Do Credit Rating Announcements Matter?

Finance Master's thesis Timo Brandstack 2010

Department of Accounting and Finance HELSINGIN KAUPPAKORKEAKOULU HELSINKI SCHOOL OF ECONOMICS Aalto University School of Economics Master's Thesis Timo Brandstack Abstract March 15, 2010

DO CREDIT RATING ANNOUNCEMENTS MATTER?

OBJECTIVES OF THE STUDY

This study has two main objectives: First, it aims to find out how much impact different types of credit rating announcements have on the credit default swap (CDS) market. Second, the study searches for evidence of possible herding behaviour between the major credit rating agencies.

DATA AND METHODOLOGY

Credit rating data comprises of the investment grade level credit rating actions issued by Standard & Poor's, Moody's, and Fitch for U.S. companies included in S&P 500 index at the end of the observation period from January 1, 2000 to June 4, 2009. CDS data consist of 334, 190 spread observations for five-year contracts linked to companies subject to credit rating actions in the credit rating data set. CDS market reactions to credit rating announcements are studied by analysing adjusted spread changes during [-90, 90] day window around the credit rating announcements. Herding behaviour is studied by comparing quantities of rating announcements that closely follow rating actions by other agency to same direction credit quality wise across multiple time windows.

RESULTS

I find that during the whole observation period the CDS market seems to generally anticipate and react to negative rating announcements, whereas positive rating announcements are found in general less significant. Most significant CDS market response is related to negative view watchlist announcement. Moreover, I find CDS market reactions around rating announcements by S&P and Moody's stronger than Fitch's during the whole observation period. However, burst of the credit crisis has increased the significance of Fitch's and Moody's rating announcements simultaneously weakening the impact of S&P's announcements. Considering the market impact, I find that among negative rating announcements, it matters more whether a downgrade is preceded by corresponding watchlist announcement than how many notches the credit rating actually moves.

My herding study results show that among major rating agencies only every fifth rating action occur within [-60, 60] day window around rating action by other agency to same direction credit quality wise, when simultaneously rating a same company. Furthermore, my study finds no specific evidence of herding behaviour between S&P and Moody's. However, there remains a slight possibility that Fitch would be influenced by S&P's rating actions. Herding results concerning specifically agency pair Moody's and Fitch are mixed due to small sample size. In general, I find that herding is an uncommon practice among the major credit rating agencies.

KEYWORDS

Rating agency, rating announcement, credit default swap market, herding behaviour

1

Aalto-yliopiston kauppakorkeakoulu Pro Gradu -tutkielma Timo Brandstack

Tiivistelmä 15. maaliskuuta 2010

ONKO LUOTTOLUOKITUSILMOITUKSILLA MERKITYSTÄ?

TUTKIELMAN TAVOITTEET

Tutkielmalla on kaksi päätavoitetta: Ensimmäiseksi, tutkimus ottaa selvää kuinka paljon erityyppiset luottoluokitusilmoitukset vaikuttavat luottoriskinvaihtosopimus (CDS) markkinaan. Toiseksi, tutkimus etsii viitteitä mahdollisesta matkimiskäyttäytymisestä suurimpien luottoluokittajien välillä.

LÄHDEAINEISTO JA TUTKIMUSMENETELMÄT

Luottoluokitusilmoitusaineisto koostuu Standard & Poor's:n, Moody's:n, ja Fitch:n ilmoituksista koskien vähäriskisiä Yhdysvaltalaisia yrityksiä, jotka kuuluivat tarkkailujakson 1. tammikuuta 2000 – 4. kesäkuuta 2009 lopussa S&P 500 indeksiin. CDS-aineisto kattaa 334 190 hintamerkintää viisi vuotisille CDS-sopimuksille, jotka liittyvät luottoluokitusilmoituksien kohteena oleville yrityksille. CDS markkinan reaktioita luottoluokitusilmoituksiin tutkitaan tarkastelemalla kontrolloituja CDS-hintojen muutoksia [-90, 90] päivän ikkunassa ilmoituksen ympärillä. Matkimiskäyttäytymistä tutkitaan vertailemalla luottoluokitusilmoitusten lukumääriä, jotka seuraavat nopeasti toisen luottoluokittajan luottoluokitusilmoitusta saman suuntaan, toimistojen välillä eri ajanjaksoilla.

TULOKSET

Tutkielmani osoittaa, että täydellä tarkkailujaksolla CDS-markkina yleisesti ennakoi ja reagoi negatiivisiin luottoluokitusilmoituksiin, kun taas positiiviset ilmoitukset ovat tavallisesti merkitykseltään vähäisempiä. Voimakkain CDS-markkina reaktio liittyy negatiivisiin tarkkailulistailmoituksiin. Täydellä tarkkailujaksolla CDS-markkina reagoi S&P:n ja Moody's:n luottoluokitusilmoituksiin voimakkaammin kuin Fitch:n. Luottokriisin puhjettua kuitenkin Fitch:n ja Moody's:n ilmoitusten merkitys on kasvanut samalla kun S&P:n ilmoitusten merkitys on heikentynyt. Lisäksi tutkimustulokseni osoittavat että negatiivisten ilmoitusten joukossa on enemmän merkitystä sillä onko luottoluokitusten laskua edeltänyt vastaava tarkkailulistailmoitus, kuin että kuinka monta pykälää luottoluokitus tosiasiassa muuttuu.

Tulokseni näyttävät että vain joka viides luottoluokitusilmoitus suurten luottoluokittajien kesken tapahtuu [-60, 60] päivän ikkunassa toisen toimiston samansuuntaisen ilmoituksen ympärillä toimistojen seuratessa yritystä samanaikaisesti. Lisäksi en löydä erityistä näyttöä, että S&P:n ja Moody's:n välillä olisi matkimiskäyttäytymistä. Tulokseni eivät kuitenkaan pysty täysin pois sulkemaan mahdollisuutta, etteivätkö S&P:n luottoluokitusilmoitukset vaikuttaisi Fitch:n luottoluokituksiin. Tulokset Moody's:n ja Fitch:n keskinäisestä matkimisesta eivät anna luotettavaa kuvaa ilmiöstä, sillä otoskoko tällä toimistoparilla jäi pieneksi. Yleisellä tasolla voin sanoa, ettei matkiminen luottoluokitusilmoituksissa ole vallitseva tapa suurten luottoluokittajien keskuudessa.

AVAINSANAT

Luottoluokitustoimisto, luottoluokitusilmoitus, CDS-markkina, matkimiskäyttäytyminen

TABLE OF CONTENTS

| 1 | Intr | troduction | 7 |
|---|-------|------------------------------------|----|
| | 1.1 | Motivation | 7 |
| | 1.2 | Research framework and hypotheses | 9 |
| | 1.2. | CDS respond study | 10 |
| | 1.2.2 | P.2 Herding study | 14 |
| | 1.3 | Contribution of the study | 18 |
| | 1.4 | Limitations of the study | 19 |
| 2 | Bac | ckground information | 20 |
| | 2.1 | Credit rating industry | 20 |
| | 2.2 | Major credit rating agencies today | 22 |
| | 2.3 | Credit ratings | 23 |
| | 2.4 | Credit rating process | 25 |
| | 2.5 | Quasi-official role of the NRSROs | |
| | 2.6 | Credit default swaps | 27 |
| | 2.7 | CDS market development | |
| | 2.8 | Credit crisis | |
| 3 | Lite | terature review | |
| | 3.1 | Rating announcements market impact | |
| | 3.1. | .1 CDS market response | |
| | 3.1.2 | .2 Stock market response | |
| | 3.1. | .3 Bond market response | |
| | 3.2 | Herding studies | |
| 4 | Des | scription of the data sets | |
| | 4.1 | CDS market respond study | |
| | 4.1. | .1 CDS spread data | |
| | 4.1.2 | .2 Descriptive statistics I | |
| | 4.1. | .3 Credit rating data | 40 |
| | 4.1.4 | .4 Descriptive statistics II | 41 |
| | 4.2 | Herding study | 42 |

| | 4.2.1 | 1 Data | 12 |
|----|--------|--|-------------|
| | 4.2.2 | 2 Descriptive statistics III | 43 |
| 2 | 4.3 | Limitations of the data | 46 |
| 5 | Met | hodology | 17 |
| 4 | 5.1 | CDS market respond study | 17 |
| | 5.1.1 | 1 Determining adjusted spread changes (ASCs) | 17 |
| | 5.1.2 | 2 Applied statistical tests | 19 |
| 4 | 5.2 | Herding study | 50 |
| 6 | Emj | pirical results | 55 |
| (| 5.1 | CDS respond study | 55 |
| | 6.1.1 | 1 CDS market reactions by rating types | 55 |
| | 6.1.2 | 2 Asymmetric spread adjustment | 71 |
| | 6.1.3 | 3 Impact of the credit crisis | 73 |
| (| 5.2 | Herding study | 77 |
| | 6.2.1 | 1 Agency pair level herding findings | 77 |
| | 6.2.2 | 2 General level herding findings | 34 |
| 7 | Sum | 1mary and conclusions | 36 |
| , | 7.1 | Summary | 36 |
| | 7.2 | Conclusions | 38 |
| - | 7.3 | Topics for further research | 39 |
| Re | ferenc | ces |) () |

List of figures

| Figure 1. Illustration of analysed interdependencies | 9 |
|---|----|
| Figure 2. Scenario analysis around the first hypothesis | 11 |
| Figure 3. Scenario analysis around the seventh hypothesis | 17 |
| Figure 4. Structure of credit default swap contract | 28 |
| Figure 5. Notional amounts of outstanding CDS contracts at year-end | 29 |
| Figure 6. CDS sample size development | 39 |
| Figure 7. Average CDS spread development within sample companies | 40 |

| Figure 8. Illustration of factors affecting the timing of rating action | |
|--|----|
| in relation to rating action by other agency | 52 |
| Figure 9. Negative view announcement | 58 |
| Figure 10. Single notch downgrade from negative view watchlist | 59 |
| Figure 11. Cancelled negative view announcement | 61 |
| Figure 12. Straight single notch downgrade | |
| Figure 13. Double notch downgrade | |
| Figure 14. Positive view watchlist announcement | |
| Figure 15. Single notch upgrade from positive view watchlist | |
| Figure 16. Straight single notch upgrade | |
| Figure 17. New rating announcement | 71 |
| Figure 18. Comparison of CDS market reactions around negative view watchlist | |
| announcement by S&P before and after the credit crisis | 76 |
| Figure 19. Comparison of CDS market reactions around negative view watchlist | |
| announcement by Moody's before and after the credit crisis | |
| Figure 20. Comparison of CDS market reactions around single notch downgrade | |
| by Fitch before and after the credit crisis | 76 |
| Figure 21. Herding rating action observations (S&P and Moody's) | 80 |
| Figure 22. Herding rating action observation differences: Moody's – S&P | 80 |
| Figure 23. Controlled herding rating action observation differences: Moody's – S&P | 80 |
| Figure 24. Herding rating action observations (S&P and Fitch) | |
| Figure 25. Herding rating action observation differences: Fitch – S&P | |
| Figure 26. Controlled herding rating action observation differences: Fitch – S&P | |
| Figure 27. Herding rating action observations (Moody's and Fitch) | |
| Figure 28. Herding rating action observation differences: Fitch – Moody's | |
| Figure 29. Controlled herding rating action observation differences: Fitch – Moody's | |

List of tables

| Table 1. Rating actions classification table | 13 |
|---|----|
| Table 2. NRSROs approved by SEC as of September 25, 2008 | 21 |
| Table 3. Rating scales for issuer-specific ratings by major credit rating agencies | 24 |
| Table 4. Rating action sample for CDS market respond study | 41 |
| Table 5. Description of rating action sample for herding study | 45 |
| Table 6. CDS market reaction around negative view watchlist announcement | 57 |
| Table 7. CDS market reaction around single notch downgrade from negative view watchlist | 59 |
| Table 8. CDS market reaction around cancelled negative view watchlist announcement | 61 |
| Table 9. CDS market reaction around straightsingle notch downgrade | 63 |
| Table 10. CDS market reaction around double notch downgrade | 65 |
| Table 11. CDS market reaction around positive view watchlist announcement | 66 |
| Table 12. CDS market reaction around upgrade from positive view watchlist | 68 |
| Table 13. CDS market reaction around single notch upgrade | 69 |
| Table 14. CDS market reaction around new rating announcement | 70 |
| Table 15. Comparison of CDS market reactions around negative view watchlist | |
| announcement by S&P before and after the credit crisis | 74 |
| Table 16. Comparison of CDS market reactions around negative view watchlist | |
| announcement by Moody's before and after the credit crisis | 75 |
| Table 17. Comparison of CDS market reactions around straight single notch | |
| downgrade by Fitch before and after the credit crisis | 75 |
| Table 18. Herding study results | 78 |

List of appendices

| Appendix 1. List of companies included in the CDS study sample | |
|---|----|
| Appendix 2. List of companies included in herding study sample | 93 |
| Appendix 2.1. List of companies simultaneously rated by S&P and Moody's | 93 |
| Appendix 2.2. List of companies simultaneously rated by S&P and Fitch | 94 |
| Appendix 2.3. List of companies simultaneously rated by Moody's and Fitch | 95 |

1 Introduction

This thesis constitutes of two distinct, but related research topics: First, the thesis analyses what kind of impact different types of credit rating announcements by major credit rating agencies' have on the CDS spreads. The second part of the study is about possible herding behaviour between the agencies. The link between these two parts is that they both analyse impacts of credit rating announcements and describe the role of credit rating agencies in the market place.

1.1 Motivation

Credit rating agencies are commercial companies specialized in analysing the probabilities of default in the reviewed entities. In the aftermath of the recent financial crisis, market participants have criticised credit rating agencies of a failure in their task to measure risks appropriately. Accompanied by these accusations many are now questioning the quasi-official role that the major credit rating agencies possess. This quasi-official role refers to the fact that many regulations and statues restrict regulated institutes from investing in lower rated debt. Furthermore, credit rating agencies' quasi-official role was recently boosted by the adoption of Basel II, which is a regulatory framework set to regulate banks globally. Inspired by this discussion of how the role of credit rating agencies, I refer to the three largest agencies: Standard & Poor's, Moody's Investor Service, and Fitch Ratings.

This thesis is structured around two main research questions: First, how do different types of credit rating announcements impact the credit default swap market? Second, do rating agencies herd each other on their credit rating announcements? The first question aims to uncover whether the agencies actually add new information to the market. If they do, should credit default swap (CDS) spreads adjust immediately to the corresponding new risk level following the credit rating announcement. The second research question is set to find out whether the major credit rating agencies tend to imitate each other's credit rating announcements. If the major agencies do not imitate each other, should other agencies' credit rating announcements not influence agency's credit rating behaviour.

Second reason to do this study, in addition to topical discussion around credit rating agencies, is that there has not for long existed a chance to study credit rating announcements' impact on CDS spreads with a similar scale as presented in this paper. This is because the very market has existed only some ten years. CDS market started its rapid growth in 1998 when International Swaps and Derivatives Association (ISDA) standardized the contract. CDS is a contract that normally provides the buyer with an insurance against a default by a particular company or sovereign entity. In turn, buyer pays the seller periodic stream of payments, which is on annual basis referred to as CDS spread. Previous studies of this subject have all used global data, because of otherwise insufficient sample size. This thesis, however, presents first market-specific findings of interplay between the major credit rating agencies and CDS market participants. Data for this study is collected exclusively from the U.S. market.

Furthermore, this study is the first to analyse how the credit crisis has affected investors' perceptions of credit rating actions. As discussed in the first paragraph of this section, credit crisis has cumulated some criticism against rating agencies, but before this thesis it has remained unknown how CDS market has actually viewed the role of credit rating agencies during the crisis. In this study, I split the samples of every credit rating agency's most observations including rating action type half at the point of mid-2007 and then compare the CDS market responses between the two periods. The reason why comparisons are not presented for all rating action types is simply the lack of sufficient amount of observations for other types of announcements. Unfortunately, insufficient sample size prevents me also to present same comparison for the herding study.

Finally, the fourth reason to pursue this study is that there exists no previous herding study concerning major credit rating agencies. This is especially surprising considering the herding optimal circumstances around the decision making process. Shiller (1995) finds in his study that herding behaviour is most likely to take place in situations where "decision-making setting is complex and there exists restrictions of time, information and ability for decision maker". However, there exists also a balancing force, which is the agencies' own reputation. If the market would observe some agencies to capitalize herding-strategy it would be highly damaging for agency's reputation leading it to lose its business in the long run. This study will investigate whether the reputation is so important for credit rating agencies that they fear to engage in herding behaviour, or are there indications of imitative behaviour.

1.2 Research framework and hypotheses

In this thesis, I study the impact of credit rating announcements on CDS market and possible herding behaviour that may exist between the agencies. The study focuses on the three largest credit rating agencies that are Standard & Poor's (S&P), Moody's Investor Service (Moody's) and Fitch Ratings (Fitch). The study presented in this paper is a classical event study examining the impact of credit ratings before, at, and after the announcement. The aim of this thesis is to draw a bigger picture of the dynamics that prevail between credit rating agencies as well as between the agencies and investor community. Figure 1 illustrates these studied dynamics. Note that, CDS market's impact on credit rating agencies is not directly studied. However, as CDS market's anticipation preceding credit rating announcements is analysed one can also indirectly infer something about CDS market's impact on credit rating agencies as well. For the purposes of this study, I define that terms credit rating announcement and credit rating action are used synonymously and the both refer to actual downgrades and upgrades, and reviews for downgrade and upgrade and their cancellations.

Figure 1

Illustration of analysed interdependencies. The figure shows that I study all other interdependencies between major credit rating agencies and CDS market, but the direct impact that CDS market has on the credit rating agencies.



This study is a continuum for a very short line of studies that have analysed the rating announcements' effect on CDS market. Until the writing process of this thesis, there were only two academically published articles of this subject by Norden and Weber (2004) and Hull et al. (2004). Furthermore, there are two studies around the same subject done by a group of Bank of International Settlements'

researchers referred as Micu et al. (2004) and Micu et al. (2005). These papers studied whether rating announcements carry any new information to markets. Results from these papers are in line with the findings from stock and bond market reactions: Downgrades and reviews for downgrades had their effect on CDS spreads while the results from upgrades and reviews for upgrades were more mixed. What comes to credit rating agencies' herding studies, there is none that have come into my attention. Herding studies among finance seems to cluster especially around analysts' behaviour.

As stated already, this study is organized under two main research topics: One studying credit rating announcements' CDS market impact, and the other studying possible herding behaviour between the agencies. As these main research topics are rather distinct in many respects most of the main chapters in this thesis are subcategorised under the headings -CDS response study- and -herding study-. The CDS response study follows roughly the framework presented in the Norden and Weber (2004) paper, but also influences from other papers are absorbed. The herding study, however, is constructed methodologically without any aid of previous research, but for the hypothesis building process some guidance was attained from the herding studies of analysts' behaviour.

1.2.1 CDS respond study

In the CDS response study, I test whether rating announcements carry new information to CDS market. If so, CDS spread changes before announcement day should not show any statistically significant abnormal performance or the market could be seen anticipating the following rating action. Hence, the more there is anticipation in CDS market the less there is actual new information in the rating announcement. Furthermore, if rating announcement is true news for the market, should CDS spreads immediately peak after the announcement day to adjust the corresponding new risk level assuming that the market is efficient enough. According to this rationale, I end up with the same hypothesis that was tested also in Norden and Weber (2004) paper.

Hypothesis 1: Markets do not anticipate rating announcement, but react immediately as it occurs.

If the first hypothesis holds, rating announcements truly add information to the market. However, if it turns out not to hold, there are three possible scenarios that may prevail as described in Figure 2: First the market anticipates the rating announcement, but there is no reaction when the actual rating announcement occurs. Second, CDS market anticipates the rating announcement, but still reacts at the moment of the announcement. Third, the market neither anticipates nor reacts at the time of the rating announcement. These scenarios may be interpreted in the following manner: In the first scenario, rating announcements are yesterday's news as their information content is already reflected in the CDS spreads. In the second scenario, the market partially reflects the information revealed before the credit rating announcement, but the announcement still has its effect to the market. In the third scenario, there is no link between credit rating announcement and CDS market.

Figure 2

Scenario analysis around the first hypothesis. The figure illustrates the fact that the first hypothesis is not rejected only when market anticipation is abcent and there is significant announcement effect at the point of rating announcement.



Announcement effect

In the CDS respond study, I also analyse the symmetry of the market reactions regarding positive and negative rating announcements. Previous researches by Norden and Weber (2004) and Hull et al. (2004) have found that the intensity of market reaction is much greater with negative rating events compared to positive ones. Norden and Weber (2004) suggests that the plausible reasons to explain this phenomenon might include information processing bias (see Dichev and Piotroski 2001), and disciplinary effect on firms management (see Vassalou and Xing 2003). Also an extensive list of credit

rating announcement effect studies on stock and bond markets has found the same phenomenon. In order to test the asymmetry of information content in rating announcement, I construct my second hypothesis.

Hypothesis 2: CDS market reaction is stronger among negative rating announcements compared to positive ones.

Until this point, my study design resembles much the work done by Norden and Weber (2004). However, what there is particularly interesting in my study compared to the previous is that I can divide my rating actions much more specifically to different rating action types with the aid of larger sample. Therefore I am able to construct the following hypothesis three and four to analyse more exhaustively how rating announcements affect the CDS market. Norden and Weber (2004) categorized rating actions to four different types: downgrades and upgrades, and reviews for downgrades and reviews for upgrades. In this study, I categorise rating announcements to 13 different types. At this stage it is worth mentioning that review for downgrade is synonymous to negative view watchlisting and review for upgrade is synonymous to positive view watchlisting.

My main categorization of rating actions is based on whether the rating action moves credit rating to positive or negative direction. Positive rating action refers to improved credit quality, where as negative rating action refers to deteriorated credit quality. Furthermore, I categorize rating actions to three types regarding how many notches they move the credit rating on credit rating scale (see Table 3). The alternatives here are: singe notch, double notch, or multiple notch rating change. Finally, I categorize my rating actions based on whether they are preceded with corresponding watchlist announcement. However, this categorization only relate to single notch rating changes, because for double and multiple notch rating changes there are not sufficient samples.

In addition to these aforementioned eight types of rating actions related to actual rating changes, I test the impact of negative and positive view watchlist announcements, but also what effect their cancellations have on the market. So far, I have described 12 different rating action types that have either positive or negative effect credit quality wise. There is left one more type of rating announcement that has no predetermined direction that being the new rating announcement, also referred to as initial rating announcement. The following Table 1 summarizes the categorization of different rating announcement types.

| Rating action classification table. The table presents breakdown of all studied rating action types dividing into six positive ones and |
|---|
| six negative ones regarding their expected price reaction. New rating announcements having no expected market reaction are studied |
| as well. |

| Annonuncement | | Number of notches | Rating action type | Expected market |
|-------------------------|---------------|-------------------|---|-----------------|
| | | moved | | reaction |
| | | | | |
| Rating change Downgrade | | 1 | Straight single notch downgrade | - |
| | | 1 | Single notch downgrade from negative view watchlist | - |
| | | 2 | Double notch downgrade | - |
| | | >2 | Multiple notch downgrade | - |
| | Upgrade | 1 | Straight single notch upgrade | + |
| | | 1 | Single notch upgrade from positive view watchlist | + |
| | | 2 | Double notch upgrade | + |
| | | >2 | Multiple notch upgrade | + |
| Watchlist | Negative view | 0 | Negative view watchlist announcement | - |
| | | 0 | Cancelled negative view watchlist | + |
| | Positive view | 0 | Positive view watchlist announcement | - |
| | | 0 | Cancelled positive view watchlist | + |
| New | | 0 | New rating announcement | ? |

As already mentioned, this more specific classification of rating actions allows me to test hypotheses that couldn't be tested in previous researches of the field. I assume that the more notches moved in a rating change the stronger the market reaction should be. I argue this, because greater distance moved on the credit rating scale should signify greater change in actual credit quality, which should then again result to stronger change in CDS spreads. Based on this rationale, I present my third hypothesis:

Hypothesis 3: Magnitude of CDS market reaction correlates to number of notches moved in rating change

Further on, I assume that CDS market reaction is stronger when rating change occurs without preceding corresponding watchlist announcement. As the watchlisting signals that the reviewed company is under a process that might result to rating change the market has an opportunity to react to already that information, which would mean less of a revelation at the point of actual rating change from the watchlist. As a result of this discussion my fourth hypothesis is the following:

Table 1

Hypothesis 4: CDS market reaction is stronger when rating change is not preceded by corresponding watchlist announcement.

Norden and Weber (2004) didn't subcategorize rating announcements in respect of preceding watchlistings. The researchers had mixed both the downgrades with and without the watchlistings. If this fourth hypothesis holds it would explain why they found negative watchlist announcement more powerful announcement compared actual downgrade. The reason is that having both types of downgrades mixed in the same group, the less impacting downgrades from negative view watchlist dilutes the compound effect of the whole group. Furthermore, there is not the same problem with negative view watchlistings as there are no watchlistings for watchlistings.

My fifth hypothesis relates to the interesting timing of my study and it finds out the impact of the credit crisis, which burst at the mid-summer of 2007 when two major mortgage related hedge funds of Bear Sterns investment bank were found to have lost merely all of their assets. According to my understanding there are two major factors affecting the changing role of credit rating agencies due to the crisis. First, credit rating agencies' role could be seen diminishing due to decreased investor trust originating from failures in predicting the default probabilities of reviewed entities. However, one could argue the opposite as well: The credit crisis undoubtedly has added volatility in market, which has made it more difficult for investors to make their own analysis of companies' creditworthiness. Under these difficult times, investors could be seen relying more strongly on professional insights of credit quality by credit rating agencies' changing role the hypothesis five is as follows:

Hypothesis 5: The credit crisis has not influenced the credit rating actions' CDS market reactions.

1.2.2 Herding study

In the herding study part of my thesis, I study whether rating announcements by one agency impacts the other agencies' credit rating behaviour. In other words, I will look for evidence whether all or some of the agencies imitate rating actions by others. This imitative behaviour pattern is commonly referred to as herding behaviour in finance. In the absence of herding behaviour, the trigger for rating announcement is on the actual corporate or macroeconomic field. However, one cannot escape from the conception that also rating actions by other agencies would affect the decision to review credit ratings.

The herding study in this thesis analyses herding rating actions, which are rating actions that follow in 60 days rating action by other agency to same direction credit quality wise. If, for example, S&P issues a rating action that signals decreased credit quality for a company (downgrade, negative view watchlisting or cancelled positive view watchlisting) the rating actions issued during the following 60 days by Moody's and/or Fitch indicating also decreased credit quality are/is deemed as herding rating action(s). The logic is simply the following: If there are rating actions that imitate rating actions by other agencies, should these rating actions occur relatively short after the rating action they are to imitate.

If the credit rating agencies would operate in a perfect world, in which they had all fully relevant information to make the credit rating decisions and all the agencies had perfectly competent employees to analyse that information, should they all issue credit rating actions simultaneously. In this case, lag between two rating actions couldn't be explained by any other reason that the agency with lagging rating action imitates the leading one. This is because, if the credit rating agency with lagging rating action would have done its own credit rating review process it would have also observed the same event that triggered the rating action by the leading agency and then the two credit rating agencies would have ended up issuing their rating actions simultaneously. In this case, now that we know that the agency with lagging rating action couldn't have done its own credit review process, there is left no other trigger for its rating action than the rating action by the leading agency.

However, this is not true state of affairs in the real world, which is full of various sources of imperfections that make credit review processes also imperfect. Imperfect credit review process cause inevitably lag between agencies' credit rating actions and thus all credit rating actions that occur shortly after other agency's rating actions cannot be truly deemed as imitative ones. However, one can reasonably argue that two agencies still should be more likely to issue rating actions, triggered by the same event, on the same day than with some number of lag days between the rating actions. Otherwise, one could interpret those rating actions, cumulated abundantly to some lag day, being triggered by other agency's rating action instead of the underlying event itself. Lag day refers to spread in days

between the leading and lagging rating action. Possible finding, where there would be more paired rating action observations with some specific spread of days between them compared to number of simultaneous rating action observations, where the spread equals zero, would be a strong evidence of herding behaviour. Based on this discussion, I state that if the following hypothesis does not hold, the possibility of herding behaviour according to my opinion is substantial.

Hypothesis 6: Credit rating agencies issue their rating actions, triggered by the same event, on a same day.

Furthermore, if we assume that those imperfections that cause lag between rating actions plague all agencies similarly, would agencies then have the same probability to issue rating action same number of days before or after the rating action by other agency. To illustrate the idea, let's assume that a market event affecting some company's credit quality occurs and the company is simultaneously rated by two agencies. Assuming that it would take the same number of days for both the agencies to run their credit review processes and both the agencies have observed the event at the same time, then both the agencies would end up issuing their rating actions simultaneously as hypothesis six predicts. However, there are various sources that cause imperfections to agencies at the same likelihood they should not alter the leading or lagging probabilities for either of the agencies' benefit or loss. This discussion allows me to present my seventh hypothesis:

Hypothesis 7: Credit rating agencies have similar likelihoods to lead and lag each others

In previous paragraph, I set an assumption that the credit review process would take the same number of days from both the example agencies, but it is obviously too bold assumption to hold in the real world where are also continuous imperfections in credit review processes in addition to random ones. Continuous imperfections slow down rating agencies' credit review processes on continuous basis, which lead to the rejection of the seventh hypothesis if, within an agency pair, agencies suffer of these imperfections on a different scale. These continuous imperfections originate, for example, from employees' skill differences or differences in information sources between agencies. These imperfections are the very reason for herding behaviour, as they represent the flaws that the imitating agency is trying to cover by imitating the leading agency. According to this rationale, existence of different scales of continuous imperfections would be necessary condition for persisting herding behaviour patterns between agencies. Based on this discussion, I argue that there prevail three plausible scenarios around the seventh hypothesis (see Figure 3): First, there are no discrepancies in agencies continuous imperfections and thus no herding behaviour between the agencies (scenario 1). In this situation the hypothesis seven is not rejected. Second, there prevail only differences in levels of continuous imperfections between the agencies, but no herding behaviour (scenario 2). In this case hypothesis seven is violated and thus rejected. Third, there are differences in agencies' credit review processes on continuous basis and also herding behaviour (scenario 3). In this case hypothesis seven is also rejected. Unfortunately it is impossible to say, whether the hypothesis seven is rejected because of situation described in the second or the third scenario.

Figure 3

Scenario analysis around the seventh hypothesis. In every scenario the vertical line at the centre represents the point of time when other agency issues rating action. The curved line around the vertical line represents agency's probability function to issue rating action to same direction credit quality wise in relation to the other agency's rating action. The thick horizontal line at the bottom of every scenario represents time line.

Hypothesis seven is not rejected and it is very likely that there exists no herding behaviour between the agencies.

Scenario 1. The hypothesis seven is not rejected as the agency has similar likelihood to lead and lag the other agency.

T

Hypothesis seven is rejected, but it cannot be stated whether it is only because of continuous imperfections (scenario 2) or the continuous imperfections and herding behaviour combined (scenario 3).

Scenario 2. The hypothesis seven is rejected as the agency has higher likelihood to lag the other agency, because of continuous imperfections that hinder agency's credit review process.



Scenario 3. The hypothesis seven is rejected as the agency has higher likelihood to lag the other agency. In this figure the difference between probability functions two and three describes the effect of herding behaviour that speeds up the credit review process.



Based on the study by Clement and Tse (2005) attributes such as agency's size, age, and frequency of rating actions would increase agency's likelihood for issuing bold rating actions. As bold rating actions are the exact opposites of herding rating actions, I argue that the smaller, younger, and less frequent agency is to issue rating actions, the more likely it is to engage in herding behaviour. According to this rationale, Fitch that is the smallest, youngest and less frequent to issue rating actions would show the most indications of herding behaviour. These attributes that makes Fitch the most inclined to herding behaviour are demonstrated in chapters 2 and 4. This section culminates to my eight and final hypothesis in my thesis.

Hypothesis 8: Of the three major credit rating agencies Fitch is most likely to engage in herding behaviour.

1.3 Contribution of the study

This study has four major elements of scientific contribution: First, my study is the first market specific study to uncover what impact credit rating actions have specifically on large U.S. companies' CDS spreads. I argue that compared to previous studies done with global data, results from my study have better prediction power for the future. This is, because in my sample companies' geographic location, corporate culture, and size do not vary. More importantly, by analysing exclusively U.S. companies one can be sure that the three most important credit rating agencies are U.S. headquartered: S&P, Moody's and Fitch. Including also, for example Japanese companies, into the sample, but not Japanese credit rating agencies, would cause noise as also Japanese credit rating agencies' credit rating actions would impact on CDS spreads of Japanese companies. This is just what previous studies had to do in order to increase their sample sizes.

The second contribution relates to the ability of this study to subdivide credit rating actions more accurately. Previous studies have only considered negative- and positive watchlist announcements in addition to downgrades and upgrades. This study, however, subdivides rating actions into 13 different types as presented in Table 1. Previous studies have found that negative view watchlist announcements have more effect on CDS spreads than actual downgrades that hardly have significance at all, which feels intuitively surprising. This study, however, will prove that downgrades not preceded by

corresponding watchlisting have also market impact, while downgrades following negative view watchlist announcements have virtually no market effect, what so ever. The problem with previous studies has been to combine all downgrades into one group while the information content between downgrades following negative view watchlisting is much less than downgrades without watchlisting. Furthermore, this study is the first to compare differences in market reactions between rating actions that move the credit rating different number of notches.

The third contribution is the unique opportunity occurred by timing of the study to present comparison of the CDS market responses between periods before and after the hit of the credit crisis. Albeit it is not clear how the credit crisis affects the role of credit rating agencies the opportunity to study it cannot be neglected. The line between these two periods is drawn across the mid summer of 2007 when two mortgage related hedge funds by Bear Stearns reported their troubles. Because of the topic nature of this subject there has not yet occurred any study to research the same subject.

The fourth scientific contribution of my study is the whole herding study as regardless of my extensive efforts to find previous articles or working papers of herding behaviour between the agencies none were found. The reason why it is not studied may relate to inherent difficulties to study the phenomenon. The following section, which discusses limitations of the study, will explain in more detail these difficulties. Despite the obstacles, I found the idea of herding behaviour between the agencies so interesting, that I wanted to tackle it.

1.4 Limitations of the study

As discussed already, the main limitations of this study plague the herding study part. Herding, in the context of credit rating agencies, refers to imitation of rating actions. As already stated, herding rating actions are rating actions that follow in 60 days rating action by other agency to the same direction credit quality wise. However, whether rating action that meets the qualifications set for herding rating action is actually product of imitation is impossible to say. The reason why other agency lags another may derive also from continuous imperfections described in previous section.

Furthermore, there is a chance that some herding rating actions have absolutely no real link to the previous rating action, which they are considered to mimic. To count for this fact, one should search for the reason for every credit rating action and then match the causes of these rating changes to rating chances of each agency, which obviously is a task out of the scope of this paper. There is just an idea that if there exist rating actions that imitate other agencies' rating actions, should these rating actions occur relatively shortly after the rating actions they are to imitate. Due to the aforementioned problem, there is no real means for me to say how much herding rating action observations should there amount for one agency in order to state with certainty that there exists herding behaviour. In other words, I am able to say with statistical significance whether there are unproportional amount of herding rating actions for one agency compared to another, but it is still unfortunately a slightly different issue than stating that there truly exists herding behaviour.

Also my study is unable to track intra-day herding if there would exist some, because I have data only on business day level. This is, however, a pitfall that I am not in any extent capable to circumvent as it would require hourly level credit rating data that I do not have for this study.

2 Background information

This section is about to familiarize reader with the key concepts discussed in this thesis. The goal is to equip reader with sufficient background information to assist in better understanding the following of the thesis. First the focus will be on credit rating agencies and credit ratings. Subsequently, CDS contract and CDS market will be discussed in more detail.

2.1 Credit rating industry

Credit rating industry was born at the beginning of 20th century in the United States. Moody's was the first major credit rating agency to be established in 1909. Standard & Poor's predecessor Poor's agency was formed soon after Moody's in 1916 and Fitch followed suit in 1924. Initially credit rating agencies generated their revenues by selling their credit ratings to investors, but it was ultimately seen difficult to prevent investors from circulating these credit ratings among the investor community. In the 70's the

business logic changed and the major credit rating agencies started also collect fees from rated companies, while still selling their credit ratings to investors. In the 70's, also another change in credit rating industry took place as Securities Exchange Commission (SEC) granted the three major credit rating agencies (S&P, Moody's, and Fitch) status as Nationally Recognized Statistical Rating Organization (NRSRO). The formation of NRSRO concept further on boosted the oligopolistic nature of the credit rating industry as the federal and state laws regulating financial institutions holdings of corporate debt in terms of credit ratings so forth referred to credit ratings issued only by NRSROs.

Today the major credit rating agencies solely collect their rating operations revenues from rated companies, which cause conflicts of interests between investors, credit rating agencies, and issuer firms. As issuer firms subscribe ratings from credit rating agencies they could at least theoretically link the size of fee to the level of credit rating or at least make the subscription contingent on what kind of rating they would receive. Even though these agency costs in credit rating industry are at least moderate problem, they don't affect the study presented in this paper. Furthermore, the credit rating industry has changed from the 70's by the amount of NRSROs approved by SEC. The following Table 2 lists all NRSROs approved by the SEC as of September 25, 2008. Nevertheless the increased amount of NRSROs the industry has remained very oligopolistic as the three major agencies cover currently over 90% of the global credit rating market.

Table 2

NRSROs approved by SEC as of September 25, 2008. The table lists all credit rating agencies holding NRSRO status granted by United States Securities and Exchange Commission as of September 25, 2008.

| Agency | Home Country | Established |
|---|---------------|-------------|
| 1) Moody's Investor Service | United States | 1909 |
| 2) Standard & Poor's | United States | 1916 |
| 3) Fitch Ratings | United States | 1924 |
| M. Best Company * | United States | 1899 |
| 5) Dominion Bond Rating Service, Ltd | Canada | 1976 |
| 6) Japan Credit Rating Agency, Ltd | Japan | 1985 |
| 7) R&I, Inc. | Japan | 1998 |
| 8) Egan-Jones Rating Company ** | United States | 1994 |
| 9) LACE Financial | United States | 1984 |
| 10) Realpoint LLC | United States | 2001 |

* Specialized only on insurance companies

** Does not collect fees from rated companies

There are a few interesting facts in the list presented above: First, the NRSRO status has also been granted for three foreign rating agencies, but none of them is European. One possible reason for this might be that U.S. institutions hold in absolute terms more assets in Canada and Japan than in Europe. Second, interesting notion is that none of the three major credit rating agencies is actually the oldest of the credit rating agencies: M. Best Company was formed already in 1899, but on the contrary to the major agencies it only concentrates on insurance industry with its ratings, where as the major agencies rate broad range of business sectors. One more interesting detail is that one of the U.S. credit rating agency rookies, Egan-Jones Rating Company, seeks for competitive advantage by using the old school rating agency business model by collecting its fees from investor rather than rated agencies, which alleviates conflicts of interests between the parties.

2.2 Major credit rating agencies today

The following paragraphs describe the standing of three largest agencies and their rating operations today. The aim is to rank the agencies according to the size of their rating operations for the purposes of eighth hypothesis. Data regarding only rating operations was relatively scarce to obtain, but for all the agencies' rating operations' revenue figures were reported, which thus acts as a proxy of size in my study. Furthermore, assuming that price per rating would be approximately the same across the agencies, the revenue figures would also give a reliable picture of the relative numbers of entities rated by the agencies.

Moody's Investor Service is part of Moody's Corporation. The parent company is divided into two business segments: Moody's Investor Service (MIS) and Moody's Analytics (MA). The MIS segment publishes credit ratings on a wide range of debt obligations and the entities that issue such obligations in the markets worldwide, including various corporate and governmental obligations, structured finance securities and commercial paper programs. MIS's revenues in 2008 reached \$1,204.7 million and the operating profit totalled to \$537 million. Amount of corporate issuers rated by MIS at the year end 2008 totalled to 13,000.

Standard & Poor's is a brand for McGraw-Hill companies financial services division. Standard & Poor's is further on divided into two subdivisions: Credit Market Services and Investment Services. The Credit Market Services segment provides independent global credit ratings, covering corporate and government entities, infrastructure projects and structured finance transactions. In 2008 revenues generated by S&P's Credit Market Services reached \$1,754.8 million, which makes it the biggest credit rating agency worldwide.

Fitch Ratings is part of Fitch Group owned 80% by Fimalac Group. Fitch Ratings generates revenue by assigning ratings to issuers, new debt issues, and by monitoring previously rated fixed-income obligations. In 2008 Fitch ratings revenues totalled to \$ 727 million and operating profit was reported as \$ 267.6 million. These figures show that Fitch is the smallest of the agencies analysed in this thesis. Furthermore, Fitch Ratings is reported to rate 1,724 corporate entities, which is significantly less than the number of rated corporate entities by Moody's. Unfortunately information about the number of corporate entities rated by S&P was not available.

Based on the information presented above, I conclude that the Standard & Poor's is the biggest of the rating agencies, Moody's is the second biggest and Fitch is the smallest. The order is tracked by revenues generated by rating operations, but also other size related parameters presented above supports the conclusion.

2.3 Credit ratings

Credit ratings are views of creditworthiness issued by credit rating agencies for corporate or sovereign entities or specific issues of securities. Currently the global credit rating market is dominated by the three biggest agencies that are Standard & Poor's, Moody's Investor Service, and Fitch's Ratings. Table 3 presents credit rating scales for these three major credit rating agencies. The higher is the credit rating the lower is the expected probability of default.

Table 3

Rating scales for issuer-specific ratings by major credit rating agencies. The table lists all corresponding credit rating symbols and explains their risk describtions.

| | Agency | | | |
|-------------------|--------|---------|-------|--------------------------------------|
| | S&P | Moody's | Fitch | Risk describtion |
| | AAA | Aaa | AAA | Prime |
| | AA+ | Aa1 | AA+ | |
| | AA | Aa2 | AA | High grade |
| | AA- | Aa3 | AA- | |
| Investment grade | A+ | A1 | A+ | |
| investment grade | Α | A2 | Α | Upper medium grade |
| | A- | A3 | A- | |
| | BBB+ | Baa1 | BBB+ | |
| | BBB | Baa2 | BBB | Lower medium grade |
| | BBB- | Baa3 | BBB- | |
| | BB+ | Ba1 | BB+ | |
| | BB | Ba2 | BB | Speculative grade |
| | BB- | Ba3 | BB- | |
| | B+ | B1 | B+ | |
| | В | B2 | В | Highly speculative grade |
| Secondative grade | B- | B3 | B- | |
| speculative grade | CCC+ | Caa | CCC+ | Substantial risk |
| | CCC+ | Ca | CCC+ | Extremely speculative |
| | CCC- | С | CCC- | In default, small chance of recovery |
| | D | / | DDD | |
| | D | / | DD | In default |
| | D | / | D | |

The above presented rating scale is divided into two main categories. The upper category is referred to as investment grade and the lower is speculative grade. The division between these two categories is quite harsh as there are many institutional investors with restrictions to hold speculative grade bonds. Speculative grade bonds are commonly referred to as junk bonds as well. Also covenants related to debt securities often link their debt service schemes or immediate callability to the threshold between investment and speculative grade. Investments in investment grade bonds are viewed as sound and safe, where as investors preferring speculative bonds are likely after for better yields.

Credit ratings are usually divided into different subcategories based on the following attributes: issueversus issuer-specific ratings, long- versus short-term ratings, and local versus foreign currency ratings. Issue-specific ratings relate to some specific issue of securities. In this category credit rating parameters include structure of security, collateral, degree of seniority, among the overall financial health factors of issuing entity. Issuer-specific ratings refer to overall capacity of reference entity to meet its financial obligations. There is often strong correlation between issue- and issuer-specific ratings, but at least theoretically they may deviate a lot from each others. Short-term credit ratings describe the outlook for company during the next 12 months, whereas long-term credit ratings try to describe credit quality over longer term. Division between local and foreign currency credit ratings refers to considerations of country and currency risk. Reference entity's ability to pay its obligations in foreign currency may be lower than in local currency, because of weakening exchange rates and increasing local currency inflation. This paper concentrates on issuer-specific, long-term, local currency credit ratings, more of which is discussed in chapter four.

In addition to new (initial) credit ratings and credit rating changes credit rating agencies communicate with investors by watchlist announcements, news releases, and conversations with investors (Johnsson, 2004). Issuing a watchlist announcement agency signals that there is an ongoing credit rating review process. Watchlisting can be positive, negative, or neutral one indicating likely direction of possible rating change. Neutral watchlistings refer to market events that likely have some impact on reference entity's creditworthiness, but the direction is yet unknown. In this thesis, I will focus primary on credit rating changes and positive and negative watchlistings, but also evidence of new credit rating announcements are revealed on as nice-to-know basis.

2.4 Credit rating process¹

In the following paragraphs I describe S&P's credit rating process. As credit rating processes of all major agencies are very similar to each other the process description applies in broad sense for all the agencies. S&P's process description was chosen to be discussed as the most credit rating actions in my data set are issued by S&P.

The credit rating process typically initiates when issuer requests credit rating by S&P. If there is in S&P's opinion adequate information on which to ground the credit rating decision the process

¹ The information presented in this paragraph is gathered and from Standard and Poor's General Description of the Credit Rating Process published on April 10, 2009

continues. Next, there will be formed an analytical team, which gathers public and non-public information for which to base their financial forecasts and models on. Historical financial performance data, peer group comparisons, and industry and/or macroeconomic data are considered. Analytical team members also meet the issuer company's management to discuss about the key credit rating decision factors.

The actual credit rating decision is then made by rating committee vote, not by an individual analyst. The committee bases its decision for the work made by analytical team. After reaching an agreement in the vote, the rating committee then informs the issuer firm of its credit rating decision. The issuer may then appeal the rating by offering S&P new meaningful information, which would affect the credit rating decision. After reviewing the new information the credit rating committee votes second round. Next, the issuer company will be notified again on rating decision after which the credit rating will be issued to public or in the case of confidential ratings the credit rating will be only released to the issuer.

Normally, after the initial rating release S&P continuously maintains surveillance on the credit rating. Relevant public information is gathered and reviewed, but also periodic meetings with issuer company management are arranged. In these meetings management may reveal also non-public information to S&P's representatives that tries to capture throughout picture of company's creditworthiness. In general the surveillance process and initial rating process are very similar, with only exception that in surveillance process the amount of information that the company offers on continuous basis may be less than in the case of initial rating decision.

2.5 Quasi-official role of the NRSROs

Many institutional investors such as mutual funds and pension funds are restricted to invest in lower rated debt by NRSROs. Normally these institutions are accepted only to invest in investment grade rated debt. The distinction between investments grade and speculative is drawn between rating classes BBB- / BB+ (S&P and Fitch) and Baa3 / Ba1 (Moody's). Micu et al. (2005) state in their article that: "Since 1980s market participants and regulatory authorities have increasingly made use of thresholds other than investment- /speculative grade, but it remains still the most significant, especially for defining permissible investments". Also, many regulations and statutes restrict regulated institutions

from investing in lower rated debt, which is particularly the case in United States, where my data was collected. Furthermore, many covenants in various debt contracts are linked to issuer's credit rating. For example, a downgrade under a predefined level could trigger immediate repayment of a loan or cause a higher coupon rate to become applied.

2.6 Credit default swaps²

Credit default swaps are the most commonly traded credit derivative instrument. They can also be called as credit swap or default swap, but in this thesis they are referred to as credit default swap or CDS. The idea of CDS contract is that it allows one party to transfer its credit exposure on a reference entity to another party by means of bilateral agreement. Reference entity is commonly a corporation or a sovereign entity, but ultimately it can be whatever parties involved in the contract agrees on. In this theses reference entities are U.S. companies included in S&P 500 index.

In a CDS contract a buyer makes a series of periodical payments to a seller, where as the seller guarantees the buyer an insurance against credit event in a predetermined reference entity. Commonly credit event is a default in the reference entity, but it can also be other things as well, such as restructuring or bankruptcy filing. Annual periodical CDS payments are referred to as CDS spread and they are announced normally as basis points multiplier of nominal value of the agreement. If credit event takes place in the reference entity the buyer has a right to receive agreed compensation from the seller. Naturally, the riskier reference entity is, the wider is the CDS spread. Figure 4 describes the structure of CDS contract in more detail.

² The information presented in this paragraph is collected mainly from Moorad Choudhry (2006)

Figure 4

Structure of credit default swap contract. The figure illustrates that protection seller demands periodical payments in order to protect protection buyer from default in predetermined reference entity (Choundry, 2006)



CDS contract has a predetermined maturity date, but the contract can mature also in the case of credit event. Credit event terminates the contract and net settlement from the seller to the buyer takes place in one of two forms: cash settlement or physical settlement. The cash settlement obligates the seller to deliver the buyer either the total nominal value of the contract or nominal value less recovery value of some predetermined reference asset. Reference asset normally is commercial or sovereign bond issued by the reference entity. This procedure is efficient in all other aspects, but the problem is to determine right recovery or market value for the reference asset at the time of default. The second alternative is that the buyer physically delivers agreed reference asset to the seller in order to receive the default payment. This method is in practice more complicated in administrative sense, but it does not require difficult valuation of the reference asset at the time of default. In theory the value of protection should be immune to what type of settlement is written down on contract, but in practice different preferences of counterparties in the contract matters slightly.

2.7 CDS market development

The CDS market has grown rapidly during the last 11 years since International Swaps and Derivatives Association (ISDA) standardized the first version of a CDS contract in 1998. Figure 5 describes CDS market development based on ISDA 2009 market survey. Explanation for such a high volume numbers

is that the market size is measured in notional terms, which is far different from the degree to which cash changes hands under CDS contracts. The notional market size actually describes the cash flow situation what would prevail if all contracts would face a credit event, and that is even under the financial crisis not indeed the case. Only small fraction of contracts will face the credit event and other mature untriggered. However, all the contracts need to honour their periodical payment schemes, but these are also very little compared to their notional values. Interesting in the following Figure 5 is that when CDS spreads started to rise in 2008 (see Figure 7) the notional amount of CDS contracts plunged. Perhaps the contract sellers got scared, which would have affected also to the volume of CDS market.

Figure 5

Notional amounts of outstanding CDS contracts at year-end. The figure describes steady CDS market development untill 2008 when CDS market shrank compared to the peak of 2007. Notional amount figures represent amount of cash changing hands if all the contracts would face credit event during the year. Source: ISDA annual market survey 2009



Notional amounts of outstanding CDS contracts at year-end

The CDS market originally started as an inter-bank market to exchange credit risk without selling the underlying loans, but it now involves financial institutions from insurance companies to hedge funds. Furthermore, the maturities in CDS market have evolved: Initially maturities of CDS contract varied, but later the five-year contract became far the most popular one. Today also three-, seven-, and ten-year contracts are traded, but they lose in popularity to five-year ones. (Jakola, 2006)

The fast development of CDS market has also raised some criticism for lagging legislation for the industry. Mainly the critics demand more transparency to the market, which is now operated on overthe-counter basis. Also the bankruptcy of Lehman Brothers' and difficulties in AIG has taught a lesson that there is counterparty risk also in CDS contracts. Suppose you have bought protection from AIG against default in Lehman Brothers'. The contract is very much worthless if AIG is simultaneously in default as Lehman Brothers'. Nevertheless, it was observed that the CDS market remained more functional during the heat of the credit crisis than the comparable bond markets, which merely melt down as investors were too scared of each other.

2.8 Credit crisis

This thesis provides reader with a unique insight on how the prolonged 2007 begun credit crisis has affected the relation of credit rating agencies and CDS market. The most devastating financial and economic crisis after the Great Depression 1929 hit first in the mid summer 2007 when Bear Sterns' two subprime hedge funds were found to have lost merely all of their asset values. The crisis ultimately sent CDS spreads sky high as it is illustrated in following Figure 7 when Lehman Brothers investment bank filed for bankruptcy.

Initially, the problem was that U.S. banks granted their customers too loosely housing loans as purchased property was viewed as sufficient security against default. It didn't make the setting any easier that many of these mortgages were pooled and then shares of these mortgage pools were sold further on. There were no problems as long as property values kept on rising, but ultimately this development stopped and property values started to decline. Then it was revealed that these securitised debt obligations (CDOs) were severely misprices and many major financial institutions had to make substantial writedowns from their balance sheets, which led to turmoil of investor sentiment and merely froze, for a while, any borrowing and lending activity in the financial markets.

These huge writedowns by major financial institutions relate closely to this thesis as they commonly were rated by major credit rating agencies analysed in this study. The writedowns by these institutions occurred often without corresponding downgrade well beforehand, which harmed the reputation of credit rating agencies. As the timing of this thesis allows me to compare CDS reactions before and after the hit of credit crisis I will also do it. This thesis provides a comparison of CDS market responses between periods before and after July 1, 2007 for rating types that contained most observations for each agency.

3 Literature review

The following section summarizes relevant previous literature. The aim of this section is to give an overall view of the previous findings so that empirical results of this thesis can be better interpreted. Furthermore, familiarity of the previous literature is crucial to understand the hypothesis building process and other aspects of theoretical design described in this thesis. Main findings of rating announcements' impact on different markets are discussed first with focus on previous few CDS market studies. Then financial herding literature is discussed with focus on analysts herding studies, because of the lack of previous rating agency herding studies.

3.1 Rating announcements market impact

3.1.1 CDS market response

Previous research has studied plenty the impact of credit rating announcements on stock and bond markets. Only a while have academics been able to study credit rating announcements' effects on derivative market as well. The applicable derivative market to study credit rating announcement effect is the CDS market where buyers and sellers trade reference entities' default risk. The first academics to study relationship between CDS spread changes and credit rating announcements were Hull et al. (2004) and Norden and Weber (2004) who both published their articles in the Journal of Banking & Finance. Also a group of researchers working for International Bank of Settlements have studied the same subject twice (Micu et al, 2004; Micu et al, 2005).

Hull et al. (2004) studied the effect of Moody's credit rating announcements on CDS spreads. The CDS spread data in this study covered the period from October 1, 1998 to May 24, 2002 with reference entities worldwide and emphasis on North America. Sample included only five-year quotes and totalled to 29,032 spread observations. The findings were well in line with previous findings from stock and bond market reactions: Reviews for downgrade were found to have a significant effect on CDS spreads. Downgrades and negative outlooks didn't have significant effect and positive rating actions had even less of an effect. This study also analysed the interplay between CDS market and rating announcements

the other way around: Hull et al. (2004) found that 42.6% of downgrades, 39.8% of reviews for downgrade and 50.9% of negative outlooks came from the top quartile of CDS spread changes. These pioneering findings suggested somewhat reactive role for Moody's agency in relation to CDS market. However, this study couldn't answer in general what role credit rating agencies play in relation to CDS market as only Moody's credit rating announcements were analysed.

Norden and Weber published in 2004 a rather similar study as what is presented in this paper. They studied rating announcements' impact on CDS spreads from all three major credit rating agencies (S&P, Moody's and Fitch). The researchers analysed CDS spread observations for a maturity of five years from a period of 2000 to 2002. After data filtering they ended up with a sample of 60,827 CDS spread observations for 90 different reference entities worldwide with a geographical focus on Europe. First, they found that CDS market anticipated downgrades for all three agencies. Anticipation was observed already 90 - 60 days before the announcement day. This finding is in line with the results from Hull et al. (2004) discussed in the previous paragraph. Second major finding from Norden and Weber was that reviews for downgrade by S&P and Moody's are associated with significant negative abnormal performance in the CDS market where as actual downgrades are not. However, neither did reviews for downgrade nor actual downgrades by Fitch have significant impact on CDS market.

Micu et al. (2005) were first to study rating announcements' impact on CDS spreads with a considerable sample size. They collected global data set covering the period from January 1, 2000 to March 31, 2005. The sample, in that study, consisted of 439 issuers and 2,014 rating announcements, which is considerably more than in previous studies of that time. Empirical results in that study revealed that reviews for downgrade have a significant impact on abnormal spread change (ASC), while downgrades didn't convince in any reasonable significance levels. However, both the reviews and actual downgrades were significantly observed to be anticipated by market. On the contrary to the papers by Hull et al. (2004) and Norden and Weber (2004) this study revealed significant decrease in adjusted spread change ASC due to positive rating announcements. Furthermore, the study didn't find market anticipation preceding positive rating announcements, which is not in line with the situation with negative rating announcements. Micu et al. studied CDS market response following rating announcements already in 2004. That study, however, didn't significantly differ regarding findings

compared to the more recent study (Micu et al, 2005), but was run with considerably smaller sample size.

3.1.2 Stock market response

The potential impact of rating announcements on equity prices is more ambiguous subject and depends on the reason for the announcement (Goh and Ederington, 1993). On average, negative rating announcements should have negative effect on equity prices. This is particularly the case when negative rating announcements are motivated by changes in issuer's financial prospects, such as earnings growth. However, negative rating events can also originate from changes in issuer's capital structure when issuer's credit quality deteriorates for the benefit of stockholders. In this case, negative rating effect should in fact lead to rise in equity prices. Respectively, a positive rating event caused by leverage decrease should lead to falling equity prices.

Goh and Ederlington (1993) were first to study whether the reason for rating announcement really matters in equity market. The researchers did found that equity prices significantly adjust downwards in reaction of rating announcements stemming from deterioration in earnings prospects. Furthermore, the researchers found the expected positive price reaction following downgrades due to increase in leverage, however, the results in this category weren't statistically significant.

Other studies, that haven't considered reasons for rating announcement, have found on average that negative rating actions have also negative stock price effect, where as positive rating actions do not carry significant stock price effect. Recent studies of this line of literature are: Dichev and Piotroski (2001), who find significantly negative returns during the first month after a downgrade and no significant reaction for upgrades. Followill and Martell (1997) with findings that revealed significantly negative returns at reviews for downgrade and negligible abnormal performance around actual downgrades.

3.1.3 Bond market response

Studies of bond market reactions following credit rating actions are common and well researched line of literature. One of the first well regarded studies of this field is Katz (1974). In this study the results show no anticipation before rating actions and abnormal performance during 8 to 10 weeks after downgrades. The main difference between stock and bond market studies is that the reason for rating actions should not matter. However, there is one other factor in addition to plain default probability affecting bond yields, i.e. the general interest rate level, which is, however, easily controllable parameter.

Interestingly, the level of rating action anticipation in bond market has increased since Katz (1974) study for which the data was collected from the period 1966 to 1972. Hite and Warga (1974) found in their study significantly negative abnormal returns during the 6 months before downgrades with a sample collected from 1985 - 1995. Steiner and Heinke (2001) also report significant negative abnormal returns starting 90 days before negative rating action with data from the period 1985 to 1996.

As it was already discussed in the previous chapter that major rating agencies went through a shift in their business model during the 1970's by starting to collect their revenues from rated companies themselves instead of investors. In the light of previous literature it would seem plausible that the shift would have somehow altered the relations between credit rating agencies and bond market so that credit rating actions would have become easier to anticipate. However, this topic is not essential regarding the study presented in this paper and thus it may remain still to be researched by future studies.

3.2 Herding studies

Herding among rating agencies is an unstudied topic so far, which is somewhat surprising giving the herding optimal circumstances under which rating agencies operate. According to Shiller (1995): "Herding is a natural behaviour pattern in a variety of contexts, but usually when decision-making setting is complex and there exists restrictions of time, information and ability for decision maker". All of these parameters listed by Shiller seem to apply for the decision-making setting faced by credit

rating agencies: Rating review process includes analysis of various factors affecting reference entity's creditworthiness making the situation complex. Consumed time in credit review process is naturally minimized so that credit rating change would actually offer new information to market. Also information sources between the agencies and the skill levels of employees vary as well.

Before entering deeper into herding discussion the very concept of herding needs some clarification. According to various authors (Shiller, 1995; Trueman, 1994; Banjernee, 1992; Scharfstein and Stein, 1990) herding behaviour is regarded to take place when individuals adjust their own beliefs to correspond more closely with the publicly expressed opinions of others. Most of financial herding studies focus on security analysts' herding in their earnings forecasts. Other areas that herding studies usually covers are bank runs and mutual fund herding. However, for the purposes of this study, analysts' herding studies offer the most applicable theoretical background. The following two paragraphs present two previous analysts' herding studies that are essential regarding the study presented in this paper.

A relatively early study by Trueman (1994) reports herding findings among security analysts. The author examines earnings forecasts behaviour by analysts and finds that analysts are inclined to release earnings forecasts close to prior expectations even if their private information would justify more extreme forecasts. Furthermore, prior forecasts by other analysts were found to affect analyst's own forecast, which is the very evidence of herding behaviour. Even if there are some fundamental differences between security analysts' and rating agencies' decision making setting it is very tempting to figure that there would also be some similarities that would cause herding behaviour between credit rating agencies as well. Main difference between security analysts' and credit rating agencies' decision making setting is that security analysts normally prepare their forecasts individually, where as rating agencies conclude their rating actions in groups of analysts referred to as rating committees. In group level herding behaviour may not participate that much to decision-making process as those that have their strong own insights. The sixth and seventh hypotheses presented in the introductory of this thesis focus on finding indications of herding behaviour between the credit rating agencies.
More recent study by Clement and Tse (2005) studied what characteristics drive analysts to issue bold earnings forecasts. Bold forecast refer to a forecasts, which move farther away from the consensus forecast. On the contrary, forecasts that move closer to consensus forecast are referred to as herding forecasts in that study. They found that attributes such as general experience, prior accuracy, brokerage size and forecast frequency are positively correlated with likelihood to issue bold forecasts. Even though the researchers didn't directly investigate what parameters cause herding forecasts to be issued, it seems logical to conclude that opposites of parameters causing bold forecasts must correlate with frequency of herding forecasts. Thus lack of general experience, lack of prior accuracy, inverse of brokerage size, and inverse of forecast frequency would induce relatively more herding forecasts to be issued. These findings of parameters that are viewed to cause bold and herding forecasts are the theoretical base for my eighth hypothesis presented in the introductory.

4 Description of the data sets

The following section provides a detailed description of the data analysed in this thesis. First data for the CDS respond study will be described and then data for the herding study. There are two important issues to be clarified before entering to the detailed data description: First, the CDS respond study requires data from both credit rating announcements and CDS spreads, whereas the herding study is build solely around data of credit rating announcements. Second, the initial credit rating data set for both CDS respond study and herding study is the same, but for two reasons the final samples differ from each other: First, credit rating announcements for CDS respond study has to relate to companies subject to five year CDS contracts. Second, for the herding study, only credit rating announcements concerning companies rated in minimum by two of the major agencies simultaneously are to be included.

4.1 CDS market respond study

The data consist of U.S. companies' CDS transaction spreads for five-year contracts and corresponding issuer-specific credit rating data. The sample contains only data related to companies that are included in S&P 500 index at June 4, 2009. Furthermore, only the credit rating data above the investment grade threshold (see Table 3) is considered in this study. The data for both the CDS spreads and rating actions were retrieved from Bloomberg database and they cover the same period from January 1, 2000 to June 4, 2009. Number of companies included in this study amounts to 160 and the names are listed in Appendix 1.

4.1.1 CDS spread data

The initial CDS data set covers all U.S. companies that had CDS transaction spreads for the maturity of five years during the observation period. Number of these reference entities totals to 354. Maturity of five years is currently the most popular for CDS contracts, which makes them the most liquid ones and that is the reason why they are studied in this paper. Due to some illiquidity still existing in the market there aren't CDS transactions for every reference entity every day in my sample, which is why I need to use the most recent transaction spread available as a proxy for the missing day's one. The same

technique was used in Micu et al. (2005) paper, where as Norden and Weber (2004) and Hull et al. (2004) linearly interpolated the missing days' quotes. This interpolation technique was necessary at the time of their researches as their sample consisted of less CDS trade activity, which would have otherwise led to misleading results.

Next, I narrow down the number of companies in the CDS respond sample to only those that were included in S&P 500 index at June 4, 2009 and had investment grade level credit rating activity by at least one of the studied rating agencies (S&P, Moody's, Fitch) during the observation period. Thus, the number of reference entities in the sample declines to 160. I decided to include only investment grade level rating actions concerning companies in S&P 500 index to the sample due to the fact that small companies with poor credit quality are rarely linked to CDS contracts. The total number of CDS spread observations in my final sample equals to 334,190, which is considerably more than in the earlier studies published in academic journals in the field (Norden and Weber, 2004; Hull et al, 2004).

4.1.2 Descriptive statistics I

Figure 6 describes the sample size development across the observation period in respect to number of companies included in the sample. Such a considerable leap in sample size during the years 2002 - 2004 is explained by the fact that then occurred most of the first rating actions for the companies in my sample. The sample size growth in Figure 6 has only little to do with the overall growth in the CDS market described Figure 5. The fact that number of companies in the sample does not decline in any point of time during the observation period is because of only those companies are included in the sample that existed at the end of the data period. This data collection method causes some survivorship bias into my sample, which is discussed better in the limitations of the data section.

Figure 6

CDS sample size development. The figure illustrates how many companies are included in the CDS market respond sample in every point of time during the observation period. The sample size increses considerably during the years 2002 - 2004, after which the sample size remains quite stable.



Figure 7 describes average CDS spread development in my sample. Due to possible statistical problems caused by a small sample size, years before 2004 are omitted from this illustration. As it is easily observed from the figure, the overall credit quality of U.S. companies remained very steady during the period 2004 - mid-2007. Bear Stearns mortgage related hedge fund difficulties initiated the credit crisis in the summer of 2007, after which the CDS spreads slowly became more volatile and kept on elevating. However, the CDS spreads didn't skyrocket until the chapter 11 bankruptcy filing of Lehman Brothers on September 15, 2008. This event caused a sharp peak in the CDS spreads market wide, which can also be perceived in the Figure 7.

Figure 7

Average CDS spread development within sample companies. The figure illustrates how CDS spreads remained low and steady until the burst of the credit crisis in the summer of 2007. The dotted circle around the average spread line signifies the bankruptcy filing of Lehman Brothers. Years before 2004 are omitted from the illustration, because of insufficient sample size illustrated in Figure 6. The average CDS spread among the sample companies is also the index by which spreads of inividual sample companies are adjusted as what is explained in the methodology section of this thesis.



Average CDS spread development within sample companies

4.1.3 Credit rating data

The credit rating sample, used in my CDS reactions study, consists only of ratings that reflect issuer's creditworthiness (issuer-specific ratings). This is to avoid problems with multiple subsequent rating actions that would all respond to the same the underlying cause. This would be a problem if a company had many issues rated by same agency. Furthermore, the link between issuer-specific ratings and CDS spread changes is much stronger than issue-specific ratings and the CDS spread changes. This is because CDS spread changes are function of reference entity's probability to run in default and issue-specific ratings take into account also other aspects, such as credit quality of possible guarantors, insurers.

Rating types included in my study are the following: S&P: LT local issuer Credit, Moody's: Issuer rating, Fitch: LT Issuer Default Rating. Unlike Norden and Weber (2004), I am able to construct my credit rating sample without having to include multiple rating types from the agencies. Unfortunately, this strict sample policy leads to the result that number of Moody's observations does not reach as high as other agencies'. Still my credit rating sample contains more than double the observations than that of Norden and Weber's (2004) equalling to 861 observations in total.

4.1.4 Descriptive statistics II

My credit rating sample of 861 observations contains 37.79 % positive rating actions, while the rest 62.21 % are negative ones when omitting new rating actions. Table 1 in the introduction section explains the expected market reaction, i.e. which of the rating actions are perceived as positive and which negative ones. The domination of negative rating events suggests deteriorated overall level of credit quality, which is well in line with the average CDS spread development described in the Figure 7. The detailed breakdown of credit rating sample is presented in Table 4. Note that the final credit rating sample for CDS reactions study differs from the final credit rating sample for the herding study in respects explained at the beginning of this chapter.

Table 4

Rating action sample for CDS market respond study. The table presents breakdown matrix for total 861 rating actions includeded in the sample categorized by issuing agency and type of rating action.

| | | Agency | | _ |
|---|-----|---------|-------|-------|
| | S&P | Moody's | Fitch | Total |
| # of Companies | 142 | 42 | 127 | 160 |
| Rating action type | | | | |
| Straight single notch downgrade | 53 | 11 | 83 | 147 |
| Single notch downgrade from negative view watchlist | 55 | 33 | 9 | 97 |
| Double notch downgrade | 20 | 7 | 18 | 45 |
| Multiple notch downgrade | 4 | 0 | 3 | 7 |
| Straight single notch upgrade | 57 | 6 | 68 | 131 |
| Single notch upgrade from positive view watchlist | 23 | 9 | 2 | 34 |
| Double notch upgrade | 4 | 1 | 4 | 9 |
| Multiple notch upgrade | 0 | 0 | 0 | 0 |
| Negative view watchlist announcement | 132 | 46 | 32 | 210 |
| Cancelled negative view watchlist | 66 | 9 | 19 | 94 |
| Positive view watchlist announcement | 28 | 10 | 5 | 43 |
| Cancelled positive view watchlist | 4 | 1 | 1 | 6 |
| New rating announcement | 1 | 6 | 31 | 38 |
| Total | 447 | 139 | 275 | 861 |

Table 4 is interesting reading as it explains how the three major credit rating agencies actually communicate with the market. It seems that Moody's uses the most negative watchlistings as 75% of its every single notch downgrades were preceded by a corresponding watchlist announcement. Respectively, S&P issued approximately half of its single notch downgrades from the watchlist and half without the previous watchlisting. Fitch used the least negative watchlistings as over 90% of its single notch downgrades occurred without preceding watchlisting. The role of positive view watchlist announcements seems less important than negative ones. Fitch made almost all of its single notch

upgrades without preceding watchlisting. Also S&P seems to upgrade easily without corresponding watchlisting as approximately 71% of its single notch upgrades took place without preceding positive watchlisting. Moody's, however, issued preceding positive view watchlisting for 60% of its single notch upgrades. On the other hand, when positive watchlisting was issued it seems to have led for upgrade quite often as during the total observation period only six positive view watchlistings were cancelled. Negative watchlistings, however, were cancelled much more often. Furthermore, it is interesting that in Table 4 almost all new credit rating announcements during the observation period were issued by Fitch. This finding might indicate improved investor perception for Fitch's agency.

4.2 Herding study

4.2.1 Data

The original credit rating data in my herding study is the very same as used in the CDS market reaction study: The data consist of issuer-specific investment grade level credit rating actions from the period January 1, 2000 to June 4, 2000 by S&P, Moody's and Fitch for U.S. companies included in S&P 500 index at the end of the observation period. However, from this original sample, only rating actions relating to companies simultaneously rated by at least two major rating agencies could be included to the final sample. Companies with simultaneous rating activity by the major rating agencies are as follows: 110 companies simultaneously rated by S&P and Moody's, 219 companies rated simultaneously by S&P and Fitch, and 85 companies rated simultaneously by Moody's and Fitch. Lists of these sample companies rated simultaneously at least by two major rating agencies are shown in Appendix 2.

The reason, why I use the same original credit rating sample for both the herding study and the CDS reactions study, is that the companies included in S&P 500 index are the largest in the U.S. market and thus most inclined to have more than just one rating agency to rate them. Also companies in S&P 500 index are of the highest end regarding their credit quality, which would have made the decision to include also below investment grade level rating activity into my sample rather trivial. Furthermore, the decision to analyse only issuer-specific ratings is made to avoid problems with multiple subsequent

rating actions triggered by the same underlying event if companies had many issues rated simultaneously.

In the CDS reactions study I analyse individually 13 different rating announcement types, which are divided into six types that have negative expected spread reaction, six types that have positive expected spread reaction, and the new rating announcement having undetermined spread reaction. In the herding study I am only concerned about the direction of rating action, in addition to its timing. That is why I merge all the positive rating announcements with undetermined market reaction from the analysis. In my herding study, sample of negative rating actions equals to 1,468 and number of positive actions equals to 786, which together count to 2,254 rating actions in total. Negative announcements refer to situations where agency signals decreased creditworthiness that would cause CDS spreads to increase. Vice versa, positive rating announcements refer to situations where agency signals strengthened creditworthiness that would cause CDS spreads to decrease.

4.2.2 Descriptive statistics III

The following Table 5 shows a description of my herding study sample. Panel A shows that the sample consists of total 2,254 rating actions of which 65.13% are negative rating actions while the rest 34.87% are positive ones. The proportion of negative rating actions slightly exceeds the proportion in the credit rating sample for the CDS reactions study, which is line with the aforementioned fact that CDS contracts usually relate to companies with good credit quality. Interestingly S&P and Fitch have almost the identical proportion of negative and positive announcements, while Moody's seems to have issued slightly more positive rating actions compared to the other two agencies during the observation period. This finding likely relates to the fact that number of companies, which are rated by Moody's, in my herding study sample, is significantly less compared to companies rated by the other two agencies.

Panel B plots the herding rating action observations in my sample. Out of the total 2,254 rating actions 432 meets the qualifications set for herding rating action. In previous herding literature, that being mainly written for security analysts' earnings forecasts, herding forecast refers to one that moves closer to consensus estimate. However, in my study framework where only three players are analysed, the

consensus logic does not work. I define, that herding rating action refers to rating action, which follows in 60 days previous rating action issued by other agency into the same direction credit quality wise. The logic is to match two different rating actions together and study whether these herding rating actions unproportionally amount to one agency or whether there exists some timely patterns when these herding rating actions are issued. Note that my herding rating action definition has only two restrictions concerning the timing and the direction of the rating action and that is the reason why I pool all positive and all negative rating actions together in their own groups. For agency level herding action information Table 5 is structured so that agencies indicated on the columns refer to issuers of herding rating actions, while agencies on rows refer to agencies that those herding rating actions are supposed to imitate.

Panel C in Table 5 plots the theoretical maximums of herding actions. These actions are rating actions by other agency to which agency have had a chance to respond. Agencies indicated on columns in the table refer to ones who either issued herding rating action or could have done it as a response to rating actions by agency indicated on the row. Note that total number of theoretical maximums of herding rating actions amounts more than total number of all rating actions in the sample. This is because the sample includes also companies that are simultaneously rated by all three agencies, which leads to fact that one rating action can be viewed as triggering rating actions for herding rating actions by the two other agencies simultaneously. The panel D plots percentage figures, which indicate what proportion of every rating action that in theory could have triggered a herding rating action, actually triggered one. These figures are all very close to each other between the range from 12.96% to 18.84%. Agency indicated on column refers to issuer of herding rating action and agency on row refers to one that those herding rating actions are to imitate.

The Panel E describes the ratios between two agencies theoretical maximums for herding rating actions. I name this ratio as "lazy ratio" because it describes how many times more (or less) an agency has issued rating actions for which other agency could have responded by issuing a herding rating action during the observation period. Consider, for example Fitch's lazy ratio with S&P. S&P has issued in total 811 rating actions that could have triggered a herding action by Fitch, while Fitch only issued 532 actions for which S&P was able to react. Thus the Fitch's lazy ratio with S&P equals to 532/811=0.66, which describes the relative frequency of Fitch's rating announcements to S&P's rating

action behaviour. The use of lazy ratio, as a control variable for rating action activity, is discussed more in methodology section. Note that lazy ratios in the top right hand corner and bottom left hand corner are inverse figures to each others. According to the information revealed by lazy ratios S&P and Moody's are approximately equally active to issue rating actions while Fitch seems to issue approximately 1/3 less rating actions than S&P and Moody's. A likely reason for Fitch's lesser credit rating activity is its tendency to prefer straight upgrades and downgrades, where as S&P and Moody's tend to issue watchlistings before actual rating changes (see Table 4).

Table 5

Description of rating action sample for herding study. Panel A presents breakdown of rating actions to positive and negative ones in both absolute and relative terms. Panel B plots numbers of herding rating actions where the column agency follows the agency in row. Panel C plots the rating actions by the row agency, for which the agency in column has been able to respond with its own rating action meaning that the company to which the row agency's rating action relates had to be simultaneously rated by the column agency also. Panel D presents how many times, in relative terms, the opportunity to issue herding rating action has actually led to one. Panel E presents lazy ratios, which illustrate the relative frequency of rating action issuances between the agencies on the column and row. Lazy ratios are determined by dividing row agency's theoretical maximum of herding actions with the row agency.

| | | Agency | | |
|--|---------|---------|---------|---------|
| | S&P | Moody's | Fitch | Total |
| Panel A: Rating actions | | | | |
| Positive actions | 467 | 120 | 199 | 786 |
| Negative actions | 825 | 282 | 361 | 1468 |
| Positive actions as % of all actions | 36,15 % | 29,85 % | 35,54 % | 34,87 % |
| Negative actions as % of all actions | 63,85 % | 70,15 % | 64,46 % | 65,13 % |
| Total # of actions | 1292 | 402 | 560 | 2254 |
| Panel B: Observed herding rating actions | | | | |
| with S&P | N/A | 75 | 142 | 217 |
| with Moody's | 60 | N/A | 39 | 99 |
| with Fitch | 85 | 31 | N/A | 116 |
| Total | 145 | 106 | 181 | 432 |
| Panel C: Theoretical maximum of herding actions | | | | |
| with S&P | N/A | 398 | 811 | 1209 |
| with Moody's | 382 | N/A | 301 | 683 |
| with Fitch | 532 | 200 | N/A | 732 |
| Total | 914 | 598 | 1112 | 2624 |
| Panel D: Observed herding rating actions as % of theoretical maximum | | | | |
| with S&P | N/A | 18,84 % | 17,51 % | 17,95 % |
| with Moody's | 15,71 % | N/A | 12,96 % | 14,49 % |
| with Fitch | 15,98 % | 15,50 % | N/A | 15,85 % |
| Average | 15,86 % | 17,73 % | 16,28 % | 16,46 % |
| Panel E: Control factor for rating action frequencies (lazy ratio) | | | | |
| with S&P | N/A | 0,96 | 0,66 | |
| with Moody's | 1,04 | N/A | 0,66 | |
| with Fitch | 1,52 | 1,51 | N/A | |

4.3 Limitations of the data

I collected CDS spread data for companies that were reference entities to CDS contracts at June 4, 2009. This particular data mining method causes some survivorship bias to my CDS market reactions sample. Survivorship bias refers to automatic exclusion of companies that no longer exist at the end of period. In study framework, the survivor bias causes my sample to exclude companies that went bankrupt, merged with some other company, or some other ways ceased to exist during the observation period. However, the magnitude of this bias remains low as I only have data of companies with investment grade level credit rating, which means that the companies in my sample are least likely of all companies to go bankrupt.

Furthermore, for CDS respond study, I accept observations of credit rating announcements from the very beginning until the very end of the total observation period. This causes some censoring bias to my CDS respond sample, because for those rating actions that have occurred during the first and last 90 days in my observation period, I cannot have full [-90, 90] days CDS data to study. However, considering the very wide total observation period, the effect of this bias is well diluted.

5 Methodology

This section explains how the data described in previous sections are processed and tested for the hypotheses. The methodology described in CDS market reaction study is in line with methodological frameworks in previous studies, but the one described in the herding study is invented by the author for the purposes of this study.

5.1 CDS market respond study

The methodology in CDS market reaction study follows in most respects the one presented in Norden and Weber (2004) paper. The researchers studied also S&P's, Moody's and Fitch's rating announcements' effects on CDS market. Norden and Weber (2004) studied whether rating announcements causes adjusted CDS spread changes (ASCs) deviate from zero with statistical significance. This section starts by explaining how I process my data to have a sample of ASC observations. Then the focus turns to the applicable statistical tests to uncover the statistical significance behind the findings.

5.1.1 Determining adjusted spread changes (ASCs)

In the data processing, my first phase is to link rating actions of the studied agencies with the corresponding CDS spread data. The day, on which rating action is issued, is now on referred as day zero. I take both 90 days of CDS spread data before day zero and 90 days after it in order to capture the impact of rating action. Hull et al. (2004) and Norden and Weber (2004) both used the 90 days observation window before and after the day zero. Micu et al. (2005), however, applied only [-60, 60] window. To be able to better compare my results with the previous studies, I choose to use the wider event window.

Next, I adjust the CDS spreads against effects of market wide events. A proper example of market wide event would be the collapse of Lehman Brothers, which caused a sharp peak in CDS spreads on September 19, 2009 (see Figure 7). If not adjusted, all the CDS spread observations close to that event would be contaminated, as the purpose is to exclusively study the effects of rating actions. The

adjustment is done by constructing an index that reflects the performance of average credit quality and then adjusting changes in CDS spreads with changes in the index. The index that I use is the average of all CDS spread observations across the observation period. In fact, my index is the very same what is illustrated in Figure 6. Next, I calculate the ASCs applying the following formula:

Equation (1): ASC(i,j) = CDS(i)-CDS(j)-[I(i)-I(j)]

The formula states that adjusted spread change for the period from i to j [ASC(i,j)] equals the difference in CDS spreads between the beginning and the end of that period [CDS(i) - CDS(j)] subtracted with a corresponding difference in the index [I(i) - I(j)]. For the purposes of better graphical illustration of results I also determine cumulative abnormal spread change development across event windows. The cumulative adjusted spread change (CASC) is defined as a sum of all preceding ASCs in the event window:

Equation (2): CASC(i) = ASC(1) + ASC(2) + ... + ASC(i)

This sample processing technique is the very same as presented in Norden and Weber (2004) study with two exceptions: First, they eliminated rating actions from their sample that were preceded with similar rating action 90 days earlier. This was to avoid CDS spread data contamination caused by multiple events in the time window. Second, Norden and Weber (2004) constructed own indexes for every rating class and adjusted the spread changes with the CDS spread index that matched the contemporary rating of the company. I choose not to follow Norden and Weber (2004) study in these respects for the following reasons:

First, I do not eliminate rating actions that occurs close to each other as I have a credit rating sample twice as large compared to Norden and Weber (2004), and because in larger samples random occurrences even out better each other. Furthermore, according to my opinion, the exclusion of consequent similar events would give too strong impression of rating actions influence. For example, if Fitch would emit 100 negative view watchlist announcements under a hypothetical observation period and 50 of them would occur soon after respective announcements by S&P and Moody's, it would be reasonable to expect a weak announcement effect for these negative view announcements. However,

the rest 50 negative view announcements would by the same logic carry a stronger market impact as investors in these cases were not warned by other agencies beforehand. Now, concentrating only to announcements, which are not preceded with a similar announcement, would naturally give too strong image of agency's role in market as it is totally up to the very agency if it responds more slowly than other agencies.

Second, I do not construct own indexes for every credit rating class because I have more homogeneous sample than Norden and Weber (2004). First, my sample has only U.S. companies included, which suggests geographical homogeneity. Second, my sample companies do not differ much from each other regarding their size as they are all relatively big, because of the restriction that they need to be included in S&P 500 index. Third, and most importantly, my sample companies have all investment grade credit quality status, which suggests homogeneity in credit quality wise.

5.1.2 Applied statistical tests

Student's t-test

The most popular test to measure impact of credit rating announcement on CDS market in the previous literature has been student's t-test. Likewise in previous studies, I use the t-test to find out on which significance level average of ASC observations deviates from zero. If rating announcement carries no impact on market, average ASC should not significantly deviate from zero. But, if the rating announcement has its impact, then the mean ASC should be either bigger or smaller than zero depending on what expected market reaction is attached to rating announcement. This rationale also suggests me two use 1-tailed test, as the direction to which the mean should deviate is known. Moreover, Micu et al. (2005) also used particularly 1-tailed test in their study. A minor problem with t-test is that it implicitly assumes that sample observations are normally distributed around their mean. The following equation (3) describes how the test parameter is determined.

Equation (3):
$$t = \frac{\overline{x} - \mu_0}{s/\sqrt{n}}$$
 \overline{x} = average ASC observation
 μ_0 = zero
 s = sample standard deviation
 n = sample size

Sign test

The sign test escapes from the problem around assumptions on residuals' distribution as it only regards them positive or negative ones. The idea of the sign test is simply to measure on which significance level proportion of positive or negative observations deviates from half of total observations. In my setting, the test measures whether adjusted spread changes, on a given time interval, are significantly more positive or more negative ones. The test parameter, which is normally distributed, is determined by the following equation (4):

Equation (4):
$$J = \left(\frac{n^+}{n} - 0.5\right) \frac{n^{1/2}}{0.5}$$
 $n^+ =$ number of total observations $n =$ number of positive observations

5.2 Herding study

Due to the lack of applicable previous research, methodology presented in this section is invented solely by the author. The basic idea is to pair match rating actions of different agencies that have moved into the same direction credit quality wise and have occurred within a 60 day time window. The latter of these matched actions is defined as herding rating action. The logic is simple: If there are rating actions that imitate previously issued rating actions should these actions occur relatively soon after the rating action they are supposed to imitate. As I have already stated previously, in perfect world, rating actions by different agencies for same companies should occur simultaneously as there would exist no reason why they wouldn't. However, in real world, I assume that there are three factors affecting the length of lag between rating actions:

50

- 1) Continuous imperfections
- 2) Random imperfections
- 3) Herding behaviour

The continuous imperfections refer to factors such as availability of relevant data on a continuous basis for credit review process and professionalism of employees running the process. Credit rating agencies base their credit review process on public information released to market, but also on private information gathered in meetings with company executives. Especially, in these meetings with company representatives' there might be serious differences between agencies on what kind of information they receive on a continuous basis. Furthermore, continuous imperfections refer to quality of mind power running the review process. Some agencies might just have employees superior to employees of other agencies in respect to how accurately and fast they can run the credit review process. One more factor to cause continuous imperfections is the credit review process required in agencies, before issuing credit rating actions. It might be very plausible that in some agencies information needs to be processed more throughout than in other agencies, which cause naturally lag between credit rating actions. As a conclusion of this discussion I state that differences in data availability on continuous basis, mind power of employees, and requirement standards in credit rating review process between the credit rating agencies result in differences in reaction times to market events.

Random imperfections refer to small differences, in for example in data availability or human errors that cause lag either to increase or decrease, but with the same likelihood to both directions. As sample size increases these random imperfections are supposed to cancel out each other on average level. Assuming that there would not exist continuous imperfections, described in previous paragraph, these random imperfections would lead agency's credit rating action probability function, centred on the event of other agency's credit rating action, to resemble a normal distribution function. Furthermore, if there wouldn't exist continuous imperfections the likelihood for credit rating action occurring some number of days before or after the credit rating action of other agency should be equal.

Herding behaviour affects length of lag as well, but it affects to the opposite direction than continuous imperfections as the whole logic of herding behaviour is to cover own flaws (i.e. continuous imperfections) by imitating actions of others. According to this rationale the findings that would show unproportional number of credit rating events taking place relatively shortly after other agency's credit rating action would indicate herding behaviour. However, it is impossible still to say with certainty whether the findings are still only due to continuous imperfections or is there actual herding behaviour in place. Note that I have assumed that herding only speeds up the credit review process of the herding agency. In the real world there may also be other ways to engage in herding such as issuing rating actions out of insecurity of having conflicting credit rating with some other rating agency. However, what all the herding rating actions must have in common are: First, they can never occur before the action that they are to imitate. Second, the lag compared to the leading rating action cannot be very long or the herding agency wouldn't anymore benefit in issuing the herding rating action. These insights show that, irrespective of the exact reasons or ways to practice herding, the result is the same: Herding activity results in unproportional number of rating actions taking place soon after rating actions by other agency. The following Figure 7 illustrates the discussion presented above.

Figure 8

Illustration of factors affecting the timing of rating action in relation to rating action by other agency. The figure describes how factors 1. Continuous imperfections 2. Random imperfections 3. Herding behaviour affect the location and shape of agency's rating action probability distribution function around other agency's rating action. The vertical line in the middle of the figure represents point of time when an agency issues a rating action. The curve illustrates the rating action probability by another agency responding to the same event that causes the rating action by the other agency.



Figure 8 illustrates how the three factors [Continuous imperfections (1), Random imperfections (2), and Herding behaviour (3)] alter the place and shape of the probability function for rating action. It is insightful to understand that if there wouldn't exists continuous imperfections there wouldn't exist rational reason for herding behaviour, but the existence of continuous imperfections doesn't necessarily result in herding activity between the agencies. So it is impossible to distinct these two factors' effects. As it is impossible to search evidence exclusively from herding factor, I search evidence of the combined effect of factors one and three. The combined effect of these factors would harm the symmetry of the illustrated probability function.

Inspired by the discussed rationale, I find out how many herding action observations, in which agency A lags agency B, there are for each lag day from 1 to 60. Vice versa, I determine the same number of herding rating action observations in which agency B lags agency A in 60 days. If the probability function for agency's rating actions relative to other agency's rating action is symmetrical, differences in observed numbers of herding rating actions between the agencies in any time window should not statistically differ from zero. The following mathematical representation describes the number series subject to my statistical tests in a given time window.

Equation (5): Herding actions' diff. in X days window = [(AB1)-(BA1)], [(AB2)-(BA2)],...,[(ABX)-(BAX)]

In the representation the first letter in parenthesis indicates leading agency and the second letter lagging agency. The number behind the letters indicates lag day from which the number of observations are gathered. For example, if there would exist five observations in which agency B would lag agency A one day and respectively number of observations in which agency A would lag agency B would amount to seven the content of [(AB1)-(BA1)] would be replaced by figure minus two.

Herding actions' differences are subject to student's t test and sign test. The tests are discussed already in CDS respond section in this chapter so the discussion of those tests is not repeated here. The purpose of these statistical tests is to find out whether the number series statistically differ from zero. If the tests show no indication that the number series would statistically differ from zero, I conclude that there is no evidence of combined effect of factors one and three. Thus there would not be any evidence of herding behaviour either. However, if the numbers differ significantly from zero there remains possibility for herding behaviour.

I will run these aforementioned statistical tests for different time windows in order to find out on which time window(s) the likelihood for herding behaviour is strongest. The maximum time window is 60 days as I restricted herding rating action to occur in 60 days after the rating action it is supposed to imitate. The other time windows are: 30 days, 14 days, and 7 days. As herding behaviour is deemed to cause rating actions to follow more close the rating actions they are supposed to relate, I consider findings violating the hypothesis seven in shorter event windows (7 days and 14 days) stronger proherding evidence compared to violating findings under the wider windows (30 days and 60 days).

As stated previously, there prevail substantial differences between agencies' frequencies to issue rating actions. Fitch seems to issue approximately 1/3 less credit rating actions than S&P and Moody's. This fact causes that number of rating actions, for which Fitch can react is substantially higher than the number of rating actions by Fitch for which S&P and/or Moody's can react. In the data description section, I determined the lazy ratios, which illustrate how many more times agency issues rating actions for which the other agency can react. For example, Fitch's lazy ratio with S&P was found to equal 0.66. Hence, in order to control results against deviating rating action frequencies between Fitch and S&P, I multiply all Fitch's herding rating actions observations by a factor 0.66. The same logic I apply to other agency pairs as well. In the empirical results section findings are reported from both the controlled and uncontrolled samples.

6 Empirical results

This section discusses the empirical results of my thesis. First, I show the results of CDS market reactions study, after which I present the pioneering findings of possible herding behaviour between the major credit rating agencies. In this section I test the hypotheses, listed in the introduction section, and find out if they are in line with my empirical results.

6.1 CDS respond study

This section presents my results of CDS market reactions around credit rating announcements by the major credit rating agencies. First, I show my CDS market reactions results for every rating type by each of the three agencies that had sufficient sample size and test whether the first hypothesis holds (see page 10). Along with this discussion, I also test the hypotheses three and four when the results allow (see pages 13 and 14). Then I analyse my results in order to find out if they support the second hypothesis testing the asymmetry between positive and negative announcements, which is found among previous studies. Finally, I present comparisons of rating announcements' CDS market responses between the periods before and after the hit of the credit crisis.

6.1.1 CDS market reactions by rating types

The main results reported in this section are in line with the previous studies of the field. I find the strongest announcement window effect attached to negative view watchlist announcements. T-test results show 1% significant market impact for every agency at the announcement window. The second strongest market impact is related to straight downgrades, which mean that the downgrade is not preceded by corresponding watchlisting. However, downgrade from the negative view watchlist does not seem to induce any effect on the market at all. On the contrary, announcement to cancel negative view watchlisting without the downgrade has market impact according to my findings. Cancelled negative view watchlist announcement by S&P has market impact on 5% level. Interestingly, that is the most influential positive rating announcement in my results. Furthermore, I find that the magnitude of market impact depends more on whether the rating announcement is preceded with the corresponding watchlist announcement than how many notches it moves the credit rating.

In the following presentation of results a careful reader spots that in every rating type the announcement effect in the [-1, 1] window shown on table might not match to the illustration of cumulative adjusted speard change in corresponding figure. This is because the data for figures is collected in intervals of every thirth day, which is obviously two wide window to capture the delicate effect in the [-1, 1] window around the rating announcement.

Negative view watchlist announcement

Results detailed in the following Table 6 reveal that negative view watchlist announcements by all three agencies have significant impact on the CDS market. In the announcement window [-1, 1] both t-test and sign test reports market impact at 1% significance level for S&P and Moody's. T-test also shows 1% significance for Fitch's announcements, but sign test remains significant only at 5% level. These findings are well in line with the most recent CDS reactions study, Micu et al. (2005), but slightly contradict Norden and Weber (2004), as it did not find Fitch's negative view watchlist announcement having significant market impact. In fact, Figure 9 illustrating the development of median cumulative abnormal spread change shows the widest change in the spreads around Fitch's announcement. One plausible explanation for this might be the fact pointed out in the data description section that Fitch issues in proportion less negative watchlistings than straight downgrades compared to other major agencies giving more weight on its negative view watchlistings. However, due to the smaller sample size, S&P and Moody's have slightly better statistical significance among their announcements. Furthermore, the jump in the spreads in Figure 9 from 7.07 bps to 24.11 bps occurs actually in [-6, 3] window, which also explains why the announcement effect in the [-1, 1] window remains not that significant.

Out of the major rating agencies, Moody's is the only one without findings suggesting significant market anticipation before its negative view watchlist announcement. CDS market seems to anticipate S&P's negative view watchlistings significantly during the 30 days period before the announcement. Also Fitch's announcements seem to have some market anticipation, but of less significance and over a longer period of time compared to S&P's announcements. Micu et al. (2005) reported significant market anticipation for every agency, but my findings support market anticipation only for S&P and Fitch. Interestingly, S&P's negative view watchlistings seem also to follow with downward sliding

CDS spreads during [31, 60] and [61, 90] time windows after the announcement. The same effect is not discovered among Moody's and Fitch's announcements. Possible explanation for this finding may be that market continuously over react to S&P's negative view watchlistings. Based on my findings of negative view announcements' market reactions, the first hypothesis is rejected for S&P and Fitch because of the market anticipation and remains not rejected for Moody's. The first hypothesis states that markets do not anticipate rating announcement, but react immediately as it occurs.

Table 6

CDS market reaction around negative view watchlist announcement. Panels A, B and C presents agency specific results of CDS market reactions in 7 different time windows. T-test tracks whether average adjusted spread change statistically differs from zero and sign test studies whether proportion of positive and/or negative adjusted spread changes differs statistically significantly from 50%.

| | | [-90, -61] | [-60, -31] | [-30, -2] | [-1, 1] | [2, 30] | [31,60] | [61,90] |
|---------|----------------------|------------|------------|-----------|-----------|-----------|-----------|-----------|
| Panel A | | | | | | | | |
| | median ASC (bps) | 1,7642 | 0,8313 | 2,9665 | 1,9095 | 0,8201 | -2,8602 | -2,9610 |
| | %- of ASC > 0 | 0,59 | 0,53 | 0,61 | 0,70 | 0,53 | 0,41 | 0,40 |
| | t-test sign | - | + | + | + | + | - | - |
| | t-test p-value | 0,3682 | 0,2575 | 0,0131 | 0,0025 | 0,2573 | 0,0396 | 0,0322 |
| S&P | t-test sgn. level | | | ** | *** | | ** | ** |
| | sign test sign | + | + | + | + | + | - | - |
| | sign test p-value | 0,0184 | 0,2431 | 0,0074 | 0,0000 | 0,2431 | 0,0184 | 0,0118 |
| | sign test sgn. level | ** | | *** | *** | | ** | ** |
| | n | 132 | 132 | 132 | 132 | 132 | 132 | 132 |
| Panel B | | | | | | | | |
| | median ASC (bps) | 1,8736 | 2,0720 | 1,0855 | 1,6308 | -0,7633 | 0,8448 | -2,1225 |
| | %-ofASC>0 | 0,61 | 0,61 | 0,52 | 0,70 | 0,46 | 0,54 | 0,41 |
| | t-test sign | - | + | + | + | - | - | + |
| | t-test p-value | 0,4082 | 0,2659 | 0,1896 | 0,0006 | 0,3840 | 0,4972 | 0,4233 |
| Moody's | t-test sgn. level | | | | *** | | | |
| | sign test sign | + | + | + | + | - | + | - |
| | sign test p-value | 0,0702 | 0,0702 | 0,3840 | 0,0040 | 0,2777 | 0,2777 | 0,1191 |
| | sign test sgn. level | * | * | | *** | | | |
| | n | 46 | 46 | 46 | 46 | 46 | 46 | 46 |
| PanelC | | | | | | | | |
| | median ASC (bps) | 3,0821 | 0,5283 | 2,4057 | 0,9857 | 1,4481 | -0,4993 | -2,0001 |
| | %- of ASC > 0 | 0,66 | 0,56 | 0,63 | 0,69 | 0,63 | 0,47 | 0,47 |
| | t-test sign | + | + | + | + | + | + | - |
| | t-test p-value | 0,4966 | 0,0377 | 0,0717 | 0,0040 | 0,0626 | 0,4579 | 0,1751 |
| Fitch | t-test sgn. level | | ** | * | *** | * | | |
| | sign test sign | + | + | + | + | + | - | - |
| | sign test p-value | 0,0385499 | 0,2397501 | 0,0786496 | 0,0169474 | 0,0786496 | 0,3618368 | 0,3618368 |
| | sign test sgn. level | ** | | * | ** | * | | |
| | n | 32 | 32 | 32 | 32 | 32 | 32 | 32 |

* indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level

Figure 9

Negative view watchlist announcement. The figure Illustrates development of median cumulative adjusted spread change around rating action.



Single notch downgrade from negative view watchlist

CDS market doesn't react at all to single notch downgrades from negative view wachlist, based on my findings detailed in the following Table 7 and Figure 10. In the announcement window [-1, 1] spreads do not show any increase due to the announcement by S&P or Moody's. Fitch's single notch downgrades amounted only to nine, which is why they are omitted from the analysis. These findings are line with the rationale that the market has already reacted to negative view watchlisting and expects the downgrade to take place, which is the reason why the following downgrade conveys no new information. Also the anticipation particularly in the [-60, -30] window before S&P's announcement is in line with the presented logic as it takes between 6 - 8 weeks (i.e. 42 - 56 days) for S&P to terminate its negative view watchlisting by either cancelling it or issuing the downgrade. Moody's announcement has lesser of anticipation, but sign test in [-90, -60] window shows also 5% significant anticipation, while t-test remains insignificant. Based on these discussed findings not suggesting market impact the first hypothesis is rejected for both S&P and Moody's concerning single notch downgrade from negative view watchlist.

58

Table 7

CDS market reaction around single notch downgrade from negative view watchlist. Panels A and B presents agency specific results of CDS market reactions in 7 different time windows. T-test tracks whether average adjusted spread change statistically differs from zero and sign test studies whether proportion of positive and/or negative adjusted spread changes differs statistically significantly from 50%.

| | | [-90, -61] | [-60, -31] | [-30, -2] | [-1,1] | [2, 30] | [31,60] | [61,90] |
|---------|----------------------|------------|------------|-----------|-----------|-----------|-----------|-----------|
| Panel A | | | | | | | | |
| | median ASC (bps) | -2,0222 | -1,9753 | -2,3065 | -0,0536 | -0,7992 | -1,2437 | 1,0194 |
| | %- of ASC > 0 | 0,44 | 0,38 | 0,42 | 0,47 | 0,49 | 0,42 | 0,60 |
| | t-test sign | - | - | - | + | + | + | + |
| | t-test p-value | 0,1364 | 0,0462 | 0,0109 | 0,3881 | 0,0746 | 0,4086 | 0,2357 |
| S&P | t-test sgn. level | | ** | ** | | * | | |
| | sign test sign | - | - | - | - | - | - | + |
| | sign test p-value | 0,1726 | 0,0398 | 0,1125 | 0,3429 | 0,4464 | 0,1125 | 0,0690 |
| | sign test sgn. level | | ** | | | | | * |
| | n | 55 | 55 | 55 | 55 | 55 | 55 | 55 |
| Panel B | | | | | | | | |
| | median ASC (bps) | 4,5498 | 0,6083 | -0,9997 | 0,0696 | -1,8600 | -1,6588 | -2,0772 |
| | %- of ASC > 0 | 0,67 | 0,55 | 0,45 | 0,52 | 0,42 | 0,39 | 0,36 |
| | t-test sign | + | + | + | + | - | + | - |
| | t-test p-value | 0,3581 | 0,1329 | 0,3471 | 0,3911 | 0,0319 | 0,3905 | 0,1526 |
| Moody's | t-test sgn. level | | | | | ** | | |
| | sign test sign | + | + | - | + | - | - | - |
| | sign test p-value | 0,0277555 | 0,3007541 | 0,3007541 | 0,4309022 | 0,1920441 | 0,1115087 | 0,0585925 |
| | sign test sgn. level | ** | | | | | | * |
| | n | 33 | 33 | 33 | 33 | 33 | 33 | 33 |

* indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level

Figure 10

Single notch downgrade from negative view watchlist. The figure Illustrates development of median cumulative adjusted spread change around rating action.



Cancelled negative view watchlist announcement

In line with the discussion in the previous section is the finding that out of the two possible ways to terminate negative view watchlisting, cancellation seems to induce more market impact than the actual downgrade as Table 8 and Figure 11 explain. S&P's announcement to cancel negative view watchlisting has significance on 1% level according to sign test, and significance on 5% level according to t-test. Sign test shows market anticipation before S&P's announcement in the [-30, -2] window at 1% significance level, while t-test shows no significance in the anticipation. Fitch's announcement to cancel negative view watchlisting has no market impact, what so ever, within any period around the announcement. Moody's number of observations in cancelling negative view watchlisting amounted only to nine, which is why it is excluded from the analysis in this section.

Findings this far support the idea that the CDS market reacts already so intensely to S&P's negative view watchlistings that the following downgrade is already priced on the spreads, which causes cancellation of the watchlisting to actually deliver new information to market as it means that the expected downgrade is not to take place. The reason why Fitch's announcements to cancel negative view watchlisting have no market impact may relate to the fact that the majority of Fitch's negative view watchlisting were taken back during the observation period. Fitch cancelled 19 out of its 32 negative watchlistings suggesting that the cancellation of Fitch negative view watchlisting is not that big of a news for the market. Based on my findings, the first hypothesis is rejected for Fitch, because of the lack of announcement effect and for S&P, because the test results cannot rule out the possibility of market anticipation.

Table 8

CDS market reaction around cancelled negative view watchlist announcement. Panels A and B presents agency specific results of CDS market reactions in 7 different time windows. T-test tracks whether average adjusted spread change statistically differs from zero and sign test studies whether proportion of positive and/or negative adjusted spread changes differs statistically significantly from 50%.

| | | [-90, -61] | [-60, -31] | [-30, -2] | [-1, 1] | [2, 30] | [31,60] | [61,90] |
|---------|----------------------|------------|------------|-----------|----------|---------|----------|----------|
| Panel A | | | | | | | | |
| | median ASC (bps) | -0,4528 | -1,6867 | -4,9824 | -0,9082 | -2,3673 | -0,3031 | 0,0944 |
| | %- of ASC > 0 | 0,48 | 0,44 | 0,35 | 0,29 | 0,41 | 0,50 | 0,50 |
| | t-test sign | + | + | + | - | + | + | - |
| | t-test p-value | 0,1051 | 0,0962 | 0,3214 | 0,0451 | 0,2776 | 0,3577 | 0,1378 |
| S&P | t-test sgn. level | | * | | ** | | | |
| | sign test sign | - | - | - | - | - | | |
| | sign test p-value | 0,4028 | 0,1624 | 0,0069 | 0,0003 | 0,0698 | 0,5000 | 0,5000 |
| | sign test sgn. level | | | *** | *** | * | | |
| | n | 66 | 66 | 66 | 66 | 66 | 66 | 66 |
| Panel B | | | | | | | | |
| | median ASC (bps) | 10,0496 | -2,2876 | 116,9393 | -20,2933 | 13,7017 | -65,2965 | -11,1133 |
| | %- of ASC > 0 | 0,38 | 0,33 | 0,54 | 0,50 | 0,33 | 0,33 | 0,33 |
| | t-test sign | + | - | + | - | + | - | - |
| | t-test p-value | 0,1231 | 0,3785 | 0,1463 | 0,2483 | 0,2049 | 0,1523 | 0,3042 |
| Fitch | t-test sgn. level | | | | | | | |
| | sign test sign | - | - | + | - | - | - | - |
| | sign test p-value | 0,4093 | 0,2456 | 0,0541 | 0,1257 | 0,2456 | 0,2456 | 0,2456 |
| | sign test sgn. level | | | * | | | | |
| | n | 19 | 19 | 19 | 19 | 19 | 19 | 19 |

* indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level

Figure 11

Cancelled negative view watchlist announcement. The figure Illustrates development of median cumulative adjusted spread change around rating action.



Cancelled negative view watchlist announcement

Straight single notch downgrade

Straight single notch downgrade by S&P induces market impact on 5% level according to both t-test and sign test. However, it precedes with statistically significant market anticipation, which prevents non-rejection of the first hypothesis for S&P. Sign test reports market anticipation on 5% level and ttest on 10% level in the window [-30, -2]. According to intuition, straight downgrades should be triggered by strong and unexpected market events, because the agency issuing it does not require time to consider the downgrade more precisely on the watchlist. Thus should straight downgrades not be preceded with any significant anticipation over long term, but as the agency needs to carry a formal credit review process, there likely exists CDS market reaction (anticipation) just before the announcement, which is exactly the case in my findings concerning S&P's announcements.

Fitch's straight single notch downgrade has ambiguous market impact as sign test is unable to find any significance of market reactions in the [-1, 1] window, while t-test shows significance on 5% level. As a result of mixed market impact, I reject the first hypothesis for Fitch as well. On the contrary to S&P, which issues approximately half of its downgrades with and half without a corresponding watchlisting, Fitch issues merely all its single notch downgrades without the watchlisting. This rating action behaviour by Fitch is likely to dilute the market impact of its straight downgrades, which is in line with my empirical results as well.

Based on the findings detailed in Table 9 and Figure 12 in comparison with the previously reported findings it is obvious that straight single notch downgrades have more market impact than single notch downgrades from watchlist. These findings allow me not to reject the fourth hypothesis regarding negative announcements. The fourth hypothesis states that CDS market reaction is stronger when rating change is not preceded with corresponding watchlist announcement. Because of the assumed asymmetry between market impacts concerning positive and negative announcements, the fourth hypothesis is tested separately among these groups. This finding shows that previous studies of rating announcements' CDS market impact have suffered from the pooling of downgrades to the same category. Downgrades with the preceding watchlisting and without it are two very distinct announcement types. Straight single notch downgrades have a market impact close to the magnitude of

negative view watchlistings, while downgrades from the watchlist seem not to have market impact at all. Having these announcements analysed under same the category have led previous studies to exaggerate the impact of downgrades with the preceding watchlisting and underestimate the impact of downgrades without it.

Table 9

CDS market reaction around straight single notch downgrade. Panels A and B presents agency specific results of CDS market reactions in 7 different time windows. T-test tracks whether average adjusted spread change statistically differs from zero and sign test studies whether proportion of positive and/or negative adjusted spread changes differs statistically significantly from 50%.

| | | [-90, -61] | [-60, -31] | [-30, -2] | [-1,1] | [2, 30] | [31,60] | [61,90] |
|---------|----------------------|------------|------------|-----------|--------|---------|---------|---------|
| Panel A | | | | | | | | |
| | median ASC (bps) | 0,5717 | 0,9205 | 2,4163 | 0,7011 | -1,3341 | 1,1952 | 0,3773 |
| | %- of ASC > 0 | 0,53 | 0,53 | 0,62 | 0,64 | 0,47 | 0,53 | 0,53 |
| | t-test sign | - | + | + | + | - | + | - |
| | t-test p-value | 0,1866 | 0,1808 | 0,0520 | 0,0006 | 0,2388 | 0,4460 | 0,3601 |
| S&P | t-test sgn. level | | | * | *** | | | |
| | sign test sign | + | + | + | + | - | + | + |
| | sign test p-value | 0,3401 | 0,3401 | 0,0371 | 0,0197 | 0,3401 | 0,3401 | 0,3401 |
| | sign test sgn. level | | | ** | ** | | | |
| | n | 53 | 53 | 53 | 53 | 53 | 53 | 53 |
| Panel B | | | | | | | | |
| | median ASC (bps) | -0,2769 | 1,3737 | 0,3223 | 0,0009 | -1,7880 | -1,4790 | -1,0231 |
| | %- of ASC > 0 | 0,48 | 0,59 | 0,51 | 0,51 | 0,46 | 0,43 | 0,46 |
| | t-test sign | + | + | + | + | - | - | - |
| | t-test p-value | 0,0843 | 0,1346 | 0,0795 | 0,0158 | 0,3793 | 0,0740 | 0,0222 |
| Fitch | t-test sgn. level | * | | * | ** | | * | ** |
| | sign test sign | - | + | + | + | - | - | - |
| | sign test p-value | 0,3710 | 0,0498 | 0,4563 | 0,4563 | 0,2211 | 0,1136 | 0,2211 |
| | sign test sgn. level | | ** | | | | | |
| | n | 83 | 83 | 83 | 83 | 83 | 83 | 83 |

* indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level

Figure 12

Straight single notch downgrade. The figure Illustrates development of median cumulative adjusted spread change around rating action.



Straight single notch downgrade

event window in days

Double notch downgrade

The findings detailed in Table 10 and Figure 13 contradicts the intuition, which would suggest a strong market reaction to be attached to double notch downgrades. Findings of market impact in the [-1, 1] window for S&P's announcements are mixed, because t-test finds no significance, what so ever, even if t-test finds significance on 5% level. What comes to Fitch's corresponding announcements, both the tests report insignificant market impact. Already, based on these results, I am able to reject the first hypothesis for both S&P and Fitch concerning double notch downgrades. The sharp jump in CDS spreads in Figure 13 related to S&P's announcement takes place just after [-1, 1] window, which is the reason why either of the statistical tests don't show any stronger significance figures. The adjusted median spread change increases from day three approximately by half to day six, after which it returns by day nine back to approximately same level it was in the day three.

Furthermore, what there is interesting in my findings is that, both the tests report market anticipation on 5% significance level for both the agencies, but for different time windows. The anticipation preceding S&P's double notch downgrade takes place in the [-60, -31] window, while the anticipation before Fitch's announcements occurs in the window [-30, -2]. For S&P, this phenomenon might derive from the fact that I had to pool together both the double notch downgrades with and without preceding watchlisting, because of small sample size. Thus the market anticipation for the double notch downgrades would in fact be the market reaction for the preceding negative view watchlisting. This explains the findings quite well as 14 out of 20 double notch downgrades by S&P, had preceding watchlisting in my sample. Furthermore, there was also found 5% significant market anticipation in the same [-60, -31] window around S&P's single notch downgrades from negative view watchlist (see Table 7). What comes to Fitch' announcements, the market anticipation is more likely to be true anticipation rather than reaction to previous watchlisting as only 5 out of 18 Fitch's double notch downgrades had the preceding watchlisting and my findings in the Table 7 don't show market anticipation before Fitch's single notch downgrades from negative view watchlist.

My findings offer dubious evidence concerning the third hypothesis stating that magnitude of CDS market reaction correlates to number of notches moved in rating change. The CDS market impact at the moment of double notch downgrade announcement obviously lacks in statistical significance behind

the straight single notch downgrades, but it is risky to compare these two groups of downgrades with each other as in total approximately half of my double notch downgrades were preceded with the corresponding watchlisting. When comparing double notch downgrades with single notch downgrades from negative view watchlist the double notch downgrades have more market impact. However this is also not an unproblematic comparison as the double notch downgrades also include rating announcements without the preceding watchlisting. Following the prudence principal, I conclude that I do not have enough evidence to support the third hypothesis. Based on my findings, it seems to matter more whether a rating change is preceded with corresponding watchlisting than how many notches the action moves the credit rating.

Table 10

CDS market reaction around double notch downgrade. Panels A and B presents agency specific results of CDS market reactions in 7 different time windows. T-test tracks whether average adjusted spread change statistically differs from zero and sign test studies whether proportion of positive and/or negative adjusted spread changes differs statistically significantly from 50%.

| | | [-90, -61] | [-60, -31] | [-30, -2] | [-1,1] | [2, 30] | [31,60] | [61,90] |
|---------|----------------------|------------|------------|-----------|--------|---------|---------|----------|
| Panel A | | | | | | | | |
| | median ASC (bps) | 4,2119 | 27,3503 | 5,1244 | 0,0048 | 5,1445 | 1,8301 | -19,4476 |
| | %- of ASC > 0 | 0,60 | 0,75 | 0,60 | 0,50 | 0,65 | 0,55 | 0,35 |
| | t-test sign | - | + | + | + | + | - | - |
| | t-test p-value | 0,3664 | 0,0430 | 0,1276 | 0,0287 | 0,4181 | 0,4025 | 0,0491 |
| S&P | t-test sgn. level | | ** | | ** | | | ** |
| | sign test sign | + | + | + | 0 | + | + | - |
| | sign test p-value | 0,1855 | 0,0127 | 0,1855 | 0,5000 | 0,0899 | 0,3274 | 0,0899 |
| | sign test sgn. level | | ** | | | * | | * |
| | n | 20 | 20 | 20 | 20 | 20 | 20 | 20 |
| Panel B | | | | | | | | |
| | median ASC (bps) | -1,6211 | 2,0821 | 18,4054 | 0,6648 | 2,1682 | -9,7321 | -2,4221 |
| | %- of ASC > 0 | 0,44 | 0,61 | 0,72 | 0,67 | 0,61 | 0,33 | 0,39 |
| | t-test sign | - | + | + | + | - | - | - |
| | t-test p-value | 0,2793 | 0,2086 | 0,0190 | 0,3532 | 0,1699 | 0,0340 | 0,0442 |
| Fitch | t-test sgn. level | | | ** | | | * | * |
| | sign test sign | - | + | + | + | + | - | - |
| | sign test p-value | 0,3187 | 0,1729 | 0,0297 | 0,0786 | 0,1729 | 0,0786 | 0,1729 |
| | sign test sgn. level | | | ** | * | | * | |
| | n | 18 | 18 | 18 | 18 | 18 | 18 | 18 |

* indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level





Positive view watchlist announcement

On the contrary to negative view watchlist announcements, positive view watchlist announcements by S&P don't induce any CDS market impact. Table 11 and Figure 14 shows that throughout the period [-90, 90] there are no indications that positive view watchlistings would impact on the market any way. This finding is well in line with the previous studies, which have found asymmetry between market impacts of positive and negative announcements. Based on the absence of the market impact the first hypothesis is rejected for S&P concerning positive view watchlist announcement.

Table 11

CDS market reaction around positive view watchlist announcement. Panel A presents agency specific results of CDS market reactions in 7 different time windows. T-test tracks whether average adjusted spread change statistically differs from zero and sign test studies whether proportion of positive and/or negative adjusted spread changes differs statistically significantly from 50%.

| | | [-90, -61] | [-60, -31] | [-30, -2] | [-1, 1] | [2, 30] | [31,60] | [61,90] |
|---------|----------------------|------------|------------|-----------|---------|---------|---------|---------|
| Panel A | | | | | | | | |
| | median ASC (bps) | -0,0325 | 0,0296 | 0,2556 | -0,1355 | 0,6153 | 0,2938 | 0,1547 |
| | %- of ASC > 0 | 0,46 | 0,50 | 0,54 | 0,43 | 0,54 | 0,54 | 0,54 |
| | t-test sign | - | - | - | - | + | - | + |
| | t-test p-value | 0,4206 | 0,4643 | 0,4262 | 0,1042 | 0,2687 | 0,3018 | 0,1083 |
| S&P | t-test sgn. level | | | | | | | |
| | sign test sign | - | - | + | - | + | + | + |
| | sign test p-value | 0,3527 | 0,5000 | 0,3527 | 0,2248 | 0,3527 | 0,3527 | 0,3527 |
| | sign test sgn. level | | | | | | | |
| | n | 28 | 28 | 28 | 28 | 28 | 28 | 28 |

* indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level

Figure 14
Positive view watchlist announcement. The figure Illustrates development of median cumulative adjusted spread change
around rating action.



Single notch upgrade from positive view watchlist

On the contrary to findings concerning downgrades from negative view watchlist, upgrades from positive view watchlist are likely to have some market impact. According to my findings, detailed in Table 12 and Figure 15, S&P's single notch upgrades from corresponding watchlist don't have market impact in the window [-1, 1]. However, t-test shows decreasing CDS spreads on 5% significance level for the windows [2, 30] and [31, 60]. Furthermore, sign test results support decreasing CDS spreads on 10% significance level in the [31, 60] window. Based on the results in this and in the previous section it seems that the market does not yet deem positive view watchlistings as strong announcements, but upgrades from positive view watchlist ultimately leads to market reaction, even though not an immediate one. However, as the market impact is not immediate the first hypothesis has to be rejected for S&P concerning single notch upgrade from positive view watchlist. Furthermore, the lagged market reaction is only supported by t-test.

Table 12

CDS market reaction around single notch upgrade from positive view watchlist. Panel A presents agency specific results of CDS market reactions in 7 different time windows. T-test tracks whether average adjusted spread change statistically differs from zero and sign test studies whether proportion of positive and/or negative adjusted spread changes differs statistically significantly from 50%.

| | | [-90, -61] | [-60, -31] | [-30, -2] | [-1, 1] | [2, 30] | [31,60] | [61,90] |
|---------|----------------------|------------|------------|-----------|---------|---------|---------|---------|
| Panel A | | | | | | | | |
| | median ASC (bps) | -0,3825 | -0,4980 | 0,9283 | 0,0694 | -1,2653 | -1,7603 | 0,0076 |
| | %- of ASC > 0 | 0,43 | 0,39 | 0,61 | 0,57 | 0,39 | 0,35 | 0,52 |
| | t-test sign | - | - | + | - | - | - | - |
| | t-test p-value | 0,2112 | 0,1051 | 0,1093 | 0,3987 | 0,0311 | 0,0243 | 0,3819 |
| S&P | t-test sgn. level | | | | | ** | ** | |
| | sign test sign | - | - | + | + | - | - | + |
| | sign test p-value | 0,2658 | 0,1486 | 0,1486 | 0,2658 | 0,1486 | 0,0722 | 0,4174 |
| | sign test sgn. level | | | | | | * | |
| | n | 23 | 23 | 23 | 23 | 23 | 23 | 23 |

* indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level

Figure 15

Single notch upgrade from positive view watchlist. The figure Illustrates development of median cumulative adjusted spread change around rating action.



Single notch upgrade from positive view watchlist

Straight single notch upgrade

The CDS market seems to anticipate straight single notch upgrades by S&P surprisingly well. In the event window [-30, -2] t-test shows decreasing CDS spreads on 5% significance level and sign test supports declining CDS spreads even on 1% level. However, the announcement effect in the [-1, 1] window does not seem that strong for S&P. T-test doesn't show any significance, but sign test reports declining CDS spreads on 5% level. Based on the market anticipation and absence of sufficient announcement impact, I reject the first hypothesis concerning S&P's straight single notch upgrades. These findings are in line with the rationale that the companies to which upgrades relate tends to

inform investors about their improved credit quality to lower their cost of debt. Thus the role left for rating agencies' upgrades would just be to verify the underlying event with their upgrade.

Fitch's straight single notch upgrades are not anticipated by the market and there is announcement effect in [-1, 1] window significant at 1% level according to t-test. However, because sign test does not show any significance, I have to reject the first hypothesis for Fitch's as well. This finding showing such a strong and unanticipated market impact for Fitch's announcement contradicts the logic by which I reasoned S&P's findings in the previous paragraph. In fact, it seems that Fitch's straight single notch upgrades have more market impact compared to its straight single notch downgrades.

What comes to the fourth hypothesis in regards to positive rating actions, I must only rely on the findings of S&P's announcements as other agencies did not have sufficient amount of data to facilitate the comparison between single notch upgrades from watchlist and straight single notch upgrades. The fourth hypothesis tests if the CDS market reaction is stronger when rating change is not preceded with corresponding watchlist announcement. Based on the findings not suggesting statistically significant market impact related to straight single notch upgrade by S&P, I have to reject the fourth hypothesis among positive announcements.

| | | [-90, -61] | [-60, -31] | [-30, -2] | [-1, 1] | [2, 30] | [31,60] | [61,90] |
|---------|----------------------|------------|------------|-----------|---------|---------|---------|---------|
| Panel A | | | | | | | | |
| | median ASC (bps) | -0,9001 | 1,2295 | -1,1763 | -0,3093 | -1,4624 | 0,2556 | -0,1106 |
| | %- of ASC > 0 | 0,42 | 0,61 | 0,33 | 0,37 | 0,37 | 0,51 | 0,49 |
| | t-test sign | - | + | - | - | - | - | - |
| | t-test p-value | 0,1306 | 0,2250 | 0,0448 | 0,2716 | 0,0651 | 0,4290 | 0,1890 |
| S&P | t-test sgn. level | | | ** | | * | | |
| | sign test sign | - | + | - | - | - | + | - |
| | sign test p-value | 0,1166 | 0,0425 | 0,0059 | 0,0235 | 0,0235 | 0,4473 | 0,4473 |
| | sign test sgn. level | | ** | *** | ** | ** | | |
| | n | 57 | 57 | 57 | 57 | 57 | 57 | 57 |
| Panel B | | | | | | | | |
| | median ASC (bps) | 0,7038 | 0,1007 | 0,2087 | -0,2050 | -0,1967 | -0,3598 | -0,4520 |
| | %- of ASC > 0 | 0,57 | 0,51 | 0,51 | 0,43 | 0,49 | 0,47 | 0,47 |
| | t-test sign | - | - | - | - | - | - | - |
| | t-test p-value | 0,3173 | 0,2428 | 0,1079 | 0,0039 | 0,2253 | 0,0316 | 0,3046 |
| Fitch | t-test sgn. level | | | | *** | | ** | |
| | sign test sign | + | + | + | - | - | - | - |
| | sign test p-value | 0,1126 | 0,4042 | 0,4042 | 0,1126 | 0,4042 | 0,3138 | 0,3138 |
| | sign test sgn. level | | | | | | | |
| | n | 68 | 68 | 68 | 68 | 68 | 68 | 68 |

Table 13

CDS market reaction around straight single notch upgrade. Panels A and B presents agency specific results of CDS market reactions in 7 different time windows. T-test tracks whether average adjusted spread change statistically differs from zero and sign test studies whether proportion of positive and/or negative adjusted spread changes differs statistically significantly from 50%.

* indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level

Figure 16

Straight single notch upgrade. The figure Illustrates development of median cumulative adjusted spread change around rating action.



New rating announcement

During the total observation period only Fitch's new rating announcement observations were sufficient enough to be statistically analysed. Interestingly, CDS spreads seem to decline during the month before Fitch's new rating announcement, but jump up just at the moment of initial rating release. The results also have statistical significance: t-test supports the findings at 5% level and sign test at 10% level. The findings could be explained by the logic that already awareness of upcoming rating release leads investors to trust more on company's credit quality, although the initial rating on average seems to be a slight disappointment in the market. Furthermore, these findings are in line with the presumption that there is no clear positive or negative effect attached to new rating announcement.

Table 14

CDS market reaction around new rating announcement. Panel A presents agency specific results of CDS market reactions in 7 different time windows. T-test tracks whether average adjusted spread change statistically differs from zero and sign test studies whether proportion of positive and/or negative adjusted spread changes differs statistically significantly from 50%.

| | | [-90, -61] | [-60, -31] | [-30, -2] | [-1, 1] | [2, 30] | [31,60] | [61,90] |
|---------|----------------------|------------|------------|-----------|---------|---------|---------|---------|
| Panel A | | | | | | | | |
| | median ASC (bps) | -0,8776 | -0,9245 | -1,1867 | 0,4021 | -0,1266 | 0,3011 | -0,2110 |
| | %- of ASC > 0 | 0,45 | 0,42 | 0,35 | 0,65 | 0,48 | 0,52 | 0,45 |
| | t-test sign | - | - | - | + | - | + | - |
| | t-test p-value | 0,2953 | 0,2395 | 0,0211 | 0,0273 | 0,2227 | 0,1929 | 0,2562 |
| Fitch | t-test sgn. level | | | ** | ** | | | |
| | sign test sign | - | - | - | + | - | + | - |
| | sign test p-value | 0,2950 | 0,1846 | 0,0530 | 0,0530 | 0,4287 | 0,4287 | 0,2950 |
| | sign test sgn. level | | | * | * | | | |
| | n | 31 | 31 | 31 | 31 | 31 | 31 | 31 |

* indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level

Figure 17

New rating announcement. The figure Illustrates development of median cumulative adjusted spread change around rating action.



6.1.2 Asymmetric spread adjustment

My results support in general the findings reported in previous studies that the market reaction between positive and negative rating actions is asymmetric. My findings reveal that negative rating announcements have significant market impact in the [-1, 1] window among negative view watchlistings by every major agency and among straight single notch downgrades by S&P. Positive rating actions have significant market impact only among S&P's cancelled negative view watchlistings. Next, I present rating announcement impact comparisons between positive and negative actions, based on the empirical results shown in the previous section. Due to insufficient amount of Moody's positive rating actions, the following paragraphs discusses only about S&P's and Fitch's announcements.

Comparison between positive and negative view watchlist announcement is only possible for S&P, because of limitations in the other agencies' positive rating action samples. Table 6 explains that the market reacts to S&P's negative view wathclisting with 1% significance according to both t-test and sign test. However, there is no statistically significant changes in the spreads in any period around positive view watchlisting by S&P (see Table 11). This finding is a strong evidence for the second hypothesis suggesting asymmetry between positive and negative rating actions.

S&P and Fitch both have sufficient amount of data for announcement impact comparisons between straight single notch downgrades and upgrades. Findings around S&P's announcements, further on,
support the second hypothesis. T-test finds at 1% significance level S&P's straight single notch downgrades having market impact, whereas the test finds no significance among S&P's straight single notch upgrades. Sign test, however, reports significant market impact at 5 % level for both the rating types.

Unexpectedly comparison between Fitch's straight single notch upgrades and downgrades offer contradicting evidence against the second hypothesis. T-test shows statistically significant market impact at 5% level for straight single notch downgrades, but for straight single notch upgrades it shows significance at 1% level. Sign test is not able to find any significance among neither of the announcements, which alleviates the power of this contradictory piece of evidence against the second hypothesis.

Single notch upgrade and downgrade from corresponding watchlists by S&P both induce no statistically significant market impact at the moment of the announcement. However, there is asymmetry between levels of anticipation and lagged market impact according to t-test results. The single notch downgrades from watchlist have anticipation in the [-60, -31] and [-30, -2] windows whereas anticipation is absent in the case of corresponding upgrades. Among the upgrades from positive view watchlist there is a significant lagged market impact within the windows [2, 30] and [31, 60], whereas the lagged market impact is absent among the downgrades from negative view watchlist.

Based on my findings, I am not able to state that among every rating type in every agency negative rating action would weight more than the corresponding positive one, especially because of the empirical findings concerning Fitch's straight single notch upgrades and S&P's cancelled negative view watchlistings. However, in general my findings reveal that without a doubt the market puts more weight on negative announcements compared to positive ones. Hence, I am able to retain the second hypothesis not-rejected. The second hypothesis states that CDS market reaction is stronger among negative rating announcements compared to positive ones.

6.1.3 Impact of the credit crisis

My findings reveal that there are three major components of differences in the CDS market reactions around rating actions between the periods before and after the hit of the crisis. First, volatility in CDS spreads around rating announcements has increased substantially for every major agency. Second, CDS market anticipation for rating actions has decreased significantly also for every agency. Third, the announcement effect in the [-1, 1] window around the rating announcement has become stronger for Moody's and Fitch, while it has weakened for S&P. According these findings, presented also in the following Tables 15–17 and Figures 18–20, I am able to reject my fifth hypothesis stating that the credit crisis has not influenced on credit rating actions' CDS market reactions.

I decide to analyse the differences in the CDS market reactions only among every agency's rating type that contains the most observations. These announcement types are the following: Negative view watchlist announcements for S&P and Moody's and straight single notch downgrade for Fitch. If I were not proceeding as explained, I would end up dealing with insufficient sample sizes in the subsamples. For example, the number of Fitch's negative view watchlist announcements totals to 32, which is inadequate amount to be divided for the subsamples before and after the crisis.

Volatility in CDS spreads around rating actions has substantially increased by the introduction of the crisis. The results detailed in Tables 15–17 show that volatility in the adjusted spread changes has increased in every analysed time window for every major agency. The increased market wide volatility was shown already in Figure 7. However, market wide turbulences shouldn't affect the analysis in this section directly. This is because all the spread changes reported in the findings are controlled against market wide events by subtracting the corresponding spread change in the overall spread index as explained in the methodology section.

In line with the discussion of increased volatility is the fact that the level of CDS market anticipation for rating announcements has decreased after the hit of the crisis. Market anticipation for Moody's rating announcements has ceased completely. Before the crisis CDS market seems to have anticipated Moody's negative view watchlist announcements during the [-60, -31] window at 5% significance level according to both tests, but after the crisis there is no indications of anticipation left anymore.

Respectively, the level of market anticipation for S&P's rating actions has also decreased substantially due the crisis. The change between the two periods is overwhelming, because during the period before the crisis the findings report market anticipation at 1% significance level in the [-30, -2] window according to both t-test and sign test. After the crisis the tests only report market anticipation at 5% level according to t-test in the [-30, -2] window. The change in market anticipation related to Fitch's rating announcements is not that clear as the tests don't report substantial evidence of market anticipation even for the period before the crisis.

Announcement effects in the [-1, 1] window have also changed due the crisis. Moody's and Fitch's announcements' market impacts have become stronger according to both tests. However, S&P's rating announcements' impact on the CDS market has declined according to both tests. Sign test does not show any significant market impact related to S&P's announcements after the crisis anymore. Also t-test has fallen in significance from 1% level to 5% level regarding S&P's announcements.

Table 15

Comparison of CDS market reactions around negative view watchlist announcement by S&P before and after the credit crisis. Panels A and B presents CDS market reactions results before and after hit of the credit crisis in 7 different time windows. T-test tracks whether average adjusted spread change statistically differs from zero and sign test studies whether proportion of positive and/or negative adjusted spread changes differs statistically significantly from 50%.

| | | [-90, -61] | [-60, -31] | [-30, -2] | [-1, 1] | [2, 30] | [31, 60] | [61, 90] |
|----------------------|----------------------|------------|------------|-----------|-----------|-----------|-----------|-----------|
| Panel A | | | | | | | | |
| | median ASC (bps) | 1,7114 | 0,4308 | 2,8651 | 2,1403 | 1,5556 | -3,0883 | -3,4251 |
| | %- of ASC > 0 | 0,61 | 0,52 | 0,63 | 0,82 | 0,58 | 0,35 | 0,32 |
| | t-test sign | + | + | + | + | + | - | - |
| S&P | t-test p-value | 0,4338 | 0,0790 | 0,0018 | 0,0078 | 0,2900 | 0,0110 | 0,0192 |
| before | t-test sgn. level | | * | *** | *** | | | |
| July 1 2007 | sign test sign | + | + | + | + | + | - | - |
| | sign test p-value | 0,0375 | 0,3609 | 0,0121 | 0,0000 | 0,0959 | 0,0063 | 0,0015 |
| | sign test sgn. level | ** | | *** | *** | * | *** | *** |
| | volatility | 37,0769 | 32,7408 | 18,3074 | 22,4627 | 26,2884 | 22,8151 | 26,1232 |
| | n | 71 | 71 | 71 | 71 | 71 | 71 | 71 |
| Panel B | | | | | | | | |
| | median ASC (bps) | 3,2657 | 1,1528 | 3,6375 | 1,5054 | -2,7301 | -2,5508 | -0,1917 |
| | %- of ASC > 0 | 0,57 | 0,54 | 0,57 | 0,57 | 0,48 | 0,48 | 0,49 |
| | t-test sign | - | - | + | + | + | - | - |
| S&P | t-test p-value | 0,3589 | 0,4875 | 0,0314 | 0,0450 | 0,2827 | 0,0599 | 0,0842 |
| after July 1 2007 | t-test sgn. level | | | ** | ** | | * | * |
| | sign test sign | + | + | + | + | - | - | - |
| | sign test p-value | 0,1246 | 0,2610 | 0,1246 | 0,1246 | 0,3504 | 0,3504 | 0,4491 |
| | sign test sgn. level | | | | | | | |
| | volatility | 284,6803 | 65,292113 | 154,50854 | 33,411841 | 197,78137 | 280,28275 | 112,97507 |
| | n | 61 | 61 | 61 | 61 | 61 | 61 | 61 |

* indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level

Table 16

Comparison of CDS market reactions around negative view watchlist announcement by Moody's before and after the credit crisis. Panels A and B presents CDS market reactions results before and after hit of the credit crisis in 7 different time windows. T-test tracks whether average adjusted spread change statistically differs from zero and sign test studies whether proportion of positive and/or negative adjusted spread changes differs statistically significantly from 50%.

| | | [-90, -61] | [-60, -31] | [-30, -2] | [-1, 1] | [2, 30] | [31, 60] | [61, 90] |
|---------------------|----------------------|------------|------------|-----------|---------|----------|----------|----------|
| Panel A | | | | | | | | |
| | median ASC (bps) | 2,3351 | 2,0720 | 1,7586 | 0,7506 | -1,6667 | -0,1654 | -1,6986 |
| | %- of ASC > 0 | 0,72 | 0,72 | 0,61 | 0,67 | 0,39 | 0,50 | 0,33 |
| | t-test sign | - | + | + | + | + | - | - |
| Moody's | t-test p-value | 0,3152 | 0,0386 | 0,2581 | 0,0154 | 0,1558 | 0,1827 | 0,0350 |
| before | t-test sgn. level | | ** | | ** | | | ** |
| July 1 2007 | sign test sign | + | + | + | + | - | - | - |
| _ | sign test p-value | 0,0297 | 0,0297 | 0,1729 | 0,0786 | 0,1729 | 0,5000 | 0,0786 |
| | sign test sgn. level | ** | ** | | * | | | * |
| | volatility | 11,0491 | 15,6565 | 11,5179 | 6,0791 | 27,6995 | 15,1539 | 11,2933 |
| | n | 18 | 18 | 18 | 18 | 18 | 18 | 18 |
| Panel B | | | | | | | | |
| | median ASC (bps) | 1,4446 | 2,0501 | -3,5825 | 5,6297 | 0,9839 | 7,2303 | -4,2114 |
| | %- of ASC > 0 | 0,54 | 0,54 | 0,46 | 0,71 | 0,50 | 0,57 | 0,46 |
| | t-test sign | - | + | + | + | - | + | + |
| Moody's | t-test p-value | 0,4381 | 0,3640 | 0,2009 | 0,0025 | 0,3379 | 0,4117 | 0,3670 |
| after | t-test sgn. level | | | | *** | | | |
| July 1 200 7 | sign test sign | + | + | - | + | - | + | - |
| | sign test p-value | 0,3527 | 0,3527 | 0,3527 | 0,0117 | 0,5000 | 0,2248 | 0,3527 |
| | sign test sgn. level | | | | ** | | | |
| | volatility | 55,8964 | 84,0204 | 174,2950 | 18,4625 | 184,9196 | 48,6130 | 117,3014 |
| | n | 28 | 28 | 28 | 28 | 28 | 28 | 28 |

* indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level

Table 17

Comparison of CDS market reactions around negative view watchlist announcement by Fitch's before and after the credit crisis. Panels A and B presents CDS market reactions results before and after hit of the credit crisis in 7 different time windows. T-test tracks whether average adjusted spread change statistically differs from zero and sign test studies whether proportion of positive and/or negative adjusted spread changes differs statistically significantly from 50%.

| | | [-90, -61] | [-60, -31] | [-30, -2] | [-1, 1] | [2, 30] | [31, 60] | [61, 90] |
|-------------|----------------------|------------|------------|-----------|---------|----------|----------|----------|
| Panel A | | | | | | | | |
| | median ASC (bps) | 0,6102 | 1,6504 | -0,6088 | -0,2547 | 0,5655 | -0,0266 | -1,8315 |
| | %- of ASC > 0 | 0,53 | 0,69 | 0,40 | 0,42 | 0,51 | 0,49 | 0,42 |
| | t-test sign | + | + | - | + | - | - | - |
| Fitch | t-test p-value | 0,0593 | 0,0558 | 0,0856 | 0,2047 | 0,3502 | 0,0793 | 0,0050 |
| before | t-test sgn. level | * | * | * | | | * | *** |
| July 1 2007 | sign test sign | + | + | - | - | + | - | - |
| | sign test p-value | 0,3274 | 0,0056 | 0,0899 | 0,1484 | 0,4407 | 0,4407 | 0,1484 |
| | sign test sgn. level | | *** | * | | | | |
| | volatility | 18,9934 | 24,3200 | 22,0500 | 10,7641 | 26,0632 | 63,8260 | 33,5862 |
| | n | 45 | 45 | 45 | 45 | 45 | 45 | 45 |
| Panel B | - | | | | | | | |
| | median ASC (bps) | -1,8256 | -1,2097 | 8,1469 | 0,9406 | -5,0505 | -3,3430 | 0,0849 |
| | %- of ASC > 0 | 0,42 | 0,47 | 0,63 | 0,61 | 0,39 | 0,37 | 0,50 |
| | t-test sign | + | + | + | + | - | - | - |
| Fitch | t-test p-value | 0,1379 | 0,1896 | 0,0638 | 0,0230 | 0,3906 | 0,1313 | 0,1245 |
| after | t-test sgn. level | | | * | ** | | | |
| July 1 2007 | sign test sign | - | - | + | + | - | - | - |
| | sign test p-value | 0,1652 | 0,6272 | 0,0524 | 0,0972 | 0,0972 | 0,0524 | 0,5000 |
| | sign test sgn. level | | | * | * | * | ** | |
| | volatility | 107,7754 | 187,3915 | 289,9539 | 37,3855 | 401,8952 | 272,1450 | 99,2789 |
| | n | 38 | 38 | 38 | 38 | 38 | 38 | 38 |

* indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level

Figure 18

Comparison of CDS market reactions around negative view watchlist announcement by S&P before and after the credit crisis. The figure illustrates development of median cumulative adjusted spread change around rating action before and after the credit crisis.



Figure 19

Comparison of CDS market reactions around negative view watchlist announcement by Moody's before and after the credit crisis. The figure illustrates development of median cumulative adjusted spread change around rating action before and after the credit crisis.

Moody's: negative view watchlist announcement



Figure 20

Comparison of CDS market reactions around straight single notch downgrade by Fitch's before and after the credit crisis. The figure illustrates development of median cumulative adjusted spread change around rating action before and after the credit crisis.



6.2 Herding study

In this section I first present my herding behaviour findings on agency pair level concerning hypotheses six and seven. Then I sum up my major herding study results and assess whether the eighth hypotheses is in line with my findings.

6.2.1 Agency pair level herding findings

This section discusses herding study results in respect to hypotheses six and seven for every agency pair separately. Agency pairs are the following: S&P and Moody's, S&P and Fitch, Moody's and Fitch. Breakdown of herding study results is presented in Table 18. The table describes test results regarding the seventh hypothesis in four different time windows. The seventh hypothesis states that credit rating agencies have similar likelihoods to lead and lag each others. The table shows, on which significance level, the agency first expressed in agency pair heading has statistically significant amount more herding rating actions than the other agency within the agency pair. The logic is to determine differences in numbers of herding rating action observations for each lag day and then test whether the series of herding rating action differences from lag day one up to lag day 7, 14, 30, and/or 60 significantly differs from zero. I report my results for both original and controlled samples for every agency pair. In controlled samples, herding rating action observations of less frequently actions issuing agency are multiplied by its lazy ratio. The logic of lazy ratio controlling is to abolish the bias that accrues from the fact that if an agency issues more actions than the other, then the other agency has higher chance that whenever it issues rating action there is already rating action by the other agency for which it can be seen responsive.

Table 18

Herding study results. Three agency pairs are tested for herding activity by finding out whether one or the other agency has statistically significantly more herding rating actions compared to the other agency in some time window(s). Statistical tests include t-test and sign test, which test independently four different time windows. Time window signals how many days herding rating action can maximum lag the leading rating action in order to be included in the sample in that particular time window. For example, seven days time window means that only herding rating actions up to seven days lag are included into the sample. T-test measures whether average of herding rating action observations' differences statistically significantly deviate from zero. Sign test finds out whether positive or negative observations in herding rating actions' differences dominate with statistical significance. Determination of herding rating actions differences is done so that I subtract herding rating action observations of the latter agency from the corresponding observations of the first mentioned agency in agency pair heading. Test results are presented separately for uncontrolled and controlled samples. In controlled sample herding rating action observations are adjusted against differences in overall frequency in credit rating activity.

| agency pair: | Fitch's - S&P | | Moody's | s - S&P | Fitch's - Moody's | | |
|-------------------------------|---------------|------------|--------------|------------|-------------------|------------|--|
| | uncontrolled | controlled | uncontrolled | controlled | uncontrolled | controlled | |
| 60 days window | | | | | | | |
| differences' average | 0,9500 | 0,1358 | 0,2500 | 0,1997 | 0,1333 | -0,0848 | |
| t-test p value (1 tail) | 0,0118 | 0,5798 | 0,1042 | 0,1840 | 0,2974 | 0,3798 | |
| significance level | ** | | | | | | |
| positive differences-% of all | 0,6279 | 0,5000 | 0,5946 | 0,5000 | 0,5217 | 0,3750 | |
| sign test J | 1,6775 | 0,0000 | 1,1508 | 0,0000 | 0,2085 | -1,4142 | |
| sign test p-value (1 tail) | 0,0467 | 0,5000 | 0,1249 | 0,5000 | 0,4174 | 0,9214 | |
| significance level | ** | | | | | * | |
| 30 days window | | | | | | | |
| differences' average | 1,8000 | 0,5271 | 0,4667 | 0,3863 | 0,2667 | -0,0801 | |
| t-test p value (1 tail) | 0,0107 | 0,2327 | 0,0798 | 0,1387 | 0,2446 | 0,6323 | |
| significance level | ** | | * | | | | |
| positive differences-% of all | 0,7143 | 0,5200 | 0,6818 | 0,5556 | 0,5455 | 0,3333 | |
| sign test J | 1,9640 | 0,2000 | 1,7056 | 0,5774 | 0,3015 | -1,4142 | |
| sign test p-value (1 tail) | 0,0248 | 0,4207 | 0,0440 | 0,2819 | 0,3815 | 0,9214 | |
| significance level | ** | | ** | | | * | |
| 14 days window | | | | | | | |
| differences' average | 4,1429 | 1,9067 | 0,5714 | 0,4537 | 0,6429 | 0,0916 | |
| t-test p value (1 tail) | 0,0016 | 0,0158 | 0,2631 | 0,3666 | 0,1446 | 0,7687 | |
| significance level | *** | ** | | | | | |
| positive differences-% of all | 1,0000 | 0,7692 | 0,6667 | 0,5714 | 0,8000 | 0,4444 | |
| sign test J | 3,4641 | 1,9415 | 1,1547 | 0,5345 | 1,3416 | -0,3333 | |
| sign test p-value (1 tail) | 0,0003 | 0,0261 | 0,1241 | 0,2965 | 0,0899 | 0,6306 | |
| significance level | *** | ** | | | * | | |
| 7 days window | | | | | | | |
| differences' average | 5,2857 | 2,2387 | 0,2857 | 0,1249 | 0,5714 | -0,2435 | |
| t-test p value (1 tail) | 0,0350 | 0,1466 | 0,6891 | 0,8624 | 0,4571 | 0,6478 | |
| significance level | ** | | | | | | |
| positive differences-% of all | 1,0000 | 0,5714 | 0,6667 | 0,5714 | 0,6667 | 0,3333 | |
| sign test J | 2,4495 | 0,3780 | 0,8165 | 0,3780 | 0,5774 | -0,8165 | |
| sign test p-value (1 tail) | 0,0072 | 0,3527 | 0,2071 | 0,3527 | 0,2819 | 0,7929 | |
| significance level | *** | | | | | | |

* indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level

S&P and Moody's

Figure 21 plots the herding action observations between S&P and Moody's. Left part of the figure [-60, 0] illustrates number of observations where Moody's leads and S&P lags. Respectively, right part of the figure [0, 60] describes number of observations where S&P leads and Moody's lags. Even with bare eye one perceives that it is approximately as likely for S&P to lead same number of days as it is to lag, which has to be identical for the situation that Moody's is also approximately as likely to lead what it is to lag some number of days. Figure 22 illustrates the differences in herding rating action observations, which are very small (all within the range +/-3 observations) and seemingly randomly distributed for positive and negative ones. There are very little differences between Figures 22 and 23 as the lazy ratio by which Moody's herding rating action observations are adjusted is very close to one (0.96).

My statistical test results (t-test and sign test) support the first impression of the symmetry in the herding rating action distribution. Table 18 shows that for no event window cumulated herding rating action observations' differences that would significantly differ from zero. As the lazy ratio is close to one the results are approximately same for both controlled and uncontrolled samples. My statistical test results are consistent with the seventh hypothesis for the agency pair S&P and Moody's. Therefore, I can state that S&P and Moody's lead and lag each others with similar likelihoods. The non-rejection of hypothesis seven suggests absence of herding behaviour between the agencies. However, there is still a small chance that the agencies imitate each other equally much, because my test structure compares agencies' herding action observations and if the herding behaviour would be of the same intensity and timely patterns would also match, then the possible herding behaviour would remain undiscovered.

Figure 21 alleviates these concerns as it shows that there is far greater proportion of rating actions occurring simultaneously compared to observations with some number of days lag between them. In my sample, there amounted 40 paired rating action observations, in which lag is zero meaning that S&P and Moody's have in these situations issued their rating actions exactly at the same day. Next likely, I find that S&P is to lag Moody's with one day (10 observations) and third likely is Moody's to lag S&P correspondingly with just one day (7 observations). Every other combination of paired rating actions contains four or less observations. These findings are well in line with my sixth hypothesis. The sixth hypothesis argues that credit rating agencies issue their rating actions, triggered by the same event, on a

same day. This is indeed the true state of affairs based on my findings. However, it can only be assumed that the paired rating actions are triggered by the same event, as there is no meaningful way to find out it in practice. Based on my empirical findings, which are in line with hypothesis six and seven, I can state that there are no indications that either of the agencies, S&P or Moody's, would engage in herding behaviour and imitate each other.

Figure 21

Herding rating action observations. Figure presents S&P's and Moody's herding rating action sample. Left side of the figure plots rating actions in which S&P lags Moody's. Right side of the figure plots rating actions in which Moody's lags S&P.



Figure 22

Herding rating action observation differences: Moody's - S&P. Figure shows differences in number of herding rating action observations between Moody's and S&P on each lag day from 1 to 60. The figure is illustration of bar height differences between right and left part of the upper figure.



Figure 23

Controlled herding rating action observation differences: Moody's - S&P. Figure shows differences in controlled number of herding rating action observations between Moody's and S&P on each lag day from 1 to 60. Number of Moody's herding rating action observations in this sample on each lag day is multiplied with a factor of 0.96 (lazy ratio) that controlls for Moody's lesser quantity of rating actions for which S&P could have issued herding rating action.



S&P and Fitch

Figure 24 illustrates herding rating action observation distribution for agency pair S&P and Fitch. The left part of the figure [-60, 0] shows herding rating action observations where S&P lags Fitch, while the right part [0, 60] plots numbers of observations where Fitch lags S&P. On the contrary to agency pair S&P and Moody's, one cannot rely as much on symmetry of the distribution. For example, 19 observations where Fitch lags S&P with one day clearly outweigh the five observations in the opposite case where S&P lags Fitch with the corresponding one day.

My statistical test results confirm the lack of symmetry in the distribution illustrated in Figure 24. Table 6 explains that for uncontrolled sample both the t-test and sign test indicates for every time window herding action observations by Fitch to outweigh number of S&P's herding observations minimum on 5% significance level. After controlling against the general frequency of credit rating activity Fitch is still found to have on 5 % significance level more herding rating actions than S&P in the 14 days window. These findings contradict the hypothesis seven. The rejection of hypothesis seven for agency pair S&P and Fitch may originate either from continuous imperfections or herding behaviour open for Fitch's agency, where as it seems impossible that S&P would imitate Fitch's rating actions. The fact that I find Fitch issuing relatively more herding rating actions particularly in a short time window makes the finding interesting regarding possible herding behaviour, because the link between leading and lagging rating action is obviously the stronger the shorter lag is there between them.

Nevertheless the rejection of the seventh hypothesis, agency pair S&P and Fitch still passes the acid test for herding behaviour as simultaneous rating actions are the most popular ones among the paired rating actions. Number of simultaneous rating actions by S&P and Fitch totals to 49, which is far more than in the second popular case where Fitch lags one day S&P with observations totalling to 19, as explained previously. Therefore, I am able to leave the sixth hypothesis not rejected for agency pair S&P and Fitch.

Figure 24





Figure 25

Herding rating action observation differences: Fitch - S&P. Figure shows differences in number of herding rating action observations between S&P and Fitch on each lag day from 1 to 60. The figure is illustration of bar height differenences between right and left part of the upper figure.

Controlled herding rating action observation differences: Fitch - S&P. Figure shows differences in controlled number of herding rating action observations between Fitch and S&P on each lag day from 1 to 60. Number of Fitch's herding rating action observations in this sample on each lag day is multiplied with a factor of 0.66 (lazy ratio) that controlls for Fitch's lesser quantity of rating actions for



Moody's and Fitch

Figure 27 describes herding rating action observation distribution for agency pair Moody's and Fitch. The left part plots the observations, in which Moody's lags Fitch and the right part observations, in which Fitch lags Moody's. The total number of herding rating action observations for agency pair Moody's and Fitch amounted to much less than for the other two agency pairs simply because they rate fewer companies simultaneously. In my sample there were only 85 companies, which were simultaneously rated by Moody's and Fitch, while S&P and Moody's rated simultaneously 110 companied and S&P and Fitch 219 companies (see Appendix 2). Apparently, because of smaller sample size the results are somewhat mixed concerning this agency pair.

Table 6 reports statistical test results of herding behaviour between Moody's and Fitch revealing that in uncontrolled sample Fitch would have on 10 percent significance level more herding actions than Moody's in the 14 days window. This finding is in line with the herding behaviour results of agency pair S&P and Fitch. However, after controlling results against general rating action frequency the finding seems not to hold anymore. Moreover, in the controlled sample, the setting turns upside down and in 30 and 60 days windows Moody's seems to have more herding rating action observations than Fitch on 10% significance level. Given the mixed nature of findings, hypothesis seven for agency pair Moody's and Fitch remains unanswered. However, hypothesis six holds within this agency pair as well. Number of simultaneous rating actions clearly outweighs any other combination of paired rating actions. There amounted 16 simultaneous rating actions for Moody's and Fitch during the total observation period, while the second popular case was that Fitch lags Moody's with one day containing seven observations.



Figure 27

Herding rating action observations. Figure presents Moody's and Fitch's herding rating action sample. Left side of the figure plots rating actions in which Moody's lags

Figure 28

Herding rating action observation differences: Fitch -Moody's. Figure shows differences in number of herding rating action observations between Fitch's and Moody's on each lag day from 1 to 60. The figure is illustration of bar height differenences between right and left part of the upper figure.



Controlled herding rating action observation differences: Fitch - Moody's. Figure shows differences in controlled number of herding rating action observations between Fitch and Moody's on each lag day from 1 to 60. Number of Fitch's herding rating action observations in this sample on each lag day is multiplied with a factor of 0.66 (lazy ratio) that controlls for Fitch's lesser quantity of rating actions for which Moody's could have issued herding rating action.



6.2.2 General level herding findings

On general level, my study doesn't find evidence that there would prevail herding behaviour between the major credit rating agencies. Panel D in Table 5 shows that on average only 16.26% of rating actions that could have triggered herding rating action, actually triggered one. This finding substantially alleviates concerns of herding behaviour plaguing the major agencies. Furthermore, the deviation in this proportion of observed herding rating actions as percentage of their theoretical maximums' is very moderate across the agency pairs. For every agency pair the figure lies within the range 12.96% - 18.84%.

In fact, this finding raises some concerns why the major rating agencies don't react to market events in a more coherent manner. At least partially this concern is explained by the fact that these herding rating action observations don't represent the entire sample of paired rating action observation as they don't include observations of simultaneous rating actions. Taking simultaneous rating actions account as well, I find that in agency pair S&P and Moody's, an arbitrary rating announcement occurs with 22.44% likelihood within the [-60, 60] day window around the other agency's rating action to the same direction credit quality wise. Corresponding figures for the other agency pairs are: 20.55% and 17.17%

for agency pairs S&P and Fitch, and Moody's and Fitch, respectively³. Still the figures don't seem very high. The finding that such a low rate of rating actions actually occurs close to rating actions by other agency is rather unexpected. Based on my results it seems that, on general level, the trouble with the major credit rating agencies would be the lack of adequate correlation in credit rating announcements rather than the herding behaviour.

However, if omitting the results explained previous paragraph, the findings presented in the section 6.2.1 supporting the comprehension that Fitch would be the most inclined agency to engage in herding behaviour are in line with my eighth hypothesis. The eighth hypothesis states that of the three major credit rating agencies Fitch is most likely to engage in herding behaviour. The reasons for such assumption are the findings from previous herding studies stating that attributes such as age, size and frequency of announcements are irreversibly correlated with likelihood to imitate. Fitch is the youngest of the major agencies. It is less than half of the size of S&P and a slightly bigger than half of the size of Moody's measured by rating operations' revenues. Furthermore, it issues on average 1/3 less rating actions than S&P and Moody's. However, it needs to be acknowledged that the age factor doesn't likely matter much in my herding study setting as the age differences between the agencies are not significant and the agencies are all relatively old. Most probably only the differences in size and relative frequency in issuing rating actions explain alone the finding that Fitch is the most inclined to herding behaviour.

³ Figures are determined by the following formulas:

S&P and Moody's: (40+60+75) / (382+398)*100% = 22.44%

S&P and Fitch: (49+85+142)/(811+532)*100% = 20.55%

Moody's and Fitch: (16+31+39) / (200+301)*100% = 17.17%

The content of the first parentheses includes simultaneous rating actions and herding rating actions by both agencies. The content of the second parentheses includes theoretical maximums of herding rating actions for both agencies.

7 Summary and conclusions

7.1 Summary

This thesis studies major credit rating agencies' impact on CDS market and the possibility that the credit rating agencies might imitate each other's credit rating actions. The study offers unique outlook to development of credit rating agencies' role during the recent credit crisis and first specific findings how different types of credit rating announcements impact the market. Furthermore, this thesis is first study to tackle possible herding behaviour between the major credit agencies. The data were retrieved from Bloomberg's database and covers the period from January 1, 2000 to June 4, 2009. Data consists of issuer-specific credit rating actions for S&P 500 index companies by Standard and Poor's, Moody's and Fitch and the corresponding CDS spread data for five-year contracts. The CDS respond study applies traditional event study methodology used in previous researches in the field, but the methodological framework presented in the herding study is invented by author for the purposes of this study. In the herding study the basic logic is to analyse differences in observations of rating actions that closely follow rating actions by other agencies to same direction credit quality wise.

According to my findings credit rating actions seem have an impact on CDS market, but in almost all cases where the announcement effect is significant the level of preceding CDS market anticipation is significant as well. Only Moody's negative view watchlistings over the whole observation period offers a study book example how markets should react with high significance at the moment of announcement and without significant anticipation or even afterward slide to any direction after the announcement. S&P's announcements' impact the market, but in every situation where the announcement impact is significant the market anticipation is significant also. Fitch's announcements' impact on the CDS market are of less significance during the whole observation period, but the comparison between periods before and after the hit of the credit crisis shows that Fitch's role in the market has strengthened during the recent years. Also Moody's role has strengthened, but S&P's role seems to have impaired due the credit crisis.

My findings show that credit rating announcements have market impact particularly when announcements signal impaired credit quality. Positive rating actions in general have less of a market impact, which means that there is asymmetry in CDS market reactions regarding positive and negative rating announcement. Previous studies of the field have encountered the same phenomenon and the probable reason for this is companies' tendency to inform the market particularly of their improved creditworthiness to have their costs of financing to decrease. Furthermore, I find that among negative announcements it matters more whether a downgrade is preceded with corresponding watchlist announcement than how many notches the downgrade actually moves the credit rating. Also, I show that the reason why previous studies have failed to find more significance in the market impact among downgrades derives from the pooling of downgrades with preceding watchlist announcement and without it to same group. When analysed as different rating action types, I find that straight single notch downgrades have market impact, whereas single notch downgrades from negative view watchlist have not market impact at all.

My herding study findings offer pioneering insight on how rating actions by the agencies relate to each other or not. First, I find that there is very low likelihood that S&P and Moody's would imitate each others' rating actions when reviewing same companies. Second, I find that Fitch issues rating actions that follow S&P's rating actions in two weeks on 5% significance level more than vice versa even after controlling against discrepancies in overall credit rating activity between the agencies. This finding may be explained by slower credit review process or the slower credit review process and herding behaviour together, but it is impossible to say any more about the cause. Findings from relations between Moody's and Fitch remain very much unknown as the sample of simultaneously rated companies is rather small, which causes somewhat mixed results. The findings that support Fitch's tendency in herding behaviour more than S&P's or Moody's are in line with previous herding studies that have found factors such as age, size, and frequency of revisions to be irreversibly correlated with tendency to imitate. Fitch is the youngest and smallest of the agencies and it issues proportionally less rating actions than the two other agencies. In general level, I find that agencies' credit rating announcements don't occur very closely with each other. Within every agency pair the likelihood that rating action occurs within the [-60, 60] days window around the rating action by the other agency is approximately 20%. This finding substantially alleviates the concerns of herding behaviour between the agencies, but on the same time raises some new concerns why the rating agencies do not react to market events in a more similar manner.

7.2 Conclusions

According to my findings, credit rating announcements' that have impact on CDS market are usually preceded with statistically significant market anticipation. This finding doesn't mean that credit rating announcements wouldn't matter. Credit rating agencies need to carry their formal credit review processes through before release of rating announcement as they try to avoid unnecessary volatility in their credit ratings. Investors in the CDS market can instead react more quickly to market events, which is the reason why they usually seem to anticipate rating announcements. As far as credit rating announcements have market impact there is a role for credit rating agencies to serve, despite the market anticipation. Probably, without credit rating agencies the CDS market would develop to a more volatile form, as there would not exist light houses that would guide investors' crusade through market turbulences. This argument is furthermore supported by the finding that in general rating announcements' market impact has slightly strengthened due to the credit crisis. What comes to the discussion of credit rating agencies' quasi-official role, my findings don't highlight any reason why it should be cancelled.

Perhaps the most interesting finding in this study is that only every fifth rating announcement takes place close to rating announcement by other agency when two agencies simultaneously rate a same company. This finding suggests that at least in the aggregate level herding behaviour is not damaging the agencies' reputation. Even if it is good for the agencies that they do not show tendency to imitate each other, the finding raises other concerns about the reasons why major agencies so differently seem to interpret and react to market events. One plausible reason to explain the finding would be agencies' divergent appetites on how to communicate with the market. For example, Fitch seems to prefer straight rating changes more than watchlist announcements as a way to interact with the market. On the contrary, Moody's seldom issues any downgrade or upgrade without the preceding watchlist announcement. S&P is somewhere in between of these two extremes. However, this explanation is not enough to explain the whole phenomenon that must have also other reasons behind.

7.3 Topics for further research

This study gives a plenty of motivation for further research. It would be interesting to tackle the comparison of herding behaviour before and after the hit of the credit crisis. Lack of sufficient amount of observations prevents me to show the comparison in this paper. The aim could be to find out whether the strengthened role of Fitch's agency, after the hit of the credit crisis, would also show in herding findings as well. The strengthened role would mean less rating actions proportionally following rating actions by other agencies and more rating actions leading rating actions of others. Also, further studies about credit rating agencies' herding behaviour could come up with some novel methodological innovations. In this pioneering herding study, I present straightforward framework that further studies are welcomed to elaborate, as they will, to find more nuances around the phenomenon.

What comes to CDS respond study, further research could extend the number of analysed agencies. Currently there are ten NRSROs (see Table 2), so it would be interesting to investigate whether the smaller agencies would have market impact as well. Alternatively, the focus could be in studying the agency problems with credit rating agencies by comparing rating action behaviour between Egan-Jones rating agency and some other NRSRO of similar size and portfolio of reviewed entities. Egan-Jones collects its revenues directly from investors rather than rated companies like all other NRSROs do.

Furthermore, it would be interesting to find out whether diverging credit ratings by different rating agencies would affect the volatility of company's CDS spread. It can be reasoned that the CDS market should show more nervousness when two credit rating agencies possess slightly contradicting views about company's creditworthiness. Finally, my thesis gives a good motivation for further studies to investigate whether the leading rating actions among paired rating actions by two agencies have more market impact than the lagging ones. That research topic would have been the next logical step to extent this study, but in order keep my thesis focussed, I chose to leave the subject for further researches to excavate.

References

Choundry, M., 2006. The credit default swap basis. Bloomberg Press, New York.

Clement, M., Tse, S., 2005 Financial Analyst Characteristics and Herding Behavior in Forecasting. Journal of Finance 60, 307-341.

Dichev, I.D., Piotroski, J.D., 2001. The long-run stock returns following bond ratings changes. Journal of Finance 56, 173–203.

Fimalac Group's Annual Report 2007/2008

Followill, R.A., Martell, T., 1997. Bond review and rating change announcements: An examination of informational value and market efficiency. Journal of Economics and Finance 21, 75–82.

Goh, J., Ederington, L., 1993. Is a bond rating downgrade bad news, good news, or no news for stockholders?. Journal of Finance 48, 2001-08.

Hite, G., Warga, A., 1997. The effect of bond-rating changes on bond price performance. Financial Analysts Journal 53, 35–51.

Hull, J., Predescu, M., White, A., 2004. The relationship between credit default swap spreads, bond yields, and credit rating announcements. Journal of Banking & Finance28, 2789-2811.

Jakola, M., 2006. Credit Default Swap Index Options Evaluating the viability of a new product for the CBOE. Unpublished working paper. Kellogg School of Management. Northwestern University

Johnsson, R., 2004. Rating agency actions around the investment-grade boundary. Journal of Fixed Income 13, 25-37.

Katz, S., 1974. The price adjustment process of bonds to rating reclassifications: A test of bond market efficiency. Journal of Finance 29, 551–559.

Micu, M., Remolona, E., Wooldridge, P., 2004. The price impact of rating announcements: evidence from the credit default swap market. Quaterly review. Bank for International Settlements.

Micu, M., Remolona, E., Wooldridge, P., 2005. The price impact of rating announcements: which announcements matter? Unpublished working paper. Bank for International Settlements.

Moody's Annual Report 2008

Norden, L., Weber, M., 2004. Informational efficiency of credit default swap and stock markets: The impact of credit rating announcements. Journal of Banking and Finance 28, 2813-2843.

Shiller, R. J., 1995. Conversation, information, and herd behavior. The American Economic Review

85 (2), 181-185.

Standard & Poor's General Description of the Credit Rating Process published on April 10, 2009.

Steiner, M., Heinke, V.G., 2001. Event study concerning international bond price effects on credit rating actions. International Journal of Finance and Economics 6, 139–157.

The MacGraw-Hill Companies Annual Report 2008

Vassalou, M., Xing, Y., 2003. Equity returns following changes in default risk: New insights into the informational content of credit ratings. Unpublished working paper, Columbia University.

APPENDIX 1

List of companies included in the CDS study sample

1 3M Co. 2 Abbott Laboratories 3 Aetna Inc 4 Alcoa Inc 5 Allstate Corp/The 6 Altria Group Inc 7 American Electric Power Co Inc 8 American Express Co 9 American International Group Inc 10 AmerisourceBergenCorp 11 Amgen Inc 12 Anadarko Petroleum Corp 13 AON Corp 14 Apache Corp 15 Archer-Daniels-Midland Co 16 AT&T Inc 17 AutoZone Inc. 18 Avon Products Inc 19 Baker Hughes Inc 20 Bank of America Corp 21 Baxter International Inc 22 Best Buy Co Inc 23 Black & Decker Corp 24 Boeing Co/The 25 Bristol-Myers Squibb Co 26 Burlington Northern Santa Fe Corp 27 CA Inc. 28 Campbell Soup Co 29 Capital One Financial Corp 30 Cardinal Health Inc 31 Caterpillar Inc 32 CBS Corp 33 CenturyTelInc 34 Chevron Corp 35 Chubb Corp 36 CIGNA Corp 37 Citigroup Inc 38 Coca-Cola Enterprises Inc 39 Computer Sciences Corp 40 ConAgraFoods Inc 41 ConocoPhillips 42 Consolidated Edison Inc 43 Constellation Energy Group Inc 44 Corning Inc 45 Coventry Health Care Inc 46 CSX Corp 47 Cummins Inc 48 CVS Caremark Corp 49 Danaher Corp 50 Dell'Inc 51 Devon Energy Corp 52 Dominion Resources Inc/VA 53 Dow Chemical Co/The

54 DTE Energy Co 55 Eastman Chemical Co 56 Eaton Corp 57 EI Du Pont de Nemours & Co 58 Eli Lilly & Co 59 Entergy Corp 60 Exelon Corp 61 FedExCorp 62 FirstEnergy Corp 63 Fortune Brands Inc 64 FPL Group Inc 65 Gannett Co Inc 66 General Dynamics Corp 67 Goldman Sachs Group Inc/The 68 Goodrich Corp 69 H&R Block Inc 70 Halliburton Co. 71 Hasbro Inc 72 Hershey Co/The 73 Hess Corp 74 Hewlett-Packard Co 75 HJ Heinz Co 76 Home Depot Inc 77 Honeywell International Inc 78 International Business Machines Corp 79 JC Penney Co Inc 80 Johnson & Johnson 81 Johnson Controls Inc 82 JPM organ Chase & Co 83 KelloggCo 84 Kimberly-Clark Corp 85 Kimco Realty Corp 86 Kohl's Corp 87 Kraft Foods Inc 88 Kroger Co/The 89 Lexmark International Inc 90 Lincoln National Corp 91 Lockheed Martin Corp 92 Loews Corp 93 Lowe's Cos Inc 94 Macy's Inc 95 Marathon Oil Corp 96 Marriott International Inc/DE 97 Marsh & McLennan Cos Inc 98 MattelInc 99 MBIA Inc 100 McDonald's Corp 101 McKessonCorp 102 MeadWestvaco Corp 103 Merck & Co Inc/NJ 104 MetLife Inc. 105 Monsanto Co

106 Morgan Stanley

107 Motorola Inc 108 New York Times Co/The 109 Newell Rubbermaid Inc 110 Newmont Mining Corp 111 NiSource Inc 112 Noble Energy Inc 113 Nordstrom Inc 114 Norfolk Southern Corp 115 Northrop Grumman Corp 116 Nucor Corp 117 Occidental Petroleum Corp 118 Omnicom Group Inc 119 Pepsi Bottling Group Inc 120 PepsiCo Inc/NC 121 Pfizer Inc 122 Pitney Bowes Inc 123 PPG Industries Inc 124 Progress Energy Inc 125 ProLogis 126 Prudential Financial Inc 127 Raytheon Co 128 Republic Services Inc 129 Reynolds American Inc 130 RR Donnelley & Sons Co 131 Ryder System Inc 132 Safeway Inc 133 Sara Lee Corp 134 Schering-Plough Corp 135 Sealed Air Corp 136 Sempra Energy 137 Sherwin-Williams Co/The 138 Simon Property Group Inc 139 SLM Corp 140 Southwest Airlines Co 141 Staples Inc 142 Sun Microsystems Inc 143 Target Corp 144 TECO Energy Inc 145 Time Warner Cable Inc 146 Time Warner Inc 147 Travelers Cos Inc/The 148 United Parcel Service Inc 149 Unum Group 150 Valero Energy Corp 151 Walt Disney Co/The 152 Waste Management Inc 153 Wells Fargo & Co 154 Verizon Communications Inc 155 Weyerhaeuser Co 156 Whirlpool Corp 157 Williams Cos Inc/The 158 Wyeth 159 Xerox Corp 160 Yum! Brands Inc

APPENDIX 2

List of companies included in herding study sample

APPENDIX 2.1.

List of companies simultaneously rated by S&P and Moody's

1 Air Products & Chemicals Inc 2 Allegheny Technologies Inc 3 Altria Group Inc 4 Ameren Corp 5 American Electric Power Co Inc б American Express Co 7 American International Group Inc 8 Ameriprise Financial Inc 9 Assurant Inc 10 AT&T Inc 11 Bank of America Corp 12 Bank of New York Mellon Corp/The 13 BB&T Corp 14 Best Buy Co Inc 15 Burlington Northern Santa Fe Corp 16 Centerpoint Energy Inc 17 CIT Group Inc 18 Compuware Corp 19 ConAgra Foods Inc 20 ConocoPhillips 21 Consolidated Edison Inc 22 Convergys Corp 23 Covidien Ltd 24 CSX Corp 25 Deere & Co 26 Dow Chemical Co/The 27 Duke Energy Corp 28 Eastman Chemical Co 29 Eastman Kodak Co 30 EI Du Pont de Nemours & Co 31 Emerson Electric Co 32 Entergy Corp 33 Estee Lauder Cos Inc/The 34 Exelon Corp 35 Fifth Third Bancorp 36 First Horizon National Corp 37 FirstEnergy Corp

38 Ford Motor Co 39 FPL Group Inc 40 Frontier Communications Corp 41 Gannett Co Inc 42 General Electric Co 43 Goldman Sachs Group Inc/The 44 Hershey Co/The 45 Honeywell International Inc 46 Hospira Inc 47 International Flavors & Fragrances Inc. 48 International Game Technology 49 Jabil Circuit Inc 50 Johnson Controls Inc 51 JPMorgan Chase & Co 52 Kimberly-Clark Corp 53 Kraft Foods Inc 54 Lennar Corp 55 Lockheed Martin Corp 56 M&T Bank Corp 57 Masco Corp 58 McDonald's Corp 59 Merck & Co Inc/NJ 60 Monsanto Co 61 Morgan Stanley 62 Motorola Inc 63 Nordstrom Inc 64 Northeast Utilities 65 NYSE Euronext 66 Occidental Petroleum Corp 67 Office Depot Inc 68 People's United Financial Inc 69 Pepco Holdings Inc 70 Pfizer Inc 71 PG&E Corp 72 Pinnacle West Capital Corp 73 Pioneer Natural Resources Co 74 Pitney Bowes Inc

76 PPG Industries Inc 77 Procter & Gamble Co/The 78 Prudential Financial Inc 79 Pulte Homes Inc. 80 Qwest Communications International Inc 81 RadioShack Corp 82 Regions Financial Corp 83 RR Donnelley & Sons Co 84 Sara Lee Corp 85 SCANA Corp 86 Schlumberger Ltd 87 Sempra Energy 88 Sigma-Aldrich Corp 89 Sprint Nextel Corp 90 Stryker Corp 91 SunTrust Banks Inc 92 Target Corp 93 Tenet Healthcare Corp 94 Tyco Electronics Ltd 95 Union Pacific Corp 96 UnitedHealth Group Inc 97 US Bancorp 98 Walgreen Co 99 Waste Management Inc 100 Wells Fargo & Co 101 Verizon Communications Inc 102 Weyerhaeuser Co 103 Whirlpool Corp 104 Williams Cos Inc/The 105 Wisconsin Energy Corp 106 Vulcan Materials Co 107 Wyndham Worldwide Corp 108 Xcel Energy Inc 109 Xerox Corp 110 XTO Energy Inc

75 PNC Financial Services Group Inc

APPENDIX 2.2

List of companies simultaneously rated by S&P and Fitch

- 1 Abbott Laboratories
- 2 Aetna Inc
- 3 Alcoa Inc
- Allegheny Energy Inc 4
- Alleghenv Technologies Inc 5
- б Altria Group Inc
- 7 Ameren Corp
- 8 American Electric Power Co Inc
- American International Group Inc 9
- 10 Ameriprise Financial Inc
- 11 AmerisourceBergen Corp
- 12 Anadarko Petroleum Corp
- 13 AON Corp
- 14 Apache Corp
- 15 Archer-Daniels-Midland Co
- 16 Assurant Inc.
- 17 AT&T Inc
- 18 Bank of America Corp
- 19 Baxter International Inc
- 20 BB&T Corp
- 21 Best Buy Co Inc
- 22 Boeing Co/The
- 23 Boston Properties Inc
- 24 Boston Scientific Corp
- 25 Bristol-Myers Squibb Co
- 26 CA Inc.
- 27 Campbell Soup Co
- 28 Capital One Financial Corp
- 29 Cardinal Health Inc
- 30 Carnival Corp
- 31 Caternillar Inc
- 32 CBS Corp
- 33 Centerpoint Energy Inc
- 34 Centex Corp
- 35 CenturyTelInc
- 36 Charles Schwab Corp/The
- 37 Chubb Corp
- 38 CIGNA Corp
- 39 Cincinnati Financial Corp
- 40 CIT Group Inc
- 41 Citigroup Inc
- 42 Clorox Co
- 43 Comcast Corp
- 44 Computer Sciences Corp
- 45 ConAgra Foods Inc
- 46 ConocoPhillips
- 47 Consolidated Edison Inc
- 48 Constellation Energy Group Inc
- 49 Convergys Corp
- 50 Coming Inc
- 51 Coventry Health Care Inc
- 52 Covidien Ltd
- 53 CSX Corp
- 54 Cummins Inc
- 55 CVS Caremark Corp
- 56 Darden Bestaurants Inc
- 57 Dell Inc
- 58 Devon Energy Corp
- 59 Discover Financial Services
- 60 Dominion Resources Inc/VA
- бl Dow Chemical Co/The
- 62 Dover Corp
- 63 DR Horton Inc
- 64 DTE Energy Co
- 65 Duke Energy Corp
- 66 Dun & Bradstreet Corp
- 67 Eastman Kodak Co
- 68 Eaton Corp
- 69 Edison International
- 70 EI Du Pont de Nemours & Co
- 71 Entergy Corp
- 72 Equity Residential
- 73 Exelon Corp

- 74 Express Scripts Inc 75 Fifth Third Bancorp
- 76 First Horizon National Corp
- 77 FirstEnergy Corp
- 78 Fluor Corp
- 79 Ford Motor Co
- 80 Fortune Brands Inc
- 81 FPL Group Inc
- 82 Freeport-McMoRan Copper & Gold Inc 155 PNC Financial Services Group Inc

94

147 Oracle Corp

148 People's United Financial Inc

149 Pepco Holdings Inc

151 PepsiCo Inc/NC

156 PPG Industries Inc

159 Progress Energy Inc

161 Prudential Financial Inc

152 Pfizer Inc

157 PPL Com

160 ProLogis

162 Public Storage

163 Pulte Homes Inc

165 RadioShack Corp

168 Republic Services Inc

169 Reynolds American Inc

171 RR Donnelley & Sons Co 172 Ryder System Inc

170 Rockwell Automation Inc/DE

166 Ravtheon Co 167 Regions Financial Corp

173 Safeway Inc

179 SLM Corp

182 Staples Inc

174 Sara Lee Corp

176 Sempra Energy

175 Schering-Plough Corp

180 Southwest Airlines Co 181 Sprint Nextel Corp

184 State Street Corp

187 SUPERVALU Inc

189 TECO Energy Inc

193 Time Warner Inc

194 Torchmark Corp

197 Tyson Foods Inc

199 Unum Group 200 US Bancorp

205 WellPoint Inc

207 Ventas Inc

214 Wyeth

206 Wells Fargo & Co

210 Weyerhaeuser Co 211 Whirlpool Corp

215 Xcel Energy Inc

217 XL Capital Ltd

218 Yum! Brands Inc

219 Zions Bancorporation

216 Xerox Corp

190 Tenet Healthcare Corp 191 Textron Inc

192 Time Warner Cable Inc

195 Travelers Cos Inc/The

196 Tyco Electronics Ltd

198 UnitedHealth Group Inc

201 Valero Energy Corp

202 Walt Disney Co/The

203 Waste Management Inc

204 Watson Pharmaceuticals Inc

208 Verizon Communications Inc

209 Western Union Co/The

212 Williams Cos Inc/The 213 Wisconsin Energy Corp

188 Target Corp

185 Sun Microsystems Inc 186 SunTrust Banks Inc

177 Sherwin-Williams Co/The

178 Simon Property Group Inc

183 Starwood Hotels & Resorts Worldwide Inc

150 Pepsi Bottling Group Inc

153 Pinnacle West Capital Corp

154 Pioneer Natural Resources Co

158 Principal Financial Group Inc

164 Qwest Communications International Inc

- 83 Frontier Communications Corp
- 84 Gap Inc/The
- 85 General Mills Inc
- 86 Genworth Financial Inc
- 87 Goldman Sachs Group Inc/The
- 88 Goodrich Corp
- 89 Goodyear Tire & Rubber Co/The
- 90 H&R Block Inc
- 91 Halliburton Co
- 92 Harley-Davidson Inc

97 Hewlett-Packard Co

100 Honeywell International Inc

101 Huntington Bancshares Inc/OH

102 International Paper Co

103 Interpublic Group of Cos Inc

- 93 Hartford Financial Services Group Inc
- 94 Hashro Inc.
- 95 HCP Inc.
- 96 Hess Corp

98 HJ Heinz Co

104 Invesco Ltd

105 Jabil Circuit Inc

106 JC Penney Co Inc

107 Johnson Controls Inc

108 JPMorgan Chase & Co 109 Kellogg Co

110 Kimberly-Clark Corp

115 Leucadia National Corp

116 Lincoln National Corp

117 Lockheed Martin Corp

111 Kohl's Corp

114 Lennar Corp

118 Loews Corp

121 Macy's Inc

126 Masco Corp

127 Mattel Inc

128 MBIA Inc

129 McDonald's Com

130 McKesson Corp

133 MetLife Inc

134 Monsanto Co

135 Morgan Stanley

136 Motorola Inc

138 News Corp

140 NiSource Inc

141 Nordstrom Inc

139 Nicor Inc

119 Lowe's Cos Inc

120 M&T Bank Corp

122 Marathon Oil Corp

123 Marriott International Inc/DE

124 Marsh & McLennan Cos Inc

125 Marshall & Ilsley Corp

131 Medco Health Solutions Inc

132 Merck & Co Inc/NJ

137 Newell Rubbermaid Inc

142 Norfolk Southern Corp

144 Northrop Grumman Corp

145 Occidental Petroleum Corp

143 Northeast Utilities

146 Omnicom Group Inc

112 Kraft Foods Inc

113 Legg Mason Inc

99 Home Depot Inc.

APPENDIX 2.3.

List of companies simultaneously rated by Moody's and Fitch's

1 Allegheny Technologies Inc 2 Altria Group Inc 3 Ameren Corp 4 American Electric Power Co Inc 5 American International Group Inc б Ameriprise Financial Inc 7 Assurant Inc 8 AT&T Inc 9 Bank of America Corp 10 BB&T Corp 11 Best Buy Co Inc 12 Centerpoint Energy Inc 13 Chevron Corp 14 CIT Group Inc 15 Coca-Cola Enterprises Inc 16 ConAgra Foods Inc 17 ConocoPhillips 18 Consolidated Edison Inc 19 Convergys Corp 20 Covidien Ltd 21 CSX Corp 22 Dow Chemical Co/The 23 Duke Energy Corp 24 Eastman Kodak Co 25 EI Du Pont de Nemours & Co 26 Eli Lilly & Co 27 Entergy Corp 28 Exelon Corp

29 Fifth Third Bancorp 30 First Horizon National Corp 31 FirstEnergy Corp 32 Ford Motor Co 33 FPL Group Inc 34 Frontier Communications Corp 35 Goldman Sachs Group Inc/The 36 Honeywell International Inc 37 Jabil Circuit Inc. 38 Johnson Controls Inc 39 JPMorgan Chase & Co 40 Keycorp 41 Kimberly-Clark Corp 42 Kraft Foods Inc 43 Lennar Corp 44 Lockheed Martin Corp 45 M&T Bank Corp 46 Masco Corp 47 McDonald's Corp 48 Merck & Co Inc/NJ 49 Monsanto Co 50 Morgan Stanley 51 Motorola Inc. 52 Nordstrom Inc **53 Northeast Utilities** 54 Occidental Petroleum Corp 55 People's United Financial Inc

56 Pepco Holdings Inc

57 Pfizer Inc 58 Pinnacle West Capital Corp 59 Pioneer Natural Resources Co 60 PNC Financial Services Group Inc 61 PPG Industries Inc 62 Prudential Financial Inc 63 Pulte Homes Inc 64 Qwest Communications International Inc 65 RadioShack Corp 66 Regions Financial Corp 67 RR Donnelley & Sons Co 68 Sara Lee Corp 69 Sempra Energy 70 Sprint Nextel Corp 71 SunTrust Banks Inc 72 Target Corp 73 Tenet Healthcare Corp 74 Tyco Electronics Ltd 75 UnitedHealth Group Inc 76 US Bancorp 77 Waste Management Inc 78 Wells Fargo & Co 79 Verizon Communications Inc 80 Weyerhaeuser Co 81 Whirlpool Corp 82 Williams Cos Inc/The 83 Wisconsin Energy Corp 84 Xcel Energy Inc 85 Xerox Corp