean" from other type of announcements in the period [-5,5] relative to the event.

	IMR 70%		**IMR 80%**		**IMR 90%**	
VARIABLES	**Model 1 Coefficient (SE)**	**Model 2 Coefficient (SE)**	**Model 3 Coefficient (SE)**	**Model 4 Coefficient (SE)**	**Model 5 Coefficient (SE)**	**Model 6 Coefficient (SE)**
Relative day: -2	7.560	13.747	7.208	13.708	6.761	13.446
	(1.040)	(0.993)	(1.009)	(1.023)	(0.948)	(1.020)
Relative day: -1	0.107	0.118	0.091	0.096	0.076	0.065
	(0.588)	(0.508)	(0.513)	(0.410)	(0.435)	(0.278)
Relative day: 0	**0.455****	0.453	**0.456****	**0.461***	**0.447****	**0.460***
	(2.411)	(1.596)	(2.520)	(1.717)	(2.570)	(1.799)
Relative day: +1	**1.418*****	**1.059*****	**1.381*****	**1.027*****	**1.342*****	**0.995*****
	(7.948)	(4.414)	(7.890)	(4.337)	(7.813)	(4.265)
Relative day: +2	**0.553*****	0.222	**0.551*****	0.233	**0.546*****	0.245
	(3.651)	(0.869)	(3.738)	(0.936)	(3.804)	(1.016)
NAIC (probability)	0.048	-0.239	0.035	-0.255	0.021	-0.272
	(0.292)	(-0.987)	(0.217)	(-1.069)	(0.132)	(-1.159)
Inverse Mills ratio	**1.872*****	**1.653*****	**1.672*****	**1.508*****	**1.451*****	**1.332*****
	(15.980)	(10.608)	(17.680)	(11.648)	(19.813)	(12.952)
Constant	-4.277***	-3.893***	-4.398***	-4.066***	-4.379***	-4.103***
	(-19.362)	(-13.223)	(-21.229)	(-14.344)	(-23.667)	(-15.834)
Observations	3,007	1,433	3,007	1,433	3,007	1,433
R-squared (within)	0.231	0.178	0.268	0.214	0.302	0.248
Number of company-year FE	314	163	314	163	314	163
Company FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 2.10: Cumulative abnormal returns (CARs) for the "No News" portfolio split by direction of rating announcement

This table presents t-test results for CARs (in basis points) for the "No News" portfolio, split by upgrades, downgrades and affirmations over three event windows; [0,1], [0,2] and [0,3] relative to the event (for the time period July 2002 to September 2014). The sample comprises rating announcements which have occurred within 60 trading days of the FM. *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively.

	Event Window [0,1]				Event Window [0,2]				Event Window [0,3]			
Action	**N**	**Mean**	**t-statistic**	**Sig**	**N**	**Mean**	**t-statistic**	**Sig**	**N**	**Mean**	**t-statistic**	**Sig**
Downgrade	22	-70.536	-2.260	**	25	-61.150	-2.060	*	25	-78.925	-2.172	**
Affirmation	170	2.863	0.646		219	6.760	1.559		225	8.856	1.769	*
Upgrade	11	77.408	1.390		17	60.704	1.751	*	19	63.581	2.011	*

Table 2.11: OLS regressions for CARs for the "No News" portfolio

This table reports coefficient estimates of OLS regressions (with robust standard errors) for the insurance companies' trading imbalance variable (for the "No News" portfolio) for three event windows ([0,1], [0,2] and [0,3]). In the regressions, we control for the age, maturity, debt size, rating and liquidity of the bond and whether the rating action was an upgrade or a downgrade. *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively.

VARIABLES	**Event window [0,1]**	**Event window [0,2]**	**Event window [0,3]**
Buy-sell imbalance	3.947	1.423	1.711
	(6.975)	(5.612)	(6.852)
Rating	-0.123	1.451	3.065
	(3.334)	(3.040)	(3.108)
Maturity (years)	-1.261	-0.451	-0.119
	(1.159)	(0.877)	(0.950)
Age (years)	-1.939	-1.360	-1.248
	(2.741)	(2.089)	(2.453)
Liquidity	5,892.966	4,489.108	6,721.682
	(5,861.582)	(5,616.466)	(9,179.839)
Amount of debt outstanding	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Upgrade	60.733	30.325	31.054
	(46.349)	(28.443)	(27.376)
Downgrade	**-131.112*** **	**-149.802*** **	**-158.633*** **
	(39.338)	(33.891)	(41.430)
NAIC (probability)	**637.067** **	**880.967*** **	**717.267**
	(302.796)	(328.938)	(444.684)
Constant	17.074	9.848	-12.192
	(35.717)	(30.007)	(28.227)
Observations	203	261	269
Adjusted R-squared	0.165	0.180	0.141

Chapter 3: Does representativeness bias help explain the overreaction effects in bond pricing?

Abstract

In this study, we evaluate the mispricing effects of the US corporate bond market and whether these could be attributed to the representativeness bias. We contribute to the literature by exploring the credit default risk of companies as opposed to profitability measures documented so far. Using sequences of same sign news credit rating announcements by all Nationally Recognized Statistical Research Organizations that rate US corporate bonds, we provide evidence of statistically and economically significant price reversals for negative news (downgrades) up to a year after formation period. Consistent with the representativeness bias, the magnitude of the reversal increases as the number of same sign credit rating announcement increases.

3.1 Introduction

Researchers are constantly trying to investigate whether market anomalies exist in capital markets and suggest several possible explanations when detecting these. Whether the reasons behind market inconsistencies are due to specific companies' fundamentals (e.g. small-size effect), behavioral biases, or regulatory constraints (e.g. short selling constraints) are still debatable in the academic literature. In this study, we concentrate on the effect of overreaction, specifically whether the representativeness bias could explain the overreaction effects in corporate bonds.

Kahneman and Tversky (1972) defined representativeness as "the degree to which (an event) (i) is similar in essential characteristics to its parent population, and (ii) reflects the salient features of the process by which it is generated". In the context of finance, investors may try to form patterns or trends in random sequences of data thinking that the same pattern/trend will be observed in the future, thus overestimating the probability of this actually happening. The idea of representativeness bias has begun being empirically tested in the finance literature in the 1980s with De Bondt and Thaler (1985, 1987) providing evidence of overreaction effects (long-term reversals) for stocks with consecutive string of same sign news as opposed to companies with inconsistent set of news. More influential papers (both empirically and theoretically) have from then on followed (Lakonishok 1994, Barberis et al. (1998))[96] which develop the concept of investors extrapolating past consistent performance of companies and assume that past good (bad) performance will trend upwards (downwards), ignoring base rates (probability of companies who actually carry on trending upwards (downwards). Several papers have also disputed this work by either providing alternative explanations to this overreaction effect (e.g. time-varying discount rates) or not finding evidence of the representativeness bias (Chan et al., 2004).

In this study, we reevaluate the mispricing effects following consistent patterns of same sign credit rating signals by concentrating on US corporate bonds. The contribution to the literature by investigating the representativeness further is twofold. Firstly, contrary to the rest of the studies who have concentrated on stocks, we focus on US corporate bond performance.

[96] Barberis et al. (2015) have developed a consumption-based asset pricing model in which they infer to two kinds of investors; rational investors and ones who extrapolate prices.

Hirhsleifer (2001) comments that since there is a higher magnitude of overreaction effect in small companies, this may imply that you would observe greater effects in illiquid markets. Since the bond market is considered to be in general less liquid compared to the stock market, arbitrage opportunities arising due to irrational investors being prone to the representativeness bias may prove to be more difficult to be taken advantage of by rational investors, therefore pushing prices further away from fundamentals.

Secondly, the literature has so far defined consistent past performance using past returns, earnings announcements, sales growth and other accounting data. All these (with the exception of returns) are scheduled announcements implying that investors may be better prepared in forming expectations and have planned actions in the case of good or bad news. On the contrary, investors are unaware on the timing of unscheduled announcements, which could result in a different overall behavior. Furthermore, credit rating agencies act as information intermediaries and consolidate all information (business and financial risk) available in the public (and private information when it comes to issuer-paid rating agencies) into a single letter rating which is easily comprehensible by market participants. By using both quantitative and qualitative analysis, bond ratings provide a means of identifying the credit default risk of a bond or moreover the probability of a company meeting its financial obligations. While looking at profitability or other accounting measures is valuable information for a company, the important role of credit rating agencies are to reduce information asymmetries and provide credit relevant information to the market domain by combining all company related information.

We use the universe of credit rating and outlook/watchlist announcements to construct samples of sequences of positive (i.e., upgrades) and negative (i.e., downgrades) news within one year, by concentrating on the seven Nationally Recognized Statistical Research Organizations (NRSROs) (Fitch, Moody's, Standard & Poor's – S&P, Egan-Jones Rating Agency - EJR, Dominion Bond Rating Services – DBRS, AM Best – AMB and Kroll Bond Rating Agency - KBR) that rate US corporate bonds. A sequence of positive (negative) news is defined as companies being upgraded (downgraded) in more than 1 quarter within one year without having any downgrades (upgrades) in the duration of the sequence.

Results show that for all the time periods observed, there is a strong statistical significant reversal observed in the negative news portfolio. The CARs for the negative news portfolio increase during the first 6 months of post formation period with a slight decrease thereafter (all significant at the 1% level). Specifically, the mean CARs for sequences of negative news are 2.119%, 3.198%, 3.074% and 2.440% at 3, 6, 9, and 12 months after portfolio formation. These results are consistent with our hypothesis and asymmetry between future performance for sequences of negative and positive news argument of De Bondt and Thaler (1985). We further exploit post performance by implementing a strategy of buying bonds with consistent past negative news and selling bonds with consistent past positive news (equally weighted portfolios). Results indicate that for all the time points explored, the negative news portfolio seems to outperform the positive news portfolio (at the 1% level) by a range of 1.826% (3 months) to 3.478% (9 months).

If investors are prone to the representativeness bias, then we would expect the overreaction effect to be more prevalent as the number of credit rating announcements in the sequence increases. We therefore also investigate whether bonds with negative information in the past outperform at a higher magnitude bonds with positive information as the number of announcements increases. Overall, results seem to be consistent with our hypothesis; that is, the magnitude of the reversal in the sample of negative news increases as the number of quarters with negative credit rating announcements increases. At 3 months after portfolio formation, the mean reversal is 1.499%, 2.941% and 4.946% (all statistically significant at the 1% level) for 2, 3 and 4 and above quarters with negative credit rating announcements.

The remainder of the paper is organized as follows. Section 3.2 discusses the literature. Section 3.3 develops the hypothesis. Section 3.4 presents the empirical set-up constructed to test our hypotheses. Section 3.5 describes the data. Section 3.6 presents the results. Section 3.7 concludes.

3.2 Representativeness bias: Definition and literature review

The representativeness bias, which is extensively described in Tversky and Kahneman (1974), refers to the probability that one assigns to an uncertain event being influenced by prior information. The representativeness bias states that one gives more weight to recent information based on past experience, thus implying that past experience is an indication of the future performance of a company. Given a string of positive/negative news (public signals), an investor may fail to realize that these follow a random walk and observe trends in random sequences of events. Based on a small sample (of consecutive positive/negative news), an investor categorizes a firm as a trending firm, thus overestimating the probability of subsequent positive/negative news, extrapolating past performance too far into the future resulting in an overreaction. Eventually, investors will disconfirm the probability of this trending regime, which will result in a mean reversal. Barberis et al. (1998)[97,98] give a thorough description on this type of behavioral bias who present a model on investor sentiment on how an investor forms beliefs given a string of consistent positive/negative news, justifying their model in the context of earnings surprises.

One of the earliest studies, which empirically tested the overreaction hypothesis described above, is by De Bondt and Thaler (1985), pioneers in the field of behavioral finance and economics. By creating portfolios based on past good and bad performance (using returns) in the previous five years, the authors provide evidence of losers outperforming winners in the long term by about 8% annually. The reversal effect was asymmetric, meaning that reversal was much higher in magnitude for losers compared to winners, while the returns in January were much larger compared to the rest of the months. In a follow up paper (De Bondt and Thaler, 1987), in conjunction with previous results, the authors provide further evidence of the overreaction hypothesis by rejecting two alternative ones; possible differences in size and risk of companies between the two portfolios.

The work of these two authors did not go unnoticed in the academic literature, while they have received criticism by another school of thought. Certain researchers have suggested other alternatives to the difference in returns between the two portfolios, namely size and risk. An example is by Ball and Kothari (1989); the authors argued that the difference in the performance between the two portfolios comes from changes in their leverage. Intuitively, during the formation period (i.e., past returns to construct winners and losers portfolios), a series

[97] Other behavioral models have also been developed with the aim of explaining the mispricing that could occur in financial markets. One such model is by Daniel et al. (1998) where authors present a model of underreaction and overreaction using the concepts of overconfidence and self-attribution. The behavior of investors is based both on private and public signals. Hong and Stein (1999) argue that overreaction and underreaction emerges from the interaction of "momentum traders" and "news watchers" which results in initial momentum and subsequently return reversals. Although we acknowledge the fact that mispricing could be due to other behavioral biases as well, we cannot empirically test possible implications without the knowledge of private information.

[98] Similar to the representativeness bias is the "law of small numbers" which is described and modelled in Rabin (2002).

of negative returns (loser portfolio) would imply that the equity beta of those companies increased resulting in an increase in the expected return (assuming that asset and debt beta remain relatively the same). The authors provide evidence of differences in equity betas after the formation period. Furthermore, Zarowin (1990) argued that when losers and winners of the same size are compared, there is no evidence of overreaction.

The debate between alternative explanations that result in return predictability in the long-term prompted researchers for further investigation. Two papers by Chopra et al. (1992) and Lakonishok et al. (1994) provided further evidence of overreaction effects when comparing extreme losers with winners. Chopra et al. (1992), find that, based on five-year past return performance, losers outperform winners by 5-10% during the next five years while adjusting for possible size and beta risk. Effects are stronger for smaller companies. Stronger return patterns are observed in January compared to the rest of the months of the year; however, authors argue that this is not a manifestation of tax-loss selling effects. Furthermore, Lakonishok et al. (1994) revisited the well-known phenomenon of value stocks outperforming glamour stocks in the long-run and try to explain this by testing two possible scenarios. Firstly, they relate this to their overall performance in the past. Their argument is that glamour stocks are stocks which have performed well in the past, so investors expect that they will keep on trending thus extrapolating past performance too far into the future. On the other hand, value stocks are the ones which have been performing poorly in the past thus investors extrapolating in the opposite direction. The alternative scenario is that value stocks are riskier than glamour stocks. The authors define past performance using sales growth, earnings and cash flows and evidence supports the first scenario. Value stocks outperform glamour stocks on average 10-11% per year and results remain qualitatively the same after adjusting for size (effect for both large and small companies).

Fama (1998) scrutinized the work done on long-term market anomalies and attributed these to chance and not an opposition to the market efficient hypothesis as overreaction effects are as common as underreaction effects. Furthermore, he disputes that a lot of the evidence documented as being sensitive to the method used for calculating abnormal returns, which could disappear when properly addressed. He gives however credit to two models developed, namely the models by Barberis et al. (1998) and Daniel et al. (1998), in the sense that they describe well the behavioral biases they attempt to describe but cannot be generalizable to any others. In addition, Brav and Heaton (2002) discuss the two sets of theories that researchers have developed in order to explain why we observe evidence against the traditional finance models. One is based on behavioral finance theories which relax the assumption of investor rationality while the other one is based on the fact that investors may not be fully aware or understand the fundamental structure of the economy. After giving a thorough description, the authors conclude that it is sometimes difficult to differentiate between the two even though the assumptions differ.

A few more empirical studies have emerged since then, with contradicting evidence as to the overreaction effect due to the representativeness bias. Chan and Lakonishok (2004) construct portfolios of value versus growth stocks and address the various explanations that have been debated in the literature so far using an expanded sample both in terms of time period covered and by looking at international markets. Results are indicative of investors extrapolating past performance rather than differences in the riskiness of the two portfolios. Chan et al. (2004) however, use various past performance measures (earnings announcements, growth sales, net income and operating income) to test the representativeness bias with no evidence of mispricing. Lastly, Frieder (2008) tests whether small investors extrapolate past trends in earnings performance. The author provides evidence of small traders increasing their net buying behavior as the number of consecutive positive earnings surprises increases while net buying behavior is negatively correlated with future returns.

3.3 <u>Hypothesis development</u>

The complexity of financial markets and the abundant number of factors that could influence a company's valuation poses sometimes difficulties in testing the validity of models developed. It is therefore crucial that these are tested using out-of-sample data, ideally for several time periods and markets (as to avoid the possibility of data mining). The overreaction effect has been tested empirically since the 1980s. Even though there is an overall consensus as to the existence of return predictability, the reasoning behind this effect remains controversial and is widely debated in the academic literature. Up to date, there have been only a few articles which have tested the overreaction effect empirically, making it essential that more research is conducted on this.

In this study, we reevaluate the mispricing effects of companies using consistent patterns of same sign credit rating signals by concentrating on corporate bonds. In the context of type of market used in previous studies, all related work concentrated on the equity market. Contrary to the rest of the studies who have concentrated on stocks, we focus on US corporate bond performance. Hirhsleifer (2001) comments that since there is a higher magnitude of overreaction effect in small companies, this may imply that you would observe greater effects in illiquid markets. Since the bond market is considered to be in general less liquid compared to the equity market, one would expect to observe overreaction effects in the bond market following the logic of Hirshleifer (2001). Secondly, the literature has so far defined consistent past performance using past returns, earnings announcements, sales growth and other accounting data. All these (with the exception of returns) are scheduled announcements implying that investors may be better prepared in forming expectations and have planned actions in the case of good or bad news. On the contrary, investors are unaware on the timing of unscheduled announcements, which could result in a different overall behavior[99]. Therefore, our hypothesis is that given the evidence provided so far for the equity market, we would expect to observe an overreaction effect in the corporate bond market as well.

Hypothesis 1: Following a string of same sign credit rating announcements, bonds will experience a return reversal.

Assuming an overreaction effect has been established, the representativeness bias also implies that the longer the string of consecutive negative/positive announcements about a company, the higher the probability of investors categorizing a company as a trending company (Chan et al., 2004). Therefore, the magnitude of the reversal observed would be expected to increase as the number of consecutive positive/negative announcements increase. This leads us to the second hypothesis.

[99] On a further note, Antweiler and Frank (2006) study the reaction in the stock market for several types of corporate announcements. While for earnings announcements the authors observe a price drift effect, for credit rating downgrades, an overreaction effect is observed.

Hypothesis 2: The magnitude of the return reversal will increase as the number of same sign announcements increases.

3.4 <u>Methodology</u>

3.4.1 Construction of strings of consecutive same sign credit rating announcements

We use the universe of NRSROs (Fitch, Moody's, S&P, EJR, DBRS, AMB, KBR) credit rating upgrades and downgrades to construct our sample of a string of same sign credit rating signals. We obtain actions in ratings, outlooks and watchlist inclusions/exclusions from various sources; for the big three issuer-paid credit rating agencies (CRAs) (Fitch, Moody's and S&P) we obtain data from Mergent Fixed Income Securities Database (MFISD) and for the rest (DBRS, AMB, KBRS and EJR) from the CRAs' websites[100].

The formation of a string of downgrade and upgrade credit rating announcements in our study differs compared to other measures used so far in the literature for two reasons. Firstly, a company may be rated by more than one CRA. Therefore, two CRAs rating the same company within a few days may not necessarily imply that the company had a string of two downgrades but just that the two credit rating announcements were based on the same information for the company. We address this by observing whether there has been a downgrade or an upgrade during a quarter. If there has been more than one credit rating announcement in the same direction (downgrade or upgrade) within a quarter, we consider them as one event in the sequence of same sign credit rating announcements, regardless of whether multiple rating announcements during a quarter may be based on new information about a company or not. As an example, consider two scenarios where we observe at least one downgrade during quarters one and two of 2010. In the first scenario, there is one downgrade in each quarter and in the second, there are is one downgrade in quarter one and two downgrades in quarter two. For both scenarios, then number of downgrades in this string of downgrades would be two.

100 We would like to acknowledge the support of Egan-Jones Ratings for providing us access to their website thus retrieving data since 1999.

Secondly, credit rating announcements are unscheduled events as opposed to earnings announcements or other disclosure of financial information. Thus, the timing or frequency of announcements during a year could vary. As such, we define a string of upgrades (downgrades) as having at least an upgrade (downgrade) in at least two quarters, without necessarily implying that these are consecutive quarters. As an example, consider the following two scenarios; (i) a set of downgrades during the first quarter of 2010 and then one more downgrade during the second quarter of 2010 and (ii) a set of downgrades during the first quarter of 2010 and then one more downgrade in the third quarter of 2010. For both scenarios, this would be defined as a string of two downgrades. For strings of upgrades (downgrades) created, there is no downgrade (upgrade) during the time between the first and the last rating that is used in creating a sequence of good (bad) performance[101].

3.4.2 Corporate bond returns

The results reported throughout this study are cumulative monthly abnormal returns up to a year after a string of same sign credit rating announcements using TRACE enhanced (TRACE thereafter). To clean the TRACE sample, we follow Asquith et al. (2013) and Dick-Nielsen (2014)[102]. In particular, observations were deleted from the original sample because of the following reasons: (a) unavailable 9-digit CUSIP and par value volume of transaction; (b) chain of observations that resulted in a cancellation; (c) chain of observations that resulted in a correction (kept only latest observation); (d) reversals (with matched initial trades); (e) delayed reversals and delayed dissemination; (f) transactions where date occurred before offering or after maturity date of the bond[103]. For end-of-month price, we use the last available monthly price within the last 15 days of the month.

[101] We ignore the fact that affirmations could occur during a sequence of upgrades (downgrades) for the sole reason that there isn't a big enough sample to perform all the analyses for all hypotheses tested in this study (if affirmations are not ignored). For the first hypothesis where we have a sufficient number of observations, the results are qualitatively the same (not reported).

[102] Data structure of TRACE has changed since February 2012. Asquith et al. (2013) use data up until December 2006. In order to incorporate all data cleaning procedures for our sample, it was deemed appropriate to follow data cleaning process from both authors.

[103] Data for offering and maturity date were obtained from MFISD.

We employ the method suggested by Bessembinder (2009) (trade-weighted price, trades>=100,000, firm level approach[104] for companies with multiple bonds). Specifically, monthly abnormal return[105] is computed as follows

$$AR_t = return\ of\ bond\ of\ interest_t - expected\ return\ of\ matching\ portfolio_t$$

$$AR_t = \frac{(P_{t+1}+AI_{t+1})-(P_t+AI_t)}{(P_t+AI_t)} - \ expected\ return\ of\ matching\ portfolio_t \qquad (3)$$

where P_t= price at time *t*

AI_t= accrued interest[106] at time *t*

$expected\ return\ of\ matching\ portfolio_t$= average return of bonds within the same rating/maturity group

It is well known in the literature that when it comes to bonds, risk factors such as default risk and time-to-maturity result in differing variability in bond return reactions. Thus, we adjust for this by using a matching portfolio when computing the average expected return of matching portfolio based on seven rating groups (S&P rating categories AAA, AA, A, BBB, BB, B, CCC and below and the corresponding rating categories for the rest of credit rating agencies[107]) and three time-to maturity groups (0 up to but excluding 5 years, 5 up to but excluding 10 years, 10 years and above).

[104] For events in which there have been transactions for more than one bond within the same company, a market value weighted average abnormal return was computed.
[105] Following Bessembinder et al. (2009), we exclude cases where absolute value of return is greater than 20%.
[106] Data for computing accrued interest, like coupon payment frequency, are obtained from MFISD.
[107] To account for the fact that bonds may be rated by more than one credit rating agency, the average rating was used across all CRAs which rate the company of interest, i.e. for CRAs that have rated companies within one year of the date of interest.

3.5 Sample and descriptive statistics

Our sample for the analysis of this study spans the time period July 2002 to September 2013, which is the common time period between data sources used[108]. As described in the methodology section, for the formation of strings of good and bad news, we use the universe of the seven NRSROs (Fitch, Moody's, S&P, EJR, DBRS, AMB, KBR) which rate US corporate bonds, to construct a sample of same sign credit rating announcements. We utilize a "stricter" version for the number of negative (positive) news' signals in the sense that we combine all downgrades (upgrades) within one quarter and consider this set of news as one in forming the number of quarters with negative (positive) credit rating signals. Bond prices data are obtained from TRACE, in which we compute abnormal returns up to one year after formation period. We exclude sequences where there has been both an upgrade and a downgrade on the same day in any of rating announcement dates during a sequence of same sign news announcements. We also restrict the total duration of the sequence (formation period) up to one year and keep events where there have been at least two quarters with same sign news announcements during a sequence. Furthermore, we concentrate on actively traded bonds, that is, on bonds where there are prices available during the month of the last rating announcement in a sequence of events as well as at least one price available in the months following the sequence formation. Lastly, we delete sequences of events if any rating announcement in a sequence of events occurred during recession (December 2007 – June 2009) as to observe post formation returns for events during expansion period only without the possible effect of reversal arising from a different behavior during recession times.

The final sample comprises 839 sequences, in which 418 are sequences of negative news and 421 sequences of positive news. The rating distribution at the final rating announcement in the sequence is presented in table 3.1. For investment grade bonds, there is a higher percentage in the positive news sequences compared to the negative news one. Specifically, for the negative news sequences, around 51% are at investment grade level at the end of the sequence while for the positive news this corresponds to around 58%. For non-investment grade bonds, the negative news sequences seem to consist of a substantially higher percentage of the rating group "CCC

[108] Rating announcements for Fitch, Moody's S&P, EJR are available since the beginning of our sample period. Data for DBRS are available since 27/02/2003, for AMB since 03/03/2005, and KBR since 11/02/2008, which are the dates in which each CRA has become a NRSRO.

and below" compared to positive news sequences[109]. Out of negative news sequences, 30 (22, 4 and 4 in rating group BB, B and CCC and below respectively) resulted in a switch from investment to non-investment grade bonds in the duration of the sequence, while 18 (in BBB rating group) switched from non-investment to investment grade bonds in the positive news sequences.

[Insert Table 3.1]

Table 3.2 summarizes bond characteristics split by negative and positive sequences of news. The two groups of sequences are similarly distributed. The mean (median) total debt (in amount outstanding) is around 2.4 (0.8) and 2.4 (0.9) million for the negative and positive news sequences of events respectively. The average age (maturity) is 3.7 (8.0) and 3.8 (8.0) years for negative and positive news respectively.

[Insert Table 3.2]

Furthermore, table 3.3 provides summary statistics on the overall sequences for each of negative and positive sets of news. We restrict our formation period of sequences of events up to one year. The distribution of the time within sequences and time between ratings is reported in months. For most events, there is a slightly higher time within sequences observed in negative news compared to positive news (around half a month). The time between rating within sequences is on the average higher for positive news compared to negative news; specifically, the average time between rating within a sequence is 3.9 and 4.1 months for the negative and positive news respectively. As described in section 3.4.1, in forming sequences of same sign news announcements, we look at credit rating announcements at the quarterly level and indicate whether there has been a rating announcement during a quarter regardless of whether within a quarter we could have more than one announcement. The total number of quarters of negative and positive news are almost identical with a slight difference in their means (2.4 and 2.3 months in negative and positive news respectively). The total number of rating announcements within a sequence ranges between 2 to 12 and 2 to 8 in the negative and positive news group respectively. The median number of events is 3 (2) for negative (positive) news. The last variable in table 3.3 shows the total number of notches that a bond has been

[109] Results are qualitatively the same if we remove from the analysis the rating group "CCC and below".

downgraded/upgraded to during the sequence. The computation of the number of notches is determined by comparing the average rating between all CRAs rating a specific bond just before the first rating signal in the sequence and the last average rating at the end of the sequence[110]. The average (median) change in notches within sequences is -1.5 (-1.0) for negative news and 1.0 (1.0) for positive news[111].

[Insert Table 3.3]

3.6 <u>Results</u>

3.6.1 Does the bond market experience return reversals after a sequence of same sign credit news announcements?

The representativeness bias implies that after a sequence of negative (positive) news, investors will become overly pessimistic (optimistic) about future performance and will therefore extrapolate too far into the future. This in turn will lead to a reversal when expectations are not confirmed, resulting in an outperformance for companies with consistent past negative news and underperformance for ones with consistent past positive news.

The results are presented in table 3.4. Future performance (cumulative abnormal returns) for each portfolio is calculated for 3, 6, 9 and 12 months after formation period (given as a percentage) along with their associated p-value. Events where there has been an upgrade or downgrade during the future performance time period investigated is excluded from analysis (i.e. for 3-month cumulative abnormal returns, we delete cases where there has been an upgrade (downgrade) for negative (positive) news during the 3-month period, whereas for 6-month cumulative abnormal returns, we delete cases where there has been a downgrade/upgrade during the 6-month period). We thus expect the sample size to decrease as the future performance time

[110] Rating announcements are given integer values for their ratings (1 for AAA, 2 for AA+, 3 for AA, 4 for AA-, 5 for A+, 6 for A, 7 for A-, 8 for BBB+, 9 for BBB, 10 for BBB-, 11 for BB+, 12 for BB, 13 for BB-, 14 for B+, 15 for B, 16 for B-, 17 for CCC+, 18 for CCC, 19 for CCC-, 20 for CC, 21 for C and 22 for D and the corresponding rating categories for the rest of credit rating agencies). Consider a bond which is rated by one CRA only. If the CRA downgrades a bond from A+ to A, then this would result in a change of -1 notches. If the CRA downgrades a bond from A+ to A with a negative outlook, then this would result in a change of -1.5 notches.

[111] There is one case in which a series of downgrades results in an increase in average rating. For the negative news sample, this is due to the fact that in the duration of a sequence, an additional CRA started rating the specific bond with a higher rating compared to the rest CRAs, resulting in a higher average at the end of the sequence.

window increases. Results show that for all the time periods observed, there is a strong statistical significant reversal observed in the negative news portfolio. The CARs for the negative news portfolio increase during the first 6 months of post formation period with a slight decrease thereafter (all significant at the 1% level). Specifically, the mean CARs for sequences of negative news are 2.119%, 3.198%, 3.074% and 2.440% at 3, 6, 9, and 12 months after portfolio formation. A similar trend (in the opposite direction) is observed for the set of positive news with results not being statistically significant however. The results for negative news lend the support of our hypothesis or otherwise called winner-loser effect and asymmetry between future performance for sequences of negative and positive news argument of De Bondt and Thaler (1985). We further exploit post performance by implementing a strategy of buying bonds with consistent past negative news and selling bonds with consistent past positive news (equally weighted portfolios). Results indicate that for all the time points explored, the negative news portfolio seems to outperform the positive news portfolio (at the 1% level) by a range of 1.826% (3 months) to 3.478% (9 months)[112].

[Insert Table 3.4]

3.6.2 Does the magnitude of the return reversal increase as the number of quarters with negative/positive announcements increase?

In the previous section, we have provided evidence of statistically and economically significant results consistent with reversals following a period of negative news announcements. The representativeness bias, implies that the longer the string of negative/positive news, the higher the probability of investors categorizing a company as a trending company after a set of same sign news announcements. We therefore further exploit whether overreaction effects could be explained by the representativeness bias by splitting our sample into subgroups of how many quarters we observe a sequence of same sign news announcements. Consistent with the representativeness bias, we would expect a higher magnitude of the winner-loss effect with a

[112] Reversal in market reactions was also tested for sequences of negative (positive) signals without conditioning on whether there haven't been other upgrades (downgrades) in post formation period. The results were qualitatively the same and are thus not reported.

higher number of quarters with negative/positive credit rating announcements, which would be a test for our second hypothesis.

The results are shown on table 3.5. CARs are computed for 3, 6, 9 and 12 months after formation period for 2, 3 and 4 and above quarters of same sign credit rating announcements. Due to sample size restrictions, we do not perform any further partitioning for cases where the number of quarters with same sign news announcements is greater than four. Overall, results seem to be consistent with our hypothesis; that is, the magnitude of the reversal in the sample of negative news increases as the number of quarters with negative credit rating announcements increases. Consider the sample of events 3 months after portfolio formation. The mean reversal is 1.499%, 2.941% and 4.946% (statistically significant at the 1% and 5% level) for 2, 3 and 4 and above quarters with negative credit rating announcements[113].

Similarly, consider a strategy of buying bonds with a string of negatives news announcements and selling bonds with a string of positive news announcements. At 6-month post formation period, we observe statistically significant results for all three subgroups, i.e. 2, 3 and 4 and above quarters of same sign credit rating announcements. At the 1% level (10% for 4 quarters and above group), we provide evidence of positive returns (following the strategy described) of 2.540%, 5.228% and 13.989% for 2, 3 and 4 and above quarters respectively. For all post formation periods tested (except at 12 months), the magnitude of the returns has the highest value for the sample of at least 4 quarters of same sign news announcements.

[Insert Table 3.5]

As a robustness check, we also investigate whether results are consistent with overreaction effects by looking at the number of notches a rated bond has decreased (increased) given a set of negative (positive) credit rating announcements. One could interpret the change in the number of notches as an overall outcome following a string of same sign news announcements. In this scenario, one may expect that investors would become more pessimistic if the overall decrease in the number of notches during a sequence is higher compared to sequences with a smaller overall change in rating (i.e. smaller change of number of notches).

[113] The sample for 4 quarters and above is small and could be subject to power issues. When allowing the formation period to increase up to two years (i.e., resulting in a larger sample size), the magnitude of the reversal is statistically significant for 6 and 9 months (higher magnitude compared to events with 2 or 3 quarters with negative announcements).

We therefore partition each portfolio of same sign news announcements into two subgroups; (i) negative (positive) news announcements that resulted in a decrease (increase) on average of at most one notch ("≤ 1" group thereafter)[114], (ii) negative (positive) news announcements that resulted in a decrease (increase) on average of more than one notch ("> 1" group thereafter). CARs for several time periods are reported in table 3.6. The overall trend is similar to the one described when looking at the whole sample (table 3.4). For all post formation periods tested, the mean CAR reversal in negative news portfolio for the ">1" group is greater compared to the "<=1" sample of sequences. The mean reversal ranges between 0.947% and 1.745% after sequences of negative news for the "<=1" group while for the ">1" group the mean CARs range between 3.920% and 5.363%. All results described are statistically significant. In addition, we also observe a mean reversal for sequences of positive news for the "<=1" group 9 months post formation period. The magnitude of the reversal is lower compared to the sequences of negative credit rating announcements; -1.247% for 9 months post formation period (significant at 10% level).

Furthermore, the sample of negative news announcements outperforms the sample of positive ones for all post formation time periods tested for both (i) and (ii). For the "≤ 1" group, the CAR values for the difference in abnormal returns between the sequences of negative and positive news announcements range between 1.221% and 2.863%, while for the "> 1" group CAR values range between 3.697% and 5.261%. For all time periods tested, the magnitude of the "> 1" group is higher compared to the "≤ 1" group; an indication consistent with a higher overreaction effect for sequences which resulted in a greater change in default risk.

[Insert Table 3.6]

3.7 <u>Conclusions</u>

Researchers are constantly trying to investigate whether market anomalies exist in capital markets and suggest several possible explanations when detecting these. Whether the

[114] There are cases where there is a change of 0.5 notches. These are the cases with outlooks/watchlist inclusions. If for example a company is rated as AA and there is a rating announcement for the specific company with a rating AA and negative outlook then this would be considered as a downgrade of 0.5 notches.

reasons behind market inconsistencies are due to specific companies' fundamentals, behavioral biases, or regulatory constraints are still debatable in the academic literature. The aim of this study is to investigate whether overreaction effects could be due to the representativeness bias. Using sequences of negative and positive news announcements (credit rating announcements), we observe whether investors become overly pessimistic (optimistic) about a company's future performance (using bond performance), which would subsequently lead in return reversals.

Initial results indicate that strings of negative news announcements outperform strings of positive news announcements up to a year after formation period. Results are indicative of a strong statistical significant reversal observed in the negative news portfolio. The CARs for the negative news portfolio increase during the first 6 months of post formation period with a slight decrease thereafter.

Consistent with the representativeness bias, companies with a higher level of bad news announcements, either in the context of the number of credit rating downgrades or the number of notches a bond has been downgraded to during a sequence of same sign news announcements, result in a higher return reversal. When splitting our sample by number notches with negative/positive set of news, results are consistent with our hypothesis; as the number of bad information released in the market (i.e., larger change in number of notches), the magnitude of the reversal effect increases as well.

Table 3.1: Distribution of bond ratings by portfolio

Frequency and percentage distribution of ratings for negative and positive news portfolios, for the time period July 2002 to September 2013. The universe of the seven NRSROs (Fitch, Moody's, S&P, EJR, DBRS, AMB, KBR) is used to construct a sample of consecutive same sign credit rating announcements. The rating observed is the rating at the last credit rating announcement in the sequence. To account for the fact that companies may be rated by more than one credit rating agency, the average rating was used across all NRSROs which rate the company of interest.

	Negative News	**Positive News**
Rating group	**N (%)**	**N (%)**
AA	12(2.9%)	22(5.2%)
A	81(19.4%)	95(22.6%)
BBB	119(28.5%)	128(30.4%)
BB	65(15.6%)	78(18.5%)
B	68(16.3%)	77(18.3%)
CCC (& below)	73(17.5%)	21(5.0%)
Total	**418**	**421**

Table 3.2: Summary statistics of bond characteristics

This table reports summary statistics for bonds in negative and positive news portfolios, for the time period July 2002 to September 2013. The summaries provided are for the last credit rating announcement in the sequence. Age and maturity are reported in years. Amount outstanding (provided by MFISD) assumes a par value of $1,000. For events where trades from more than one bond for a specific company occur, the average age, maturity and total debt is reported.

Variable	Portfolio	N	Minimum	P25	P50	Mean	P75	Maximum
Debt (amount	Negative News	418	33,112	350,000	800,000	2,416,684	2,229,000	76,120,797
outstanding)	Positive News	421	20,000	400,000	900,000	2,359,997	2,000,000	78,128,342
Age	Negative News	418	0.121	1.693	2.860	3.684	4.741	34.652
(years)	Positive News	421	0.085	1.770	3.263	3.790	4.918	18.274
Maturity	Negative News	418	0.214	4.449	6.589	7.983	9.672	31.564
(years)	Positive News	421	0.088	4.368	6.403	7.954	10.084	57.581

Table 3.3: Summary statistics of sequences of events

This table reports summary statistics of sequences of events in negative and positive news portfolios, for the time period July 2002 to September 2013. The summaries provided are for duration of the sequence formation. Time between first and last rating in sequence is reported in months. The number of quarters refers to the number of quarters where at least one downgrade (upgrade) was reported by at least one CRA within a sequence. The total number of events refers to the total number of downgrades/upgrades reported within a sequence of negative (positive) news. The number of notches reports the change in number of notches between average rating before the first downgrade/upgrade in a sequence and the last one.

Variable	Portfolio	N	Minimum	P25	P50	Mean	P75	Maximum
Time within sequence (months)	Negative News	418	0.099	3.781	6.148	6.378	9.107	11.967
	Positive News	421	0.066	3.255	5.523	5.877	8.515	12.000
Time between ratings (months)	Negative News	418	0.099	1.940	3.293	3.863	5.063	11.967
	Positive News	421	0.033	2.252	3.452	4.132	5.490	12.000
Number of quarters	Negative News	418	2.000	2.000	2.000	2.402	3.000	4.000
	Positive News	421	2.000	2.000	2.000	2.252	2.000	4.000
Total number of events	Negative News	418	2.000	2.000	3.000	3.189	4.000	12.000
	Positive News	421	2.000	2.000	2.000	2.637	3.000	8.000
Number of notches	Negative News	418	-12.500	-2.000	-1.000	-1.499	-0.500	0.500
	Positive News	421	0.000	0.500	1.000	0.964	1.000	5.000

Table 3.4: Differences in cumulative abnormal returns (CARs) for sequences of negative (downgrades) and positive (upgrades) news

This table presents t-test results for CARs (in percentage points) for negative and positive news portfolios as well as their differences (equally weighted portfolios) over several time periods (3, 6, 9 and 12 months) after formation period of sequences (for the time period July 2002 to September 2013). *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively. P-values are shown below mean CARs in italics.

	3 months			**6 months**			**9 months**			**12 months**		
Portfolio	**N**	**Mean (%)**	**Sig**	**N**	**Mean (%)**	**Sig**	**N**	**Mean (%)**	**Sig**	**N**	**Mean (%)**	**Sig**
Negative News	357	2.119	***	347	3.198	***	338	3.074	***	333	2.440	***
		0.000			*0.000*			*0.000*			*0.006*	
Positive News	362	-0.144		351	-0.492		345	-0.793		344	-0.134	
		0.646			*0.274*			*0.192*			*0.847*	
Difference		1.826	***		3.174	***		3.478	***		3.143	***
		0.002			*0.000*			*0.001*			*0.005*	

Table 3.5: Differences in cumulative abnormal returns (CARs) for sequences of negative (downgrades) and positive (upgrades) news, split by number of quarters with negative/positive credit rating announcements

This table presents t-test results for CARs (in percentage points) for negative and positive news portfolios as well as their differences (equally weighted portfolios) over several time periods (3, 6, 9 and 12 months) after formation period of sequences (for the time period July 2002 to September 2013), split by the number of quarters with negative/positive credit rating announcements during formation period. *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively. P-values are shown below mean CARs in italics.

		3 months			6 months			9 months			12 months		
Portfolio	**Quarters**	**N**	**Mean (%)**	**Sig**	**N**	**Mean (%)**	**Sig**	**N**	**Mean (%)**	**Sig**	**N**	**Mean (%)**	**Sig**
Negative News	2	241	1.499	***	234	2.076	***	228	1.929	**	225	1.275	
			0.002			*0.001*			*0.028*			*0.207*	
Positive News	2	282	-0.030		274	-0.465		268	-1.101		268	-0.439	
			0.932			*0.342*			*0.107*			*0.584*	
Difference	2		1.529	**		2.540	***		3.030	***		1.715	
			0.010			*0.002*			*0.006*			*0.178*	
Negative News	3	89	2.941	***	87	5.568	***	85	5.356	***	83	4.882	**
			0.009			*0.000*			*0.002*			*0.018*	
Positive News	3	70	-0.243		69	0.340		69	1.056		68	1.192	
			0.712			*0.702*			*0.451*			*0.430*	
Difference	3		3.184	**		5.228	***		4.301	*		3.689	
			0.015			*0.001*			*0.051*			*0.146*	
Negative News	4	27	4.946	**	26	5.372		25	5.762		25	4.818	
			0.037			*0.118*			*0.121*			*0.181*	
Positive News	4	10	-2.668		8	-8.617		8	-6.401		8	-1.179	
			0.470			*0.257*			*0.154*			*0.696*	
Difference	4		7.614	*		13.989	*		12.164	**		5.998	
			0.087			*0.099*			*0.036*			*0.198*	

Table 3.6: Differences in cumulative abnormal returns (CARs) for sequences of negative (downgrades) and positive (upgrades) news, split by average change in number of notches during a sequence

This table presents t-test results for CARs (in percentage points) for negative and positive news portfolios as well as their differences (equally weighted portfolios) over several time periods (3, 6, 9 and 12 months) after formation period of sequences (for the time period July 2002 to September 2013), split by average change in number of notches during a sequence. *, ** and *** represent the statistical significance at the 10%, 5% and 1% respectively. P-values are shown below mean CARs in italics.

		3 months			6 months			9 months			12 months		
Portfolio	**Notches**	**N**	**Mean (%)**	**Sig**	**N**	**Mean (%)**	**Sig**	**N**	**Mean (%)**	**Sig**	**N**	**Mean (%)**	**Sig**
Negative News	<=1	217	0.947	**	208	1.745	***	200	1.616	**	197	1.186	
			0.024			*0.001*			*0.014*			*0.141*	
Positive News	<=1	264	-0.274		257	-0.704		252	-1.247	*	251	-0.602	
			0.390			*0.134*			*0.067*			*0.460*	
Difference	<=1		1.221	**		2.449	***		2.863	***		1.789	
			0.018			*0.001*			*0.003*			*0.118*	
Negative News	>1	139	3.920	***	138	5.363	***	137	5.178	***	135	4.238	**
			0.000			*0.000*			*0.002*			*0.023*	
Positive News	>1	97	0.223		93	0.102		92	0.460		92	1.157	
			0.777			*0.926*			*0.727*			*0.388*	
Difference	>1		3.697	***		5.261	***		4.718	**		3.081	
			0.003			*0.002*			*0.026*			*0.178*	

Conclusions

Over the last few decades, there has been a vast amount of literature investigating the existence of market anomalies and how much the behavior of investors deviates from the expected ones under traditional finance theories. This had led in the evolvement of behavioral finance. The importance of investigating whether behavioral biases exist lies in the possible price distortion effects that could result in prices being pushed away from fundamentals.

The aim of this thesis is to explore two behavioral biases; namely limited attention and representativeness biases. By exploring the US corporate bond market, the aim of the dissertation is to investigate whether investors are prone to these biases and the extent to which institutional investors exert price pressure in bond pricing (when looking at limited attention).

The first chapter investigates whether investors are prone to the limited attention bias and as such, whether there is an overall price impact in the US corporate bond market when news are being recycled in the public domain. Using a sample of credit rating and outlook announcements that do not provide any new information in the market, there is evidence of a negative abnormal price reaction when it comes to downgrades, which is indicative to investors reacting towards the signal of the credit rating action without realizing the informativeness of this rating action. Furthermore, the relationship between abnormal returns and institutional trading is observed, with results being indicative of a contemporaneous relationship between their buy-sell imbalance and abnormal returns, suggesting that institutional investors exert a price pressure in bond pricing.

The second chapter focuses on one type of institutional investors, that is insurance companies, to test whether these are prone to the limited attention bias. Insurance companies are currently the largest bondholders in the US corporate bond market, holding around 25-30% of the total volume. With a unique dataset, which provides daily transaction data through the NAIC (National Association of Insurance Commissioners) schedule D, parts 3, 4 and 5, the trading behavior of insurance companies can be tested around a set of uninformative rating actions. Furthermore, insurance companies are a group of institutional investors with a homogeneous regulatory framework. By running panel regression models with fixed effects at the company and year level, there is evidence of insurance companies trading abnormally around uninformative rating actions. There is an overall increase in their trading volume. However, this does not seem to create a price pressure in the US corporate bond market.

The third chapter reevaluates the mispricing effects in an unexplored market, i.e. the corporate bond market, and whether the overreaction effects could be due to representativeness bias. The study concentrates on credit rating agencies, which act as information intermediaries with the aim of reducing information asymmetries, and consolidate all available information into a single letter rating, which is easily comprehensible by market participants. Using the rating, outlook and watchlist announcements, sequences of bad (downgrades) and good (upgrades) performance are formed with the aim of testing whether there are return reversals, by looking at the post formation cumulative abnormal returns. The results are indicative of an overreaction effect; specifically, return reversals are observed up to a year after formation period mainly following a sequence of downgrades.

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APPENDIX

Probabilities of a NAIC designation change

The following appendix describes the process carried out in computing the probabilities of a NAIC designation change given a rating action.

Insurance companies face certain regulatory constraints when it comes to the percentage of non-investment grade bonds they could hold in their portfolios. If there is predictability between a rating action and a subsequent change in the NAIC designation over the near future, then an insurance company may react at a late uninformative mover. Therefore, to control for this in our main panel regression results, we compute marginal probabilities of a NAIC designation change by running Firth logistic models[115].

Our main panel regression results are for the time period [-40, 2] relative to the event date. Therefore, in computing marginal probabilities, we need two different sets; one for the time period [-40,-1], which would indicate the probabilities of a NAIC change from "first to second" mover within 60 trading days and one for the time period [0, 2], which would indicate the probability of a NAIC change from "second to third" mover (as our sample of late mover rating actions consist of second movers) within 60 trading days. The model used for both scenarios is defined as

$$NAIC_i = Upgrade_i + Downgrade_i + Notches_{i,0.5} + Notches_{i,1} + \cdots + Notches_{i,7}$$

where

$NAIC_i$ = 1 if there has been a NAIC change within 60 trading days of the first (second) mover

0 otherwise

$Upgrade_i$ = 1 if the first (second) mover was an upgrade

[115] Firth logistic models were run to compute marginal probabilities due to quasi-complete separation between dependent and independent variables. Refer to https://www3.nd.edu/~rwilliam/stats3/RareEvents.pdf for more information.

0 otherwise

$Downgrade_i$ = 1 if the first (second) mover was a downgrade

0 otherwise

$Notches_{i,j}$ = 1 if the rating action is j notches away from a change in the NAIC designation where $j = 0.5, 1, \ldots, 7$[116]

0 otherwise

Since a bond may be rated by more than one CRA, the number of notches from a NAIC designation change were computed by looking at the bond rating given the rule that is used to convert to a NAIC designation as described in section 2.5. For upgrades (downgrades), notches would represent the number of notches away from a NAIC designation upgrade (downgrade). For affirmations, notches would represent the number of notches away from a NAIC designation upgrade[117]. The union of all rating actions were used (Fitch, Moody's, S&P, EJR, DBRS, AMB, KBR) to create the two samples used in Firth logistic models[118]. For cases where there have been multiple rating actions on the same day in another direction, the whole chain of observations were excluded (first mover, second mover if available, third mover if available). Also, cases were deleted when there has been a rating in a different direction between first and second mover (or second to third mover depending on model) as was done in the main panel regression results. Lastly, cases were excluded where there has been both a NAIC designation upgrade and downgrade within 60 trading days of the first (second) mover.

Following Firth logistic regressions, marginal probabilities were computed and used as an independent variable in the main panel regression models. Table A1.1 provides the marginal probabilities used for each model run (predictability of "first to second" and "second to third"

[116] An example of 0.5 notches would be the distance between a bond with rating BB+ with positive outlook and BBB-.

[117] The same models were run where notches would represent the number of notches away from a NAIC designation downgrade for affirmations, which resulted in qualitatively the same results.

[118] Firth logistic models were also run for two sub-samples; bonds that were traded by insurance companies during the time period of interest as well as bonds that were included in the main panel regression results. Both cases produced qualitatively the same results.

mover), depending on the direction of a rating action and how many notches away a rating is from a change in a NAIC designation[119].

[119] The possibility of informativeness of the TRMIs to the predictability of a change in the NAIC designation was tested by interacting upgrade and downgrade dummy variables with an additional dummy variable having a value of 1 if the rating action was informative (by looking at TRMI cumulative abnormal sentiment) and 0 if not. The interaction effect was not significant for neither upgrade nor downgrade.

Table A1.1: Marginal probabilities for two Firth logistic models showing predictability from "first to second" and "second to third" mover.

This table presents marginal probabilities for two Firth logistic regressions depending on the rating action and the number of notches a bond is away from a change in the NAIC designation. These probabilities are used in the panel regressions of chapter 2. For relative days [-40,-1] of the event, the "first to second" mover model probabilities are used. For relative days [0, 2], the "second to third" mover model is used. There were 40,072 observations in the "first to second" mover model and 10,986 in the "second to third" mover model. Zero notches would indicate a bond rating of AAA for upgrades and affirmations or D for downgrades. For "second to third" mover model, there were no observations with seven notches, therefore a probability of 0 was given.

		Rating action - Probabilities		
Model	**Notches**	**Upgrade**	**Affirmation**	**Downgrade**
1st to 2nd mover	0	0.00266	0.00000	0.00240
1st to 2nd mover	0.5	0.21795	0.00020	0.20077
1st to 2nd mover	1	0.09547	0.00008	0.08687
1st to 2nd mover	1.5	0.08024	0.00006	0.07290
1st to 2nd mover	2	0.02393	0.00002	0.02162
1st to 2nd mover	2.5	0.02156	0.00002	0.01947
1st to 2nd mover	3	0.00994	0.00001	0.00897
1st to 2nd mover	3.5	0.01792	0.00001	0.01618
1st to 2nd mover	4	0.00442	0.00000	0.00399
1st to 2nd mover	4.5	0.00365	0.00000	0.00329
1st to 2nd mover	5	0.00264	0.00000	0.00238
1st to 2nd mover	5.5	0.00324	0.00000	0.00292
1st to 2nd mover	6	0.00080	0.00000	0.00072
1st to 2nd mover	6.5	0.00929	0.00001	0.00838
1st to 2nd mover	7	0.01954	0.00001	0.01765
2nd to 3rd mover	0	0.00330	0.00001	0.00451
2nd to 3rd mover	0.5	0.22446	0.00078	0.28359
2nd to 3rd mover	1	0.07975	0.00023	0.10597
2nd to 3rd mover	1.5	0.06844	0.00020	0.09132
2nd to 3rd mover	2	0.02959	0.00008	0.04004
2nd to 3rd mover	2.5	0.02940	0.00008	0.03978
2nd to 3rd mover	3	0.00421	0.00001	0.00575
2nd to 3rd mover	3.5	0.00494	0.00001	0.00675
2nd to 3rd mover	4	0.00410	0.00001	0.00560
2nd to 3rd mover	4.5	0.01350	0.00004	0.01837
2nd to 3rd mover	5	0.00493	0.00001	0.00673
2nd to 3rd mover	5.5	0.01610	0.00004	0.02189
2nd to 3rd mover	6	0.00478	0.00001	0.00653
2nd to 3rd mover	6.5	0.01576	0.00004	0.02143
2nd to 3rd mover	7	0.00000	0.00000	0.00000