A closer look at credit rating processes: Uncovering the impact of analyst rotation

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Abstract

Employing a novel, hand-collected dataset entailing credit analyst information based on 17,500 publications by Fitch, Moody's and S&P, we investigate the effect of credit analyst rotation in the context of long-term ratings of S&P 500 issuers between 2002 and 2015. We find that analyst rotation and the duration of covering an issuer impact credit ratings beyond financial fundamentals as rotation is associated with rating downgrades. Our results underscore the significance of recalibrating credit rating processes and that regulation concerning credit analyst rotation was based on substantiated grounds.

Keywords: *Rating agencies, credit ratings, credit analysts, rotation policy, analyst bias, herding*
JEL classification: G14, G24, G28

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I. Introduction

In recent years, a multitude of potential challenges inherent in the structure and issuer-pays business model of credit rating agencies ("CRA") have spurred an intense debate among practitioners, policymakers and academics. The latter have been able to document biases and misaligned incentives which emerge from "selling ratings for fees" arguments frequently put forward by critics of CRAs. Issues of major importance include rating inflation, rating shopping (e.g. Skreta and Veldkamp (2009)) as well as conformity and herding among CRAs (e.g. Lugo et al. (2015)). Financial literature has also focused on CRA analysts as to whether their subjectivity affects credit ratings (e.g. Fracassi et al. (2016)), whether ratings become more favorable if CRA analysts rate an issuer they will subsequently join as an employee (Cornaggia et al. (2016)) and whether CRAs reward their analysts for accurate ratings with job promotions (Kisgen et al. (2016)). Also, recent regulation changes in some jurisdictions (E.U. Commission (2009)) have lead to mandatory coverage rotation for CRA analysts to counter potential agency issues similar to rotation policies as observed for loan officers by Hertzberg et al. (2010).

Such intense criticism of the issuer-pays business model, also in the public space, has prompted the CRAs to emphasize several counterarguments to these assertions. Not only did they stress the crucial role of reputation as the only justification for clients and investors putting their trust into the CRAs' service. CRAs have also emphasized their structured credit rating processes as a means to attain a maximum of objectivity in their credit rating decisions. Foreseeing extensive checks and balances and the requirement of allowing only committee-based ratings decisions, CRAs aim to limit the influence of personal opinion or analytic discretion potentially induced by individual CRA analysts. Some rating agencies, e.g. Fitch, have recently even ceased to publish press releases quoting CRA analysts' statements aimed at underscoring the importance of "institutional opinions" as opposed to "analyst opinions". In related efforts, internal guidelines by all major CRAs require the involvement of a certain number of CRA analysts without contact to the issuer to contribute to rating decisions. Precise mechanics of these processes and the role of heterogeneity among CRA analysts remain opaque, however, regulatory authorities were not fully convinced by the CRAs' line of argumentation targeting CRA analysts specifically with regulation (cf. E.U. Commission (2009)) by requiring analyst rotation after four to seven years depending on the CRA analyst's role. Nevertheless, we know very little if analyst rotation drives credit ratings. This ambiguity concerning the processes and the involvement of CRA analysts raises the following research question: Does CRA analyst rotation drive credit rating activity level and credit risk assessment?

In our paper, we aim to answer this question by investigating whether the individual analyst has an impact on the rating actions taken by a rating agency or whether existing processes indeed mitigate the role of personal opinion. In this context, we study the effect of CRA analyst coverage rotation on long-term issuer ratings. This includes analyst coverage duration. If the analyst's individual opinion is of secondary order, as argued by CRAs, we would expect that rating analyst changes do not impact the rating actions to be taken. Further, we examine CRA analyst rotation measuring the timing effect induced by rotation on rating-changing actions such as upgrades or downgrades and thus their likelihood. We focus on corporate ratings of Standard & Poor's 500 Index ("S&P 500") issuers published by the three leading rating agencies (Fitch, Moody's and Standard and Poor's ("S&P") between 2002 and 2015. Based on a dataset of 17,500 press releases and other publications by the CRAs, we are able to assemble a daily timeline of CRA analyst coverage of these issuers as well as rating actions.

Our main findings are as follows: First, the likelihood of rating changes increases (time to rating action decreases) following analyst rotation and decreases with coverage duration. The longer a CRA analyst covers an issuer, the lower the likelihood of rating changes. The hazard of experiencing a rating change is up to 90% higher when analyst rotation is observed. Second, analyst rotation leads to rating downgrades. On average, long-term issuer credit ratings are lower in the time period subsequent to analyst rotation by approximately 0.05-0.1 rating points based on the alphanumerical rating scale. These results are stable across rating agencies, also after including firm and time fixed effects and hold both for investment grade and sub-investment grade issuers.

The contribution of our study is threefold. First, we add to the existing literature on the behavior of CRAs and factors driving credit ratings. While existing theoretical work (e.g. Skreta and Veldkamp (2009)) constitute the first CRA-specific theoretical foundations for empirical papers discussing upward bias in credit ratings (Mählmann (2011)) or herding among CRAs (Lugo et al. (2015)), the latter are mostly centered on the financial crisis of 2008/2009. Our study extends prior work beyond this time frame and beyond the level of CRA entities by concentrating on a deeper organizational layer: credit rating analysts. Another set of prior studies on CRA analysts constitute the second stream of financial literature we aim to extend. Namely, Fracassi et al. (2016) (following theory by Bar-Isaac and Shapiro (2011)) which is directly related to ours, Cornaggia et al. (2016) and Kisgen et al. (2016) have introduced CRA analysts into the debate. Yet, to our knowledge, we are the first to shed light on analyst rotation through differentiated analyses based on data considering lead and secondary analyst roles. This allows us to empirically review recent regulatory efforts on CRA analysts and their rotation mechanism in particular for the first time. We are able to confirm that changes on the level of CRA analysts impact the rating decisions of CRAs and thus add to the empirical understanding of recently imposed regulation relating to CRA analyst rotation (cf. E.U. Commission (2009)). Finally, a broad set of papers has reviewed the role of loan officers generating bank-internal credit ratings and equity analysts creating earnings forecasts. Our study indirectly contributes to this literature by extending knowledge on the behavior of loan officers with regard to credit risk analysis. Hertzberg et al. (2010), arguing on the basis of Holmstrom (1982), consider loan officer rotation policies in the context of moral hazard concerns. Theoretical models concerning equity analysts have been created by, e.g., Scharfstein and Stein (1990) and Trueman (1994). These papers have triggered several scholars to analyze herding among equity analysts on the one hand, and analyst characteristics such as reputational concerns (Fang and Yasuda (2009)), educational background (Cohen et al. (2010)) and gender (Kumar (2010)). The effect of rotation being documented for loan officers, we broaden the knowledge with respect to CRA analysts.

The remainder of this paper is organized as follows: Section II describes the institutional background of CRAs. Section III reviews related literature and derives our hypotheses. Section IV presents our data in detail. Empirical results and robustness checks are reported in Section V. Section VI concludes.

II. Institutional background

The institutional development of CRAs has been closely linked to the growth of debt securities issued by corporations. According to the Bank for International Settlements (2018), global debt securities of financial and non-financial corporations outstanding amounted to more than USD 19 trillion at the end of 2017. Monitoring debtors and providing transparency on their creditworthiness is a key task performed centrally as a professional service by CRAs. Despite being subject to intense criticism (Lugo et al. (2015); Efing and Hau (2015)) and additional regulation in the aftermath of the financial crisis of 2008, the "big three" CRAs (Fitch, Moody's and S&P) still hold a market share of over 85% (SEC (2016)) in the United States. Fitch has the lowest market share while Moody's and S&P both hold around 35% each. Criticism includes a potential conflict of interest as a result of their fee-based business model with the rated issuer also paying for the rating (e.g. Bolton et al. (2012); Dilly and Mählmann (2016)) as well as potential herding behavior among CRAs.

Besides general research services, the CRAs mainly assign ratings regarding creditworthiness and probability of default to issuers overall, specific debt instruments (issues) and structured products. An issuer rating process constitutes the starting point of the credit rating analysis (Standard & Poor's (2014)). Specific debt instrument ratings are based on these analyses and only modified, should instrument-related factors such as terms and conditions, collateral or subordination require deviations from the long-term issuer rating. Rating processes of Fitch (2016), Moody's (2017) and S&P (2014; 2017) follow the same mechanism exhibiting no major discrepancies between the CRAs. The same applies to the fact that very little is currently known about the CRA analysts involved.

In terms of the credit rating process (cf. Fitch Ratings (2016); Moody's Investors Service (2017); Standard & Poor's (2014, 2017)), the sequence typically includes the following steps: while some ratings can be unsolicited, the process usually starts with an issuer commissioning a credit rating. As the next step, the CRA analysts (a team comprised of a lead and a secondary analyst) are assigned to the issuer and start their analytical work by requesting rating-relevant information and data such as financial statements or reports which are then provided by the issuer. The main role performed by the CRA analyst team consists of synthesizing this information into a credit opinion. The lead analyst is overseeing the analytical work which is primarily carried out by the secondary analyst. Moreover, the lead analyst is responsible for handling the relationship with the issuer[1]. It is crucial to point out that "analysts may rotate coverage responsibility over time as deemed appropriate by analytical group managers and in accordance with applicable laws and regulations" (Fitch Ratings (2016)). The reasons for analyst rotation can be manifold. Apart from team capacity and availability of expertise, resignations by CRA analysts or even sick leave can potentially trigger the change of an analyst. Across the CRAs, rotation is - overall - hardly following any standardized procedure according to discussions with practitioners. The next step in the rating process is an extensive meeting between the CRA analysts and the issuer's management team including on-site visits. After the management meeting, the CRA analysts will derive a credit rating recommendation based in the business and financial risks of the issuer in order to prepare the "rating committee". During the

[1]Please note that the commercial part of relationship management has been separated from the credit rating process at most CRAs to avoid internal conflicts of interest.

rating committee, rating recommendations by the analysts are reviewed and ratings assigned. Officially, lots of emphasis is put on this part of the rating process by the CRAs as a neutral body for objective decisions referring to it as "central to analytical quality" (Standard & Poor's (2017)). The committee comprises several analysts including the lead analyst presenting his or her recommendation, a committee chairperson ensuring compliance with internal procedures and independent "outsider" analysts. Once the rating decision has been made in the rating committee, it is communicated to the issuer by the lead analyst and the press release is aligned regarding factual correctness. The credit rating process concludes by the publication of the press release and related rating information in the online portals of the CRAs. In case the rating coverage is active, i.e. during the contract duration or as long as information is made available by the issuer, a rating decision is followed by further monitoring of the issuer. As a result, the CRA analysts typically remain in contact with the team on the issuer's side. The entire initial rating process takes between four to eight weeks to complete. The process is shorter in case of follow-up ratings.

With regard to European Union regulation on mandatory CRA analyst rotation (Regulation (EC) No. 1060/2009 as of 16th of September 2009, cf. E.U. Commission (2009)), this directive has been introduced in response to the financial crisis. It applies to CRAs with more than 50 employees with Article 7(4) stating that "A CRA shall establish an appropriate gradual rotation mechanism with regard to the rating analysts [...]". Specifically, according to Section C, point 8, maximum permissible coverage periods are explicitly determined by CRA analyst roles. Lead analysts should not cover an issuer for longer than four years, while this duration is a maximum of five years for secondary analysts and seven years for the committee chairperson. For all roles, a "cooling period" of two years is mandatory before re-assuming coverage of an issuer. While the application of this regulation has in principle been confirmed by Fitch, Moody's and S&P in the European Union, the implementation must be considered highly fragmented. First, the year of implementation might vary between European Union member states and there are exemption rules for some countries and CRAs. Second, implementation seems to heavily depend on the size of the respective office even within one CRA.

Even though this regulation does not directly apply to this study as the sample is focusing on United States issuers which are not affected by any similar regulation, it can be shown that analyst rotation is indeed seen as one way to enhance objectivity in credit ratings. Furthermore, the role of analysts in the credit rating process still appears to be more decisive than suggested by the CRAs.

III. Literature review and empirical predictions

The questions raised regarding the role of CRA analysts by the current state of the credit rating process and CRA analyst regulation forcefully demonstrate the need for scientific analysis as there might be untested factors influencing credit ratings. Commencing with a brief overview of related literature, our study adds to three research streams in the area of credit risk: first, the body of contributions regarding the factors driving credit ratings and the behavior of CRAs in general. The financial crisis of 2008/2009 in particular has triggered notable efforts examining the role of CRAs. Not primarily concentrating on the financial crisis, our paper shares a research focus with Güttler (2011) and Lugo et al. (2015). The second stream emerged more recently and has taken first steps to investigate the role of individual CRA analysts more closely. Fracassi et al. (2016) is the most directly related contribution to our study. Third, in addition to research on CRA analysts, there exists a substantial body of literature dealing with loan officers and sell-side, equity analysts which has in addition to research on CRAs. These studies are mainly concerned with loan officers' influence and incentives in the context of bank loan ratings and equity analyst-related factors for earnings forecasts. E.g., the findings regarding loan officer rotation Hertzberg et al. (2010) explicitly inform our paper.

Starting with the literature on CRAs in general, theoretical models by Skreta and Veldkamp (2009) and Bolton et al. (2012) point towards theoretical conflicts of interest and biases in CRAs' ratings. Before, Devenow and Welch (1996) had summarized theoretical approaches from other fields and their relevance to herding of CRAs in particular. The first tests of these theoretical predictions were performed by Güttler and Wahrenburg (2007) and Mählmann (2011) examining biases in credit ratings and relationship benefits. Mählmann (2011) concludes that the length of the relationship (and therefore coverage) between a CRA and an issuer results in higher average ratings. More recent publications on CRAs per se by Güttler (2011), Lugo et al. (2015) and Dilly and Mählmann (2016) provide evidence for herding among CRAs in issuer and mortgage-backed security ratings of CRAs, i.e. a CRA adjusting a ratings in response to another CRA's rating change, and inflated ratings during boom periods respectively. Methodology-wise, Lugo et al. (2015) exhibit similarity with our paper since they use a survival analysis framework which we employ in addition to our panel analysis. Jaggi and Tang (2015) introduce another aspect, "soft" information due to geographical distance between the CRA and the issuer, and show its relevance for credit rating accuracy. It can be inferred that factors beyond economic fundamentals of debtors appear to be associated with credit ratings. However, the CRA-internal processes and the CRA analyst individual and behavioral perspective do not play a role in these papers which we put at the center of our study.

More recent work by Cornaggia et al. (2016), Fracassi et al. (2016) and Kisgen et al. (2016) have changed the lack of CRA analyst-focused research and opened a new stream of research in analogy to existing work on equity analysts. These studies can be seen in relation to the first theoretical model specific to CRA analysts by Bar-Isaac and Shapiro (2011) which was primarily motivated by the financial crisis and later tested by Cornaggia et al. (2016) as well as Jiang et al. (2016). These authors extend the "revolving doors" literature dealing with CRA analyst job changes from CRAs to issuers and document ratings inflation prior to the job change. Their findings evidence the relevance of individual CRA analysts and their changes in covering issuers during the rating process and they relate to our study in terms of research focus. The CRA analyst promotions' effect on credit ratings at Moody's identified by Kisgen et al. (2016) is also closely related to our study and finds that CRA analysts achieving accurate ratings are more likely to be promoted. Once more, sizable importance is attributed to an individual CRA analyst's discretion within the CRA - beyond the influence of rating committees. Fracassi et al. (2016) scrutinize the role of CRA analysts, namely their potential "subjectivity". The authors find that CRA analyst aggregate effects do influence ratings and thus debt pricing. Also, subjective factors such as optimism or pessimism are correlated with CRA analyst characteristics such as education level. Acknowledging these efforts as notable progress for understanding CRAs, to the best of our knowledge, we assert that analyst rotation and differentiated lead and secondary CRA analyst effects appear to be overlooked in the scientific discourse. Taking these results together, there is clear evidence for the impact of CRA analyst-related factors on the credit rating process and the need for further research. We are systematically directing our efforts at this gap. In comparison to existing studies, we add the CRA analyst rotation perspective of rating changes. This is made possible by daily observations and a survival analysis approach which is yet to be applied in a CRA analyst context. Adding to the analyst characteristics utilized by Fracassi et al. (2016), we also account for differences between lead and secondary analysts and coverage tenure on both lead and secondary analyst level. We therefore also address recent regulatory efforts regarding analyst rotation (cf. E.U. Commission (2009)).

The third related literature stream deals with other types of financial analysts in contrast to CRA analyst literature. To commence with the loan officer-focused literature, theory on moral hazard reduction through rotation by Holmstrom (1982) relates to the findings of Hertzberg et al. (2010). From their analysis of loan officer rotation, the authors infer that internal credit risk ratings tend to be more informative when loan officers face the "threat" of being rotated. The mere possibility of own analysis lapses being brought to light by their successors appears to incentivize loan officers to judge more carefully. Further to rotation, the way loan officers process loan-related information has been investigated by Cole et al. (2015); Berg et al. (2013) focusing on loan officer incentives, by Qian et al. (2015) dealing with regulation and by Liberti and Mian (2009) testing the influence of organizational structure. One common finding of these contributions is an uncontested influence of individual loan officers on the loan rating and issuance process. Loan officers can be considered similar to CRA analysts since they are engaged in a very similar kind of rating task. The fact that they deal with internal ratings and therefore face less public reputation risks compared to CRA analysts, yet face adverse agency incentives which rotation seems to mitigate constitutes an important motivation for our research. Hertzberg et al. (2010) placing their study in close proximity to literature on equity analysts, empirical tests in the equity analyst strand of research strongly rely on the theoretical models of Welch (1992) who is modeling investor herding, Scharfstein and Stein (1990) focus on rational herding reasons among managers and Trueman (1994) whose model is explicitly dedicated to conformity and herding behavior in analyst forecasts. The latter concludes with the important notion that (equity) analysts might indeed be prone to following the announcements of other analysts ignoring their own private information. In a similar fashion, Scharfstein and Stein (1990) argue in a corporate manager setting that due to risk avoidance, even managers who are better than the average might prefer to follow the majority opinion. These models have been confirmed by empirical studies they paved the way for: Conformity and herding, mostly in conjunction with career concerns of equity analysts has been shown by Hong et al. (2000), Hong and Kubik (2003) and Clement and Tse (2005). According to these authors, conformity does seem to exist and to drive earnings forecasts. Besides conformity and herding, job changes of equity analysts are examined by Clarke et al. (2007) finding differentiated effects on analyst optimism and deal flow. Earlier contributions focus on the investment and firm value effects of the work of equity analysts (Womack (1996); Chung and Jo (1996)). As argued for CRA analysts, the role of individual equity analysts is undisputed and has been subject to further analyses in terms of abilities (Clement (1999)), geography (Malloy (2005)), reputational concerns (Fang and Yasuda (2009)), educational background (Cohen et al. (2010)) and gender (Kumar (2010)). Relying on the features of our dataset described above, our study is able to further close the gap in knowledge between CRA and equity analysts.

Despite the difference in angles of equity analysts and loan officers, close parallels exist with their counterparts at CRAs. Behavioral aspects do apply to any of the professions since both entail human individuals as part of profit-driven service organizations in the same financial industry. Most importantly, all these types of financial analysts are tasked to create transparency for an entity to the benefit of investors who rely on both earnings forecasts and credit ratings alike. The information produced by these types of analysts also becomes public at some point, except for bank-internal ratings, and is widely shared in online channels and even media. Thus, the relevance of their work as well as the dissemination of their personal identity including name extends beyond their organization internally and potentially becomes known to everyone. Mistakes would have comparable consequences in the case of equity and CRA analysts especially given the publicity of their work. One might argue that the well-defined formal credit rating process established by the CRAs would remove any individual analyst-related factors with the aim of arriving at an objective CRA opinion. On the other hand, the possibility of CRA analysts to affect the rating is undisputed and the real mechanics of the rating committee remain unclear, as depicted before. Such pronounced focus on formal processes also constitutes a more recent development and can't necessarily be taken for granted in the less recent past. We therefore assume pressures and individual behavioral factors influencing actions to be fairly similar for both CRA and equity analysts making the findings in the latter literature stream highly relevant.

Having exposed a variety of gaps in research on CRAs and (CRA) analysts, we aim to close these starting with the formulation of empirically testable propositions. Apart from drawing upon previous empirical findings and related theoretical models, agency theory as advanced by Jensen and Meckling (1976) and its discussion of principal-agent issues offers wide applicability under CRA circumstances. We argue that monitoring activities performed by a CRA analyst being new to the issuer are expected to be more neutral. Benefiting from an impartial view and experience gained from previously covered issuers, the cost of uncovering information relevant for rating changes is likely lower compared to CRA analysts who already exhibit familiarity with an issuer. The latter can therefore be reasonably assumed to be less inclined to change the rating. In the same vein as the "learning to gaming" scenario (cf. Mählmann (2011)), issuers might also be more cautious to “shirk” (Jensen and Meckling (1976)) at the very beginning of coverage by a newly assigned CRA analyst, e.g. by withholding or polishing information. Aiming at establishing immediate trust, thereby avoiding extreme reactions by the CRA analyst, the accuracy of information provided by issuers will be higher. Therefore, newly assigned CRA analysts can exploit the advantage of better information and are less prone to agency conflicts which will lead to more rating changes.

Proposition 1.1: A change of the CRA analyst covering an issuer is associated with an increase in rating activity.

This change is likely geared towards less optimistic ratings as Hertzberg et al. (2010) are suggesting along a similar line of argumentation that the foreseen arrival of a new loan officer covering a firm gives rise to a more conservative risk assessment. In combination with higher quality of information received by newly assigned CRA analysts as argued above, this leads to our next proposition:

Proposition 1.2: A change of the CRA analyst covering an issuer is associated with a decrease in the issuer rating.

Further exploring CRA analyst coverage tenure as initiated by Fracassi et al. (2016), monitoring costs for detecting adverse behavior of the agent, i.e. the issuer, as presented by Jensen and Meckling (1976) can be expected to rise to prohibitive levels from the point of view of a CRA analyst with increasing coverage tenure with an issuer. This is due to two potential problems: first, with increasing experience with an issuer, it might become cognitively harder to keep a neutral perspective as continuous interaction with the issuer's team makes CRA analysts accustomed to certain information. Second, following the information gaming argument by Mählmann (2011), issuers might figure out ways over time how to best release which kind of information to the CRA (analyst) in order to improve their rating. Moreover, issuers might gain the CRA analyst's trust over time, thereby reducing the level of diligence. As a result, unfavourable rating actions for the issuer are expected to occur later. This leads to the third proposition:

Proposition 2.1: Coverage tenure with an issuer of a CRA analyst is associated with lower rating activity.

More tenured CRA analysts might also be prone to another factor. The incentive for CRA analysts not to alter their rating opinion is likely to become more severe with longer coverage as such move might be perceived as contradicting their previous own view and harm their credibility in consequence. This applies for those rating changes which are not related to visible trigger events, such as public profit warnings, from an outsider's perspective in particular.

Proposition 2.2: Coverage tenure with an issuer of a CRA analyst is associated with higher issuer ratings.

IV. Data

A. Sample construction

We obtain the ratings history of S&P 500 Index constituents, i.e. large-cap United States issuers, by the CRAs from Bloomberg which yields daily rating changes, the type of rating action and company sectors[2]. Following Güttler (2011) and Fracassi et al. (2016), we focus on long-term issuer ratings[3]. These are the primary credit ratings and concerned with the overall creditworthiness of an issuer. We were also able to verify that long-term issuer ratings not only require a vast share of analysis work setting the basis for all other specific bond-related ratings (cf. also Standard & Poor's (2014)) but also receive the highest media attention when changed. For these reasons, long-term issuer ratings are the ideal setting for our research. Both rating downgrades/ upgrades and negative/ positive watchlist entries were included in the ratings history; an approach also chosen by Güttler (2011) and Lugo et al. (2015) as watchlist entries are typically followed by a downgrade or upgrade and can be seen as an early signal to the market. Due to availability of CRA analyst information, the sample included a long-term

[2]For Fitch and Moody's, we cross-check this history with information from their online portals. Regarding S&P, the rating history from Compustat is used for a cross check

[3]In the case of Moody's, the corporate family rating (CFR) or senior unsecured rating was used if a long-term issuer rating was not assigned. The CFR is practically identical to the long-term issuer rating and mostly assigned to sub-investment grade issuers. For a few issuers, the CFR was withdrawn at some point, typically when an issuer had reached an investment grade rating. In these cases, the senior unsecured rating was also used instead. Please refer to Table III in the descriptive statistics section for more details.

ratings history from 2002 until 2015 covering an entire economic cycle. The S&P 500 Index was chosen as the sample universe due to CRA analyst and financial data availability and the prominent public status of most constituents.

We hand-collected the CRA analyst information for setting up the coverage timeline from press releases, announcements, research reports and other publications available on the online portals of Fitch and Moody's. For S&P, these files were retrieved from the RatingsDirect module in S&P's Capital IQ platform (formerly known as Global Credit Portal)[4]. CRA analyst data includes their name, status of lead or secondary analyst in their coverage team[5], location and country enabling us to follow the coverage over time. Moreover, we were able to derive their gender based on name searches in other online sources such as Bloomberg Executive Profiles and LinkedIn. Coverage was assumed to start at the first appearance of a CRA analyst on a report and to last until the first appearance of the succeeding CRA analyst. This also provided the tenure of each individual CRA analyst with an issuer. Overall, approximately 17,500 files were processed in order to construct this daily CRA analyst timeline for all three CRAs in scope. Compared to a complementary study by Fracassi et al. (2016), this number is considerably higher in relation to the number of companies in their sample[6].

Lastly, control variables were downloaded from Bloomberg and S&P's Capital IQ and supplemented to the ratings and CRA analyst timeline via ticker symbols. Controlling for company size (market capitalization), profitability (EBITDA margin) as well as leverage (net debt to EBITDA ratio and debt to capital ratio), we take changes in company fundamentals as one important driver of ratings into consideration.

B. Descriptive statistics

B.1. Ratings history

The final sample consisting of 317 companies covered by Fitch, 444 by Moody's and 449 by S&P respectively, financial characteristics of these three subsamples are shown in Table I[7]. Comparing these on a cross-sectional quarterly value basis, the table reveals some statistically significant differences in the means of variables determined by t-tests. Companies covered by Moody's and S&P exhibit vast similarity in most variables in scope. Companies covered by Fitch, however, are somewhat larger in terms of revenues and market capitalization compared to both Moody's and S&P. They are more leveraged compared to the Moody's and S&P samples which also becomes evident in the Altman Z-scores which is lower for issuers covered by Fitch. When it comes to profitability measures, all three subsamples show averages around 8% in terms of profit margin and around 20% in terms of EBITDA margin. The leverage is less than 50% for all subsamples. Net debt to EBITDA ratio expresses the firms' ability to service their debt and in terms of median, and for most firms net debt exceeds EBITDA by more than five times.

[4] All analyst-related information has been hand-collected from these CRA sources.

[5] Secondary analyst status was excluded for S&P since the majority of reports did not provide this distinction in a consistent manner.

[6] We were able to provide finer granularity in terms of time frame and frequency than Fracassi et al. (2016) since our dataset entails a daily frequency and a longer scope ending in 2015. The daily frequency is of particular relevance for analyzing changes in CRA analyst coverage. Furthermore, the distinction between lead and secondary analyst is important for the internal mechanics at CRAs and their teams as outlined above and therefore explicitly accounted for only in our study.

[7] In order to capture United States large-cap, public firms, we chose the S&P 500 as the basis for our sample. Due to missing data for some firms, e.g. on CRA analysts, some firms were removed from the raw sample. Specifically, 11 firms rated by Fitch and 4 firms rated by Moody's.

These variables are used as control variables in order to take financial fundamentals into account.

- Table I about here: Financial summary statistics -

As a graphical summary, Figure I presents close parallels between the subsamples in terms of market capitalization and Altman Z-score over time. Furthermore, patterns we would expect such as the financial crisis of 2008/2009 are clearly visible in the data. Issuers covered by Fitch are largest in terms of market capitalization and lowest in terms of Altman Z-score. Overall, the market capitalization of firms in the sample has grown during the sample time period whilst Altman Z-scores exhibit a downward pattern especially following the financial crisis, but the average values of above three still suggest overall financial stability.

- Figure I about here: Market capitalization and Altman Z-score -

Scaled by multiple ratings, Table II presents details on the coverage ratios for each individual rating agency. Fitch, Moody's and S&P taken together, 460 of all S&P 500 constituents are covered. In line with their respective overall market share[8], S&P covers the highest share of companies, 98% with Moody's covering 97%. Fitch covers the lowest number of companies (69%). Contrary to intuition, not all S&P 500 constituents were covered by one or more of the rating agencies in the time frame of the study. As expected for such a class of large-cap issuers there are hardly any single rated issuers (Fitch (0), Moody's (4), and S&P (15). About two thirds of companies in the sample received a double rating by Fitch and Moody's and more than 90% by Moody's and S&P. Multiple ratings have also previously been found to influence credit ratings of corporate issuers (Mählmann (2009)), corporate bonds (Bongaerts et al. (2012)) and mortgage-backed securities (Morkoetter et al. (2017)).

- Table II about here: Multiple ratings -

Table III shows the number of rating actions and issuer coverage by CRA among those issuers that experienced a rating action. While all issuers covered by Fitch have a long-term issuer rating assigned, the situation for Moody's is more heterogeneous. Mostly for sub-investment grade issuers, a CFR was assigned instead. For 50% of instances, neither a long-term issuer rating nor a CFR had been published even though it can be regarded as the basis for all credit ratings. We therefore utilize the senior unsecured rating of an issuer instead. Furthermore, about 15% of companies did not experience any rating action[9] between 2002 and 2015.

- Table III about here: Issuer coverage by CRAs -

As far as the frequency of rating actions shown in Table IV is concerned, we observe a very similar number of downgrades/ upgrades per company for all three CRAs. On average, an issuer experienced around 1.5 downgrades and around 1.5 upgrades between 2002 and 2015. A Mann-Whitney-Wilcoxon test reveals no statistically significant difference between the CRAs in the

[8]Cf. SEC (2016) and Lugo et al. (2015).

[9]Despite the lack of changes in long-term issuer ratings of several issuers in the sample, other reports and announcements specific to these issuers have been published on an ongoing basis allowing us to extract CRA analyst information in order to construct the respective analyst coverage time line.

number of upgrades. The average values for negative and positive watchlist entries per issuer covered, both average and median, is lower for Fitch and statistically significant. This applies to the very low number of positive watchlist entries in particular. But also for negative watchlist entries, both average and median values per issuer exhibit a high difference. All types of rating actions taken together, there were about 3.5 rating actions for Fitch, 4.5 for Moody's and 4 for S&P per issuer. The maximum values are 7 and 10 rating actions, respectively. Overall, Moody's and S&P are more similar than each of these two CRAs compared to Fitch.

In addition, Table IV presents the time between ratings actions measured in days. Consistent with the number of downgrades and negative watchlist entries (i.e downward rating actions) and upgrades and positive watchlist entries (i.e upward rating actions), the average time between downward rating actions (508-708 days) is about 25% shorter compared to upward rating actions (635-950 days). Also in terms of magnitude, the difference is between 127 and 242 days and thus almost 4-8 months. Solely looking at actual downgrades and upgrades, average as well as median values for the time gap between upgrades are roughly similar and not statistically different for the three CRAs - consistent with the number of this types of rating action. The time between downgrades is roughly one year for downgrades and two years for upgrades in terms of median. With regards to the totality of long-term issuer rating actions (upward and downward rating actions taken together), the time gap between rating actions is roughly two years for issuers covered by Fitch and about 20% shorter for issuers covered by Moody's and S&P. Taking median values into account, this time gap is substantially shorter. The minimum and 5th percentile value might appear surprisingly low at all three CRAs in scope. These have to be seen in the context of closely sequenced watchlist entries immediately followed by rating changes. In conclusion, however, we infer that long-term issuer ratings are rather stable over time.

- Table IV about here: Frequency of rating actions -

For a graphical representation of the number of rating downgrades and upgrades in a dynamic time perspective, Figure II presents the patterns for all three CRAs over the observation period. We observe a trend that the rating actions are highly correlated with the overall economic development and the financial crisis in particular. The number of downgrades peaks and widely exceeds the number of upgrades during the U.S. recession in 2002 and 2003 following after burst of the dot-com bubble in 2000/2001. During the subsequent recovery and boom period of the U.S. economy between 2004 and 2006 the number of upgrades outnumbers the number of downgrades. The highest rating activity is observed during the financial crisis - not surprisingly mainly driven by downgrading activity. During the years 2008 and 2009 on average approximately 50% of the covered companies were downgraded by one of the three rating agencies. Following the recovery of the U.S. economy after the financial crisis, the CRAs also adjusted their actions with upgrades being more frequently observed as compared to rating downgrades. This time-variant dependency of rating actions undertaken by CRAs in our data sample is also confirmed by existing work (e.g., Bolton et al. (2012) and Bar-Isaac and Shapiro (2011) from a theoretical perspective, whereas Croce et al. (2011), Bangia et al. (2002) and Dilly and Mählmann (2016) state empirical evidence). In our regression analysis we incorporate this time-variant dependency by controlling for year-fixed effects (please refer to section V for more details).

- Figure II about here: Rating downgrades and upgrades over time -

B.2. CRA analyst coverage timeline

Table V presents demographic details on the CRA analysts. Based on 17,500 files containing CRA analyst information processed, we arrive at 255, 283 and 332 unique CRA analysts covering S&P 500 stocks at Fitch, Moody's and S&P,[10] respectively, during the time period of 2002-2015. Despite notable differences in market share and issuers covered, there is no major difference in the number of unique CRA analysts between the Fitch and Moody's. With regard to S&P, on the other hand, the number is almost 30% higher. These figures are in line with studies by Fracassi et al. (2016) and Kisgen et al. (2016) who arrive at similar values. Around 30% of CRA analysts at Fitch and S&P covering S&P 500 issuers are female whereas this share amounts to 23% at Moody's. Also, only less than one third of all CRA analysts at Fitch (less than 60% at Moody's) exclusively take up lead or secondary analyst roles, showing that lead and secondary analyst roles don't seem to be strictly assigned to certain CRA analysts. Regarding location, Moody's is covering S&P 500 issuers purely out of their New York office while Fitch is based both in New York and Chicago. S&P serves its clients out of several additional office locations in the United States. Yet, for all three CRAs, New York is the dominating office location.

- Table V about here: Details on CRA analysts -

Table VI reveals the CRA analyst coverage by sector, industry and issuer. We observe that CRA analysts at all three agencies mainly focus on one sector (the GICS classification according to S&P Capital IQ defines the broader "sectors" and more detailed "industries") judging from the median value. When it comes to industry types within a sector, the median value is three for Fitch and Moody's and two for S&P. In an unreported analysis, we were able to confirm that these industries are also widely similar for each individual CRA analyst. We can thus rule out the possibility of generalist versus specialist CRA analysts. No significant statistical differences between the CRAs were found using Mann-Whitney-Wilcoxon tests in terms of the number sectors covered. In terms of industries, CRA analysts at Fitch and Moody's cover three of these whereas this figure amounts to two at S&P which is also different statistically.

With regard to the number of stocks covered by CRA analysts, this amounts to four (Fitch and Moody's) and six (S&P) for lead analysts. The median is three for all three CRAs. As for secondary analysts is five (Fitch) and 8 (Moody's). The maximum number of stocks covered at least once during the sample time period is 76 for lead analysts and 109 for secondary analysts. There are no major differences in the number of S&P 500 stocks covered by CRA analysts in terms of magnitude and statistics. While, as shown before, average values point towards Moody's analysts getting in touch with more stocks (6 stocks for Moody's versus 4 for Fitch for lead analysts), the median values are identical both for lead and secondary analysts and both positions combined. From an issuer perspective, the median value of unique CRA analysts witnessed by an issuer between 2002 and 2015 is five for both lead and secondary analysts combined.

[10]The figure for S&P refers to the number of lead analysts only. Secondary analyst status was excluded for S&P since the majority of reports did not provide this distinction in a consistent manner.

A key variable for all our multivariate analyses to follow is the number of analyst changes resulting from coverage details presented before. With regard to lead analysts, the average figures suggest more rotation at Moody's and S&P while median figures of two changes are identical (cf. Table VI). Lead analysts are changing more than twice at Moody's and S&P whereas Fitch shows less than two changes. For secondary analysts, there are no differences in median but the average suggests slightly more changes at Fitch (2.6 versus 2.3 at Moody's). The maximum numbers of changes amount to 10 for lead analysts and 11 for secondary analysts. The minimum values show that some issuers never experience a change of the lead or secondary analyst. This is only a small share below the 25th percentile, however. In total, each issuer experiences on average between two and three changes of lead and secondary analysts. The differences are statistically significant at the 1% and 5% level respectively.

The figures for coverage duration of the CRA analysts measured in days in addition to the number of changes (cf. Table VI) do not yield substantial discrepancies between the Fitch and Moody's in terms of magnitude. The average and median coverage duration of lead analysts (1400 days) and both roles combined (1300 days) suggests similarity at both agencies. Consistent with the higher number of unique CRA analysts in the sample, both average and median values for coverage duration are around 200 days lower at S&P. This indeed suggests more frequent rotation at this CRA. Statistically, all these differences are significant. In total, a CRA analyst covered an S&P 500 issuer between 2002 and 2015 for around 3 years (median). Even still, lead analysts at Fitch have longer coverage periods than their counterparts at Moody's and S&P and vice versa for secondary analysts. Referring to the European Union regulation on CRA analyst rotation mentioned above, even though it doesn't apply to the S&P 500 sample in scope, both average and median values (ranging from 800 to 1500 days) seem to be in compliance with the maximum permissible coverage periods of four years for lead analysts and five years for secondary analysts. At the 75th percentile, the range is still between 1600 and 2000 days (4.4 ad 5.5 years) demonstrating that the majority of coverage periods observed would be acceptable according to regulation. This is even the case as no such regulation has currently been implemented in the United States.

- Table VI about here: CRA analyst coverage and rotation -

Figure III presents the number CRA analyst changes over time. Despite certain deviations, Fitch and Moody's exhibit similar overall patterns CRA analyst rotation. After a steady increase in the number of CRA analyst changes between 2002 and 2007/2008, this figure drops in the course of the financial crisis. It rises again until the sovereign debt crisis, decreasing once more in its aftermath. The final years of the sample are most diverging when comparing both Fitch and Moody's. While rotation at Fitch increases to a new highest level, thereby creating an upward trend between 2002 and 2015, the rotation level at Moody's at one of the lowest levels in the entire sample period. The trends for S&P start similarly with lead analyst changes reaching a peak in 2009/2010 but the level remain more stable afterwards and marks a sharp increase in 2015.

- Figure III about here: CRA analyst changes over time -

While still at a descriptive level, Figure IV provides initial evidence for the effect of rating actions prior to and after a CRA analyst change. We observe that in the six quarters prior to a lead analyst change on average 4% of rating changes occur within a period of six months. In the six quarters following an analyst change, this figures increase to 23% (quarters 1 & 2), 12% (quarters 3 & 4) and 9% in quarters 5 & 6. The figure exhibits a high similarity when plotting downgrades and upgrades separately and hold for subsamples by CRA as well. In the following section we will study the effect of rating analyst changes on rating actions in a multivariate framework.

- Figure IV about here: Share of downgrades and upgrades by quarter -

The reasons behind CRA analyst changes and as to whether these are potentially endogenous is of significance for our study. For this reason, we also analyze CRA analyst changes happening simultaneously at all three CRAs. The intuition is straightforward: if changes of the CRA analyst covering an issuer are due to its financial fundamentals, and not due to CRA-internal policies, we would expect CRA analysts assigned to an issuer to change at several CRAs at the same time due to the development of this issuer's fundamentals. As shown in Figure V, which presents the ratio of CRA analyst changes simultaneously observed at all three CRAs compared to the overall number of CRA analyst changes per year, CRA analyst changes hardly happen at the same time. The overwhelming majority of CRA analyst changes appears to follow distinct policies depending the CRA and are not related the issuer. With this fact applying to both lead and secondary analysts, the share of simultaneous coverage changes is constantly below 5%.

- Figure V about here: Simultaneous analyst changes at several CRAs over time -

V. Empirical results

We proceed with empirically testing our previously formulated research propositions. We deal with the effects of CRA (lead and secondary) analyst rotation on long-term issuer credit ratings. Moreover, the effect of individual CRA (lead and secondary) analyst coverage duration will be in focus in order to further inspect CRA analyst-related factors.

In order to analyse the effects of CRA (lead and secondary) analyst rotation on long-term issuer credit ratings, our empirical strategy is based on estimating panel regression models. Subjects in our setting are S&P 500 firms and the dataset allows us to construct a quarterly panel from Q1 2002 until Q4 2015. The dependent variable is the numeric rating of a firm in a given quarter. Table X presents the numerical reference scale for the alphanumerical ratings employed. We apply the same standardization of rating scales of the three major CRAs as done by Jewell and Livingston (1999). In parallel to the ratings history for each individual issuer, we add a quarterly timeline of lead and secondary CRA analysts covering each firm. Adopting the approach of Jayaratne and Strahan (1996) and Stiroh and Strahan (2003), we aim to measure the rotation of CRA analysts through a dummy variable taking the value of 1 if a new CRA analysts is assigned to an issuer in a specific quarter and 0 if the CRA analyst has not changed. As we observe several CRA analyst changes per issuer over the sample period, such "rotation periods" take place repeatedly. This generalized "difference-in-difference" design is also employed by, e.g. Jayaratne and Strahan (1996). We can thereby address the difficulty of determining a matching control group for the typical difference-in-difference design, which is not possible using our data, by constructing the control group from the average of all issuers in the sample. Endogeneity cannot be fully ruled out in the context of CRA analyst rotation because the assignment to and withdrawal from specific issuers is not necessarily a random affair and might be driven, for example, by early retirement or job resignations. Another identification challenge to overcome is a potential omitted variable bias as the credit rating might have changed *in absence* of the CRA analyst rotation as well. The most intuitive explanation, assuming that credit rating processes are fully functional, would be a change in financial fundamentals leading to the rating action. Using firm-quarter fixed-effects and several issuer financial fundamentals variables as controls (cf. Sufi (2007)), both firm-specific time-varying and time-invariant omitted variable concerns should be alleviated. Rotation as such could potentially be endogenously driven by financial fundamentals rather than internal policies. The descriptive analysis shown above (cf. Figure V) establishes clear evidence that CRA analyst rotation is not linked to the issuers' financial fundamentals, however. The share of simultaneous CRA analyst changes happening simultaneously at both CRAs of all analyst changes is mostly below 5% and exhibits a fairly stable pattern over time.

In addition to the panel regressions, we perform an initial test by estimating Cox proportional hazard models (Cox (1972))[11] with the same independent variables to assess if analyst rotation increases the likelihood of a rating action. Given the Cox model's ability to deal with time-to-event data without strict assumptions regarding their distribution, several prior contributions (e.g. Mählmann (2011); Lugo et al. (2015)) have made extensive use of this method. We follow their approach, making the time to rating action measured in days the dependent variable for all models[12]. Results generated by this variant of a conditional logit model permit conclusions regarding the effect of our CRA analyst-related variables on the conditional instantaneous probability of a rating action at a specific time and therefore on the credit rating activity level.

[11]As part of the class of survival models, origins of the Cox proportional hazard model can be found in medical and biological research. However, it has been widely applied in financial and economic research in the past three decades. Fields of application range from analyzing time to bank failures (Lane et al. (1986)), or corporate failures (Parker et al. (2002)), repayment of personal loans (Stepanova and Thomas (2002)) and performance of business loans (Glennon and Nigro (2005)). Further fields include post IPO performance (Jain and Martin Jr (2005)), time to reach put-call parity in options markets (Deville and Riva (2007)), venture capital investment performance (Nahata et al. (2014)) and bank runs (Iyer and Puri (2012); Iyer et al. (2016)). The individual agent level in the case of hedge fund manager careers has also been subject to investigation using Cox proportional hazard models (cf. Brown et al. (2001)). In addition, to these contributions, the issue of credit ratings by CRAs has seen particularly advanced applications: with the starting point being the papers of Güttler (2011), Mählmann (2011) and Lugo et al. (2015) have further scrutinized the drivers of credit ratings in a survival analysis context. The latter are also examples of studies identifying herding effects on a CRA level.

The reason for selecting Cox proportional hazard models over other empirical instruments is its suitability for analyses involving time to any kind of events jointly with likelihood of the events. Originally used to determine the effects of covariates on human survival probability, main advantages includes the possibility to consider censored observations, e.g. issuers that never experience a rating action during the observation time. Moreover, estimating Cox proportional hazard models enables us to adequately address the distribution underlying our time data as the model does not strictly assume any specific distribution (i.e. hazard function). Due to these advantages, it has become the most popular model for analyzing duration data (Harrell (2001)).

Key parameters for estimating Cox proportional hazard models are what constitutes subjects, failure and time and scale. In our analyses, subjects are defined to be the issuers. We define failure as a rating action (downgrade/ upgrade or negative/ positive watchlist entry) concerning the long-term issuer rating occurring on a certain date. Thus, we are dealing with multiple failures per subject data. Time is defined as the time gap between rating actions, the time a subject remains in a rating class. Subjects which don't experience any "failure" are censored at the end of the observation period. All time-related variables such as dates, time between failures and coverage duration are initially measured in days. In terms of independent variables used for our Cox regression analyses, we rely on categorical, continuous and time-varying covariates.

[12]Issuers which never experience any rating action over the sample period are censored observations. In this case, the time to being censored can be considered the dependent variable.

A. Effects on credit rating activity level

In a first step, we focus on the likelihood of credit rating actions in order to investigate the effect of CRA analyst rotation on credit rating activity level. Proposition 1.1 predicts a positive effect of rotation on the latter. We therefore expect a change in the lead or secondary CRA analyst to have a positive coefficient in a Cox proportional hazard estimation as the hazard is supposed to increase. For our analysis, we follow the approach of Güttler (2011) and Lugo et al. (2015) employing time-varying covariates to model CRA analyst changes. This enables us to account for analyst changes on a daily level. The covariate "Lead analyst change", i.e. rotation, takes the value of 1 from the day a new CRA analyst appears on a press release or similar publication by a CRA. Until that day, the covariate is assigned a 0 indicating that the CRA analyst covering the respective issuer hasn't changed yet. This approach is widely applied in various academic disciplines to estimate the effect of events parallel to the event in scope on "survival time". We use a several models to verify these propositions. The most extensive specification also encompasses these covariates and can be expressed as follows:

$$\begin{aligned} \lambda(t) &= \lambda_0(t) \times \exp\{\beta_1 \times Rotation + \\ &\quad \beta_2 \times Coverage\ duration\} \end{aligned}$$

The estimation results for rotation are reported in Panel A of Table VII. In the specifications for Fitch lead analysts, the coefficient is positive and both statistically and economically significant. The results are stable across all specifications for the three CRAs in scope and constantly at the 1% level. Exponentiating the value of the lead analyst change coefficient, e.g. in the case of Moody's in Panel A, reveals that the hazard is around 70% higher, which is statistically and economically significant, when an issuer experiences analyst rotation. As far as the results for S&P in specifications 7-9 are concerned, the magnitude is lower than for Fitch and Moody's. The coefficient for Fitch exhibits a higher hazard by 93% and 46% higher for S&P (Panel A). This pattern remains similar in terms of economic magnitude and significance in Panels B and C. The result also remains stable when adding coverage duration to the analysis. In Panel B, Moody's exhibits the economically lowest coefficients compared to the other two CRAs of approximately 46% (as compared to 90% and 55% for Fitch and S&P, respectively). Similar, though less pronounced effects can be observed for secondary analysts as we establish in a unreported analysis. We therefore conclude that CRA analyst changes have a substantial effect on the timing and therefore likelihood of rating actions. Due to the positive coefficient, the hazard rate is increased resulting in a shorter time to rating action. This result empirically supports proposition 1.1. As far as proposition 2.1 is concerned, we observe a highly significant, negative, coefficient for the variable coverage duration. It's highest (negative) for Fitch and lowest (negative) for S&P. This applies to the total sample in Panel A as well as the (sub-)investment-grade subsamples in Panels B and C. E.g., the coverage duration coefficient in Panel A for Fitch of -0.127 implies that with increasing coverage duration, the hazard of a rating change happening is around 12% lower as derived when exponentiating this coefficient value. For Moody's and S&P, the hazard is between 6% and 7% lower. Due to the coefficient estimates reported in Table VII being consistently below zero for all CRAs, we conclude that coverage duration has a negative effect on the likelihood of rating actions.

- Table VII about here: Effects of analyst rotation on rating activity level -

Based on the data discussed above, the question arises as to whether the results are driven by sample effects. Especially the characteristics of sample firms and their rating level might be a source of bias. E.g., the effect of CRA analyst changes might only apply to sub-investment grade issuers as opposed to more highly-rated ones and vice versa. Panels B and C of Table VII address this question by running two separate analyses for the subsample of investment grade issuers and those which are sub-investment grade by CRA. We define investment grade issuers as those holding a long-term issuer default rating of better than "BB" on average during their time in the sample. The calculation is based on the numerical scale shown in Table X. All issuers with an average rating of worse than "BBB" are considered sub-investment grade issuers. In summary, the three samples in Panels A, B and C hardly exhibit any differences. The coefficient estimates remain significant both statistically and economically regardless of the issuers' rating level. We therefore conclude that rotation-induced changes in rating activity level are not a phenomenon confined to specific rating levels.

B. Effects on credit risk assessment

In a second step, we now analyse if CRA analyst rotation and coverage duration are accompanied by an improvement or deterioration of the credit risk assessment. In this context, we estimate fixed-effect panel regression models. As decomposed when deriving proposition 1.2, new CRA analysts being assigned to cover an issuer could be expected to bring an unbiased perspective and more inclination to change a credit rating. Our proposition dealing with coverage duration (2.2) is based on similar reasoning. We estimate fixed-effects panel regression models. Our baseline regression specifications testing the effect of CRA analyst rotation and coverage duration on long-term issuer ratings are expressed as follows:

$$\begin{aligned} Rating_{it} &= \alpha_i + \alpha_t + \beta_1 \times Rotation_{it} + \\ &\quad \beta_n \times X_{it} + \varepsilon_{it} \end{aligned}$$

$$\begin{aligned} Rating_{it} &= \alpha_i + \alpha_t + \beta_2 \times Coverage\, duration_{itj} + \\ &\quad \beta_n \times X_{it} + \varepsilon_{it} \end{aligned}$$

The dependent variable, $\mathrm{Rating}_{\mathrm{it}}$ is the long-term issuer default rating on a numerical scale, for firm i in quarter t (cf. also Mählmann (2011); Fracassi et al. (2016)). α_{i} and α_{t} are firm and quarter fixed effects, respectively. Our independent variable in focus is $\mathrm{Rotation}_{\mathrm{it}}$: it is a dummy variable taking the value of 1 if a new CRA analysts is assigned to issuer i in a specific quarter t and 0 if the CRA analyst has not changed. We apply two different measures, the variable "Lead analyst change_2 quarters" setting the dummy to 1 for the quarter t when the analyst rotation occurred and quarter t+1 thereafter, and "Lead analyst change_4 quarters" does accordingly for the following 3 quarters (t+3). β_2 measures the effect of the time CRA analyst j has covered firm i by the time of quarter t measured in quarters. The issuer-related variables controlling for financial fundamentals summarized in vector X_{it} include leverage/ liquidity (net debt to EBITDA ratio and debt to capital ratio), firm size (market capitalization), and profit (EBITDA margin)[13]. Together with time and firm fixed effects, these control variables serve to address endogeneity and identification concerns as outlined above.

Table VIII presents a significant effect of CRA analyst changes, i.e. rotation, on the long-term issuer rating by all three CRAs in scope. Based on the numerical rating scale depicted in Table X, the significantly positive coefficient both in Panel A for the overall sample including all three CRAs and in Panel B for each CRA subsample points towards an increase in downgrading activity following changes of the CRA analyst covering an issuer. As for Panel A, the coefficient estimate increases in terms of economic magnitude and statistical significance from Lead analyst change_2 quarters to Lead analyst change_4 quarters. The latter is significant at the 1% level and shows that ratings in the 4 quarters after a CRA analyst change are, on average, 0.049 points worse on the rating scale from 1 (best rating) to 21 (worst rating). Thus, the effect appears to occur within 6 months but also 12 month after the CRA analyst rotation. In Panel B, specification 4-6 for Fitch, statistical significance remains the same for both rotation coefficients but the economic effect decreases from 0.102 to 0.086. Both for Moody's (specifications 7-9) and S&P (specifications 10-12), there is no economically and statistically significant effect for the two quarters after a Lead analyst change. Nevertheless, within four quarters, the significant coefficient estimate is 0.051 for Moody's and 0.037 for S&P stating that ratings change towards lower ratings and, compared to Fitch, happen slightly later. This result, showing slightly weaker effects in the case of Moody's and S&P, is stable including firm and time fixed effects as well as a set of fundamental issuer financial variables controlling for leverage, profitability and firm size. The figures for these financial control variables confirm intuition for EBITDA margin and the debt to capital ratio as ratings tend to be better with higher EBITDA margins (negative coefficient) and lower (positive coefficient) with higher debt to capital ratios. Despite their statistical significance, neither net debt to EBITDA ratio, nor market capitalization seem to influence ratings. Furthermore, the adjusted R-squared is stable across the specifications. Its values amount to approximately 0.1 for Fitch and S&P whereas Moody's and the overall sample exhibit 0.04 and 0.07, respectively. We interpret the results as when new CRA analysts start their coverage, they tend to exercise a more conservative judgment than their predecessors. Our analyses appear to render support to proposition 1.2.

At the same time, the empirical evidence for proposition 2.2 is mixed as the value of zero for the coefficient in absence of any statistical significance shows (cf. overall sample in Panel A). For Panel B, on the one hand, the coefficient for Fitch of 0.005 points towards a significant negative effect (positive coefficient) of coverage duration on ratings which was not predicted. With each quarter of issuer coverage by a CRA analyst, issuer ratings would - on average - be 0.005 rating points higher. With regard to Moody's, the result is close to 0 and neither statistically nor economically significant. On the other hand, the S&P subsample (specification 12) appears to render support to the proposition with a coefficient value of -0.006 and a high

[13]In unreported analyses, we apply various sets of common financial control variables. Our results are vastly not sensitive to the choice of control variables.

statistical significance. Interpretation should take the very limited economic significance of the coefficients ranging below 0.01 into account, however. The adjusted R-squared in each of the specifications 3, 6, 9 and 12 exhibits very similar results compared to the specifications dealing with CRA analyst rotation. In conclusion, proposition 2.2 is only partially supported by the analysis.

- Table VIII about here: Effect of analyst rotation on credit risk assessment -

Our results contribute to the debate on the supervision and regulation of rating agencies as we demonstrate that CRA analyst rotation correlates with higher levels of rating actions. Furthermore, we observe that the rating actions taken by a newly assigned CRA analyst are typically more conservative than rating actions taken by fellow analysts whose coverage responsibility is not altered. We empirically confirm the regulator's notion and observe that credit rating processes at major CRAs are prone to influence by CRA analyst rotation and do not eliminate individual noise. The main implications of our research appertain to CRAs and policymakers alike. As for CRAs, there is an emphasized need to bring their credit ratings processes back to the drawing board. While the current shape of these processes has certainly been proven in some ways over the years, they are most likely not suited to serve the publicly stated commitments of producing institutional rather than individual credit rating decisions. In particular, our research outcomes call for a careful assessment of internal rotation policies. However, their clients might not be particularly fond of increased rotation either due to potential benefits from "learning to gaming" (Mählmann (2011)), increasing financing costs as a result of analyst rotation or simply due to reluctance of regularly having to explain their business and financial situation to new CRA analysts. In terms of implications for policy, our results might be informative for regulators in the United States where CRA analyst-related laws have taken a different path compared to the European Union where regulatory bodies have apparently managed to stay abreast of potential drivers of credit rating processes. The applicability of CRA analyst rotation requirements in comparison with overall circumstances could be verified in light of our findings. Additionally, from the issuer's perspective, CRA analyst rotation is actually bad news as it increases the volatility of the company's ratings and is followed by abnormal downgrade activity. A CFO should therefore closely monitor the tenure of its rating analysts before issuing new bonds and debt instruments.

B.1. Robustness checks

Ratings levels of issuers might affect our inference as our results might be driven by issuers of certain rating levels only. This is especially relevant as our dependent variable in the panel regression does not allow us to control for the issuer's risk level as it serves as our dependent variable. In order to scrutinize this aspect, we perform robustness checks shown in Table IX. It depicts the analysis of two subsamples splitting the sample between investment grade and sub-investment grade issuers. The results reveal that, despite a higher economic magnitude and higher R-squared in the case of sub-investment grade issuers, the statistical significance holds for both subsamples separately. In general, the coefficient estimates are similar. We conclude that no sample effect pertaining to the rating level is behind our findings.

VI. Conclusion

In this paper, we build upon the existing literature centered on biases of CRAs and the role of CRA analysts and extend it by focusing on CRA analyst rotation and its impact on credit risk assessment. Leveraging a hand-collected dataset we are able to track CRA analysts' rotation of S&P 500 issuers between 2002 and 2015 and link it to the corresponding rating history of each individual issuer. We find evidence that analyst rotation leads to an increase in subsequent rating activity and is accompanied by rating downgrades. In contrast to the argumentation of CRAs, our results show that rating processes are prone to noise by individual analysts. Furthermore, our result provide empirical support for the recently introduced mandatory analyst rotation legislation in the European Union. The intention behind structured credit rating processes developed by the CRAs corresponds to that of CRA-related regulation: Ensuring impartial credit rating decisions by lowering the likelihood for biases and misaligned incentives. Given the astounding amounts of credit volume in the global economy, our results suggest that the influence of individuals might have been underestimated as criticism tends to zero in on CRAs as institutions.

References

Bangia, A., Diebold, F. X., Kronimus, A., Schagen, C., and Schuermann, T. (2002). Ratings migration and the business cycle, with application to credit portfolio stress testing. *Journal of Banking & Finance*, 26(2-3):445–474.

Bank for International Settlements (2018). Global debt securities outstanding by sector. Technical report, Bank for International Settlements.

Bar-Isaac, H. and Shapiro, J. (2011). Credit ratings accuracy and analyst incentives. *The American Economic Review*, 101(3):120–124.

Berg, T., Puri, M., and Rocholl, J. (2013). Loan officer incentives and the limits of hard information. National Bureau of Economic Reserach working paper no. 19051.

Bolton, P., Freixas, X., and Shapiro, J. (2012). The credit ratings game. *The Journal of Finance*, 67(1):85–111.

Bongaerts, D., Cremers, K., and Goetzmann, W. N. (2012). Tiebreaker: Certification and multiple credit ratings. *The Journal of Finance*, 67(1):113–152.

Brown, S. J., Goetzmann, W. N., and Park, J. (2001). Careers and survival: Competition and risk in the hedge fund and CTA industry. *The Journal of Finance*, 56(5):1869–1886.

Chung, K. H. and Jo, H. (1996). The impact of security analysts' monitoring and marketing functions on the market value of firms. *Journal of Financial and Quantitative Analysis*, 31(4):493–512.

Clarke, J., Khorana, A., Patel, A., and Rau, P. R. (2007). The impact of all-star analyst job changes on their coverage choices and investment banking deal flow. *Journal of Financial Economics*, 84(3):713–737.

Clement, M. B. (1999). Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics*, 27(3):285–303.

Clement, M. B. and Tse, S. Y. (2005). Financial analyst characteristics and herding behavior in forecasting. *The Journal of Finance*, 60(1):307–341.

Cohen, L., Frazzini, A., and Malloy, C. (2010). Sell-side school ties. *The Journal of Finance*, 65(4):1409–1437.

Cole, S., Kanz, M., and Klapper, L. (2015). Incentivizing calculated risk-taking: Evidence from an experiment with commercial bank loan officers. *The Journal of Finance*, 70(2):537–575.

Cornaggia, J., Cornaggia, K. J., and Xia, H. (2016). Revolving doors on Wall Street. *Journal of Financial Economics*, 120(2):400–419.

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society, Series B*, 34(2):187–220.

Croce, A., Lugo, S., and Faff, R. W. (2011). Rating alignment, rating shopping and reputation of credit rating agencies: Evidence from the subprime crisis. Working paper.

Devenow, A. and Welch, I. (1996). Rational herding in financial economics. *European Economic Review*, 40(3):603–615.

Deville, L. and Riva, F. (2007). Liquidity and arbitrage in options markets: A survival analysis approach. *Review of Finance*, 11(3):497–525.

Dilly, M. and Mählmann, T. (2016). Is there a "boom bias" in agency ratings? *Review of Finance*, 20(3):979–1011.

Efing, M. and Hau, H. (2015). Structured debt ratings: Evidence on conflicts of interest. *Journal of Financial Economics*, 116(1):46–60.

E.U. Commission (2009). Regulation (EC) No 1060/2009 of the European Parliament and of the Council of 16 September 2009 on credit rating agencies. Technical report, E.U. Commission.

Fang, L. and Yasuda, A. (2009). The effectiveness of reputation as a disciplinary mechanism in sell-side research. *Review of Financial Studies*, 22(9):3735–3777.

Fitch Ratings (2016). The ratings process (The ratings process under Fitch criteria). Technical report, Fitch Ratings.

Fracassi, C., Petry, S., and Tate, G. (2016). Does rating analyst subjectivity affect corporate debt pricing? *Journal of Financial Economics*, 120(3):514–538.

Glennon, D. C. and Nigro, P. (2005). Measuring the default risk of small business loans: A survival analysis approach. *Journal of Money, Credit, and Banking*, 37(5):923–947.

Güttler, A. (2011). Lead-lag relationships and rating convergence among credit rating agencies. *Journal of Credit Risk*, 7(1):95–119.

Güttler, A. and Wahrenburg, M. (2007). The adjustment of credit ratings in advance of defaults. *Journal of Banking & Finance*, 31(3):751–767.

Harrell, F. E. (2001). *Regression modeling strategies: With applications to linear models, logistic regression, and survival analysis*, chapter Cox proportional hazards regression model, pages 465–507. Springer New York, New York, NY.

Hertzberg, A., Liberti, J., and Paravisini, D. (2010). Information and incentives inside the firm: Evidence from loan officer rotation. *The Journal of Finance*, 65(3):795–828.

Holmstrom, B. (1982). Moral hazard in teams. *The Bell Journal of Economics*, pages 324–340.

Hong, H. and Kubik, J. D. (2003). Analyzing the analysts: Career concerns and biased earnings forecasts. *The Journal of Finance*, 58(1):313–351.

Hong, H., Kubik, J. D., and Solomon, A. (2000). Security analysts' career concerns and herding of earnings forecasts. *The Rand Journal of Economics*, 31(1):121–144.

Iyer, R. and Puri, M. (2012). Understanding bank runs: The importance of depositor-bank relationships and networks. *The American Economic Review*, 102(4):1414–1445.

Iyer, R., Puri, M., and Ryan, N. (2016). A tale of two runs: Depositor responses to bank solvency risk. *The Journal of Finance*, 71(6):2687–2726.

Jaggi, B. and Tang, L. (2015). Geographic location of the firm and credit rating accuracy. *Journal of Accounting, Auditing & Finance*, 32(2):155–181.

Jain, B. A. and Martin Jr, C. L. (2005). The association between audit quality and post-IPO performance: A survival analysis approach. *Review of Accounting and Finance*, 4(4):50–75.

Jayaratne, J. and Strahan, P. E. (1996). The finance-growth nexus: Evidence from bank branch deregulation. *The Quarterly Journal of Economics*, 111(3):639–670.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4):305–360.

Jewell, J. and Livingston, M. (1999). A comparison of bond ratings from Moody's S&P and Fitch IBCA. *Financial Markets, Institutions & Instruments*, 8(4):1–45.

Jiang, J. X., Wang, I. Y., and Wang, K. P. (2016). Revolving rating analysts and ratings of MBS and ABS: Evidence from LinkedIn. Working paper.

Kisgen, D. J., Osborn, M., and Reuter, J. (2016). Analyst promotions within credit rating agencies: Accuracy or bias? National Bureau of Economic Research working paper no. w22477.

Kumar, A. (2010). Self-selection and the forecasting abilities of female equity analysts. *Journal of Accounting Research*, 48(2):393–435.

Lane, W. R., Looney, S. W., and Wansley, J. W. (1986). An application of the Cox proportional hazards model to bank failure. *Journal of Banking & Finance*, 10(4):511–531.

Liberti, J. M. and Mian, A. R. (2009). Estimating the effect of hierarchies on information use. *The Review of Financial Studies*, 22(10):4057–4090.

Lugo, S., Croce, A., and Faff, R. (2015). Herding behavior and rating convergence among credit rating agencies: Evidence from the subprime crisis. *Review of Finance*, 19(4):1703–1731.

Mählmann, T. (2009). Multiple credit ratings, cost of Debt and self-selection. *Journal of Business Finance & Accounting*, 36(9-10):1228–1251.

Mählmann, T. (2011). Is there a relationship benefit in credit ratings? *Review of Finance*, 15(3):475–510.

Malloy, C. J. (2005). The geography of equity analysis. *The Journal of Finance*, 60(2):719–755.

Moody's Investors Service (2017). Ratings process detail. Technical report, Moody's Investors Service.

Morkoetter, S., Stebler, R., and Westerfeld, S. (2017). Competition in the credit rating Industry: Benefits for investors and issuers. *Journal of Banking & Finance*, 75:235–257.

Nahata, R., Hazarika, S., and Tandon, K. (2014). Success in global venture capital investing: Do institutional and cultural differences matter? *Journal of Financial and Quantitative Analysis*, 49(4):1039–1070.

Parker, S., Peters, G. F., and Turetsky, H. F. (2002). Corporate governance and corporate failure: A survival analysis. *Corporate Governance: The International Journal of Business in Society*, 2(2):4–12.

Qian, J. Q., Strahan, P. E., and Yang, Z. (2015). The impact of incentives and communication costs on information production and use: Evidence from bank lending. *The Journal of Finance*, 70(4):1457–1493.

Scharfstein, D. S. and Stein, J. C. (1990). Herd behavior and investment. *The American Economic Review*, 80(3):465–479.

SEC (2016). Annual report on nationally recognized statistical rating organizations - as required by section 6 of the Credit Rating Agency Reform Act of 2006. Technical report, United States Securities and Exchange Commission.

Skreta, V. and Veldkamp, L. (2009). Ratings shopping and asset complexity: A theory of ratings inflation. *Journal of Monetary Economics*, 56(5):678–695.

Standard & Poor's (2014). Corporate ratings methodology. Technical report, Standard & Poor's.

Standard & Poor's (2017). General description of the credit rating process. Technical report, Standard & Poor's.

Stepanova, M. and Thomas, L. (2002). Survival analysis methods for personal loan data. *Operations Research*, 50(2):277–289.

Stiroh, K. J. and Strahan, P. E. (2003). Competitive dynamics of deregulation: Evidence from US banking. *Journal of Money, Credit, and Banking*, 35(5):801–828.

Sufi, A. (2007). The real effects of debt certification: Evidence from the introduction of bank loan ratings. *The Review of Financial Studies*, 22(4):1659–1691.

Trueman, B. (1994). Analyst forecasts and herding behavior. *Review of Financial Studies*, 7(1):97–124.

Welch, I. (1992). Sequential sales, learning, and cascades. *The Journal of Finance*, 47(2):695–732.

Womack, K. L. (1996). Do brokerage analysts' recommendations have investment value? *The Journal of Finance*, 51(1):137–167.

VII. Tables

Table I: Summary statistics

The sample includes 317 companies rated by Fitch, 444 companies rated by Moody's and 449 rated by S&P out of constituents of the S&P 500 (dual class shares have been excluded). Figures are based on cross-sectional quarterly data from 2002 until 2015. Statistical significance levels and t-values for differences in means of issuers covered by Fitch, Moody's and S&) are obtained by two-sample t–tests. Figures are trimmed at the 1st and 99th percentile. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

								Percentiles					Difference		
Variable	Subsample	Unit	N	Mean	SD	Min	Max	5th	25th	50th	75th	95th	Fitch-Moody's	Fitch-S&P	Moody's-S&P
	S&P 500		25,094	22,804.00	33,803.00	730.00	235,821.00	2,193.00	5,506.00	11,063.00	23,210.00	92,564.00			
Market capitalization	Fitch	USD mm	16,055	26,439.00	37,037.00	1,080.00	240,537.00	2,849.00	6,754.00	13,206.00	27,450.00	108,199.00	4.39***	5.66***	1.36
	Moody's		22,352	24,802.00	35,923.00	892.20	242,334.00	2,493.00	6,017.00	12,153.00	25,572.00	102,446.00			
	S&P		22,684	24,185.00	34,949.00	858.40	238,775.00	2,439.00	5,863.00	11,881.00	25,131.00	98,433.00			
	S&P 500		25,511	3,634	5,507	34	38,490	197	690	1,603	3,793	15,546			
Revenues	Fitch	USD mm	16,216	4,780	6,485	58	44,485	332	1,053	2,437	5,331	18,893	11.78***	11.99***	0.29
	Moody's		22,717	3,991	5,782	64	40,124	257	829	1,866	4,270	16,532			
	S&P		22,989	3,965	5,829	52	39,931	238	787	1,809	4,221	16,630			
	S&P 500		23,889	24.15	15.58	-9.81	78.80	5.05	13.00	20.80	31.50	58.20			
EBITDA margin	Fitch	%	14,682	24.08	15.91	-3.30	82.90	4.91	12.80	20.30	31.30	59.50	2.14**	1.83*	0.35
	Moody's		21,142	24.35	15.57	-2.77	81.00	5.42	13.20	20.80	31.50	59.00			
	S&P		21,398	24.26	15.56	-4.17	80.40	5.20	13.20	20.80	31.30	58.90			
	S&P 500		25,346	10.31	11.63	-62.60	53.40	-4.20	4.55	8.95	15.80	29.60			
Profit margin	Fitch	%	16,102	10.00	11.53	-57.50	56.90	-4.41	4.35	8.50	15.30	29.00	2.59***	2.97***	0.39
	Moody's		22,593	10.30	11.24	-53.80	54.80	-3.86	4.55	8.80	15.50	29.50			
	S&P		22,863	10.32	11.27	-55.20	54.60	-3.83	4.56	8.88	15.50	29.50			
	S&P 500		25,056	3.52	14.06	-40.20	51.10	-20.60	-4.64	3.66	11.90	26.60			
Dividend-adjusted stock return	Fitch	%	16,049	3.05	13.49	-40.40	48.70	-20.50	-4.62	3.39	11.20	24.70	1.82*	1.87*	0.06
	Moody's		22,328	3.33	13.63	-40.00	48.60	-20.20	-4.59	3.57	11.60	25.40			
	S&P		22,659	3.36	13.77	-40.20	49.60	-20.50	-4.61	3.57	11.60	25.70			
	S&P 500		23,835	612.60	1014.00	-2452.00	5311.00	-717.50	-3.79	434.00	1044.00	2589.00			
Net debt to EBITDA ratio	Fitch	%	14,650	856.20	968.70	-1796.00	5507.00	-321.40	217.90	639.30	1316.00	2755.00	14.91***	16.71***	2.07**
	Moody's		21,073	695.10	982.50	-1999.00	5395.00	-593.80	82.82	512.10	1114.00	2602.00			
	S&P		21,338	670.80	1003.00	-2446.00	5398.00	-665.40	65.26	489.20	1102.00	2592.00			
	S&P 500		23,202	40.57	22.40	0.25	143.80	6.48	24.40	38.40	54.70	80.30			
Debt to capital ratio	Fitch	%	15,174	44.79	21.91	1.54	151.30	13.70	28.40	42.80	57.60	84.90	11.87***	12.45***	0.75
	Moody's		21,205	41.56	21.24	0.46	124.70	9.14	26.00	39.60	55.20	79.70			
	S&P		21,357	41.74	22.12	0.46	150.40	8.91	25.70	39.50	55.30	81.00			
	S&P 500		20,049	4.22	3.65	-7.38	212.50	0.90	2.09	3.44	5.19	10.70			
Altman Z-score	Fitch		11,074	3.16	1.81	-1.42	20.90	0.83	1.87	2.86	4.11	6.45	5.26***	5.52***	0.07
	Moody's		17,357	3.71	4.37	-7.38	257.30	0.88	2.02	3.21	4.66	8.15			
	S&P		17,617	3.76	4.38	-22.40	257.30	0.88	2.06	3.29	4.75	8.20			

Table II: Multiple ratings

The table shows the coverage of S&P 500 issuers by multiple credit ratings agencies: Fitch, Moody's and S&P. It entails long-term issuer ratings for the period of 2002 until 2015. In the case of Moody's, the corporate family rating (CFR) or senior unsecured rating was used if a long-term issuer rating was not assigned. The CFR is practically identical to the long-term issuer rating and mostly assigned to sub-investment grade issuers. For a few issuers, the CFR was withdrawn at some point, typically when an issuer had reached an investment grade rating. In these cases, the senior unsecured rating was also used instead.

Subsample	Number of rated issuers	in % of total sample
S&P 500 (total sample)	460	100%
By rating agency		
Fitch	317	69%
Moody's	444	97%
S&P	449	98%
Single rating		
Total	15	3%
Fitch	0	0%
Moody's	4	1%
S&P	11	2%
Double rating		
Total	445	97%
Fitch / Moody's	312	68%
Fitch / S&P	310	67%
Moody's / S&P	433	94%
Triple rating		
Fitch / Moody's / S&P	305	66%

Table III: Issuer coverage by credit rating agencies

The table shows the number of S&P 500 issuers covered by Fitch, Moody's and S&P by type of long-term issuer rating as well as the number of rating actions by type. It entails data from 2002 until 2015. In the case of Moody's, the corporate family rating (CFR) or senior unsecured rating was used if a long-term issuer rating was not assigned. The CFR is practically identical to the long-term issuer rating and mostly assigned to sub-investment grade issuers. For a few issuers, the CFR was withdrawn at some point, typically when an issuer had reached an investment grade rating. In these cases, the senior unsecured rating was also used instead.

Coverage and number of rating actions			
	Fitch	Moody's	S&P
Number of issuers covered	317	444	449
Exclusive	0	4	11
Overlap	305		
with long-term issuer rating	317	139	449
with corporate family rating (CFR)	-	50	-
with senior unsecured rating	-	207	-
with CFR & senior unsecured rating	-	48	-
Number of rating actions - Overall	923	1635	1813
Upgrade	333	486	614
Positive watchlist	27	220	167
Downgrade	422	497	597
Negative watchlist	141	432	435
Number of documents processed for data collection	4.500	6.500	6.500

Table IV: Frequency and number of rating actions by credit rating agencies

The table shows the number of rating actions per company covered as well as the time between ratings actions measured in days by rating action type for all S&P 500 issuers rated by the respective credit rating agency (CRA). It entails data from 2002 until 2015. Downward rating actions include downgrades and negative watchlist entries. Upward rating action refer to upgrades and positive watch list entries. Statistical significance levels and z-values for differences between the CRAs are obtained by a Mann-Whitney-Wilcoxon test. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

								Percentiles					Difference		
Variable	Subsample	Unit	N	Mean	SD	Min	Max	5th	25th	50th	75th	95th	Fitch-Moody's	Fitch-S&P	Moody's-S&P
Number of rating actions per issuer															
All types of rating actions	Fitch	Number	923	3.53	2.18	1.00	14.00	1.00	2.00	3.00	5.00	7.00	3.99***	1.20	2.69***
	Moody's		1635	4.54	3.00	1.00	24.00	1.00	2.00	4.00	6.00	10.00			
	S&P		1813	4.12	3.40	0.00	22.00	0.00	2.00	4.00	6.00	10.00			
Downgrades	Fitch	Number	422	1.60	1.44	0.00	8.00	0.00	0.00	1.00	2.00	4.00	1.98**	2.61***	0.70
	Moody's		497	1.38	1.38	0.00	9.00	0.00	0.00	1.00	2.00	4.00			
	S&P		597	1.36	1.45	0.00	9.00	0.00	0.00	1.00	2.00	4.00			
Negative watchlist	Fitch	Number	141	0.54	0.75	0.00	4.00	0.00	0.00	0.00	1.00	2.00	7.68***	5.04***	3.04***
	Moody's		432	1.20	1.18	0.00	7.00	0.00	0.00	1.00	2.00	3.00			
	S&P		435	0.99	1.15	0.00	8.00	0.00	0.00	1.00	2.00	3.00			
Upgrades	Fitch	Number	333	1.28	1.28	0.00	6.00	0.00	0.00	1.00	2.00	4.00	0.39	0.27	-0.12
	Moody's		486	1.35	1.36	0.00	7.00	0.00	0.00	1.00	2.00	4.00			
	S&P		614	1.40	1.51	0.00	8.00	0.00	0.00	1.00	2.00	4.00			
Positive watchlist	Fitch	Number	27	0.10	0.34	0.00	2.00	0.00	0.00	0.00	0.00	1.00	9.60***	5.87***	5.07***
	Moody's		220	0.61	0.79	0.00	3.00	0.00	0.00	0.00	1.00	2.00			
	S&P		167	0.38	0.73	0.00	4.00	0.00	0.00	0.00	1.00	2.00			
Time between rating actions															
All types of rating actions	Fitch	Days	923	742.79	752.05	4.00	4481.00	39.00	170.00	462.50	1087.75	2250.00	7.65***	4.73***	3.52***
	Moody's		1635	568.29	724.31	1.00	5046.00	21.00	83.00	251.00	784.00	2072.25			
	S&P		1813	622.58	697.12	1.00	4379.00	20.00	104.25	363.00	894.25	2105.85			
Downward rating actions	Fitch	Days	563	708.11	947.84	4.00	4864.00	25.60	104.00	292.00	991.00	2676.80	5.25***	2.56**	3.28***
	Moody's		929	508.30	830.82	1.00	5046.00	15.00	60.00	139.00	546.00	2269.60			
	S&P		1032	602.94	862.55	2.00	4857.00	20.00	72.00	204.00	760.00	2404.60			
Rating downgrades	Fitch	Days	422	762.33	955.60	4.00	4845.00	30.15	123.75	348.00	1089.50	2504.60	1.25	2.40***	1.19
	Moody's		497	800.74	897.39	8.00	4237.00	28.90	170.00	450.50	1201.50	2658.60			
	S&P		597	929.42	1012.45	2.00	4838.00	30.55	180.75	535.00	1367.50	3115.00			
Upward rating actions	Fitch	Days	360	950.82	907.86	27.00	4574.00	113.60	333.00	614.00	1299.00	2742.00	6.81***	3.73***	3.23***
	Moody's		706	635.68	848.54	1.00	4603.00	28.60	84.00	266.00	819.00	2491.30			
	S&P		781	767.92	868.11	6.00	4264.00	17.00	121.50	451.00	1063.50	2806.00			
Rating upgrades	Fitch	Days	333	1007.92	868.70	99.00	4025.00	165.40	364.00	716.00	1394.00	2709.00	0.24	0.81	0.56
	Moody's		486	1053.36	925.43	3.00	4675.00	174.85	371.25	724.00	1416.50	3071.35			
	S&P		614	1068.22	904.50	8.00	4264.00	185.70	386.50	750.00	1445.75	2963.20			

Table V: Details on CRA analysts

The table shows the number of unique credit rating analysts covering S&P 500 issuers between 2002 and 2015 at the three major CRAs by role, gender and office location based on 17,500 publications.

CRA analyst demographics			
	Fitch	Moody's	S&P
Number of unique CRA analysts	256	283	332
Lead analyst	214	219	332
Secondary analyst	224	191	-
Thereof overlap of lead & secondary analyst roles	182	127	-
Male	176	218	223
Female	79	65	109
New York	148	268	296
Chicago	94	-	8
Boston	-	-	4
Dallas	-	-	1
San Francisco	-	-	9
Washington D.C.	-	-	1
Toronto	-	5	6
London	11	7	5
Frankfurt	1	1	1
Paris	1	1	-
Milan	1	1	-
Moscow	-	-	1

Table VI: CRA analyst coverage and rotation

The table shows the total number of sectors/ industries and issuers covered by CRA analysts by role. The number of CRA analyst changes is documented in total as well as the coverage duration of CRA analysts. The data encompasses unique credit rating analysts covering S&P 500 issuers between 2002 and 2015. Statistical significance levels and z-values for differences between the analysts at each CRA are obtained by a Mann-Whitney-Wilcoxon test. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

								Percentiles					Difference		
Variable	Subsample	Unit	N	Mean	SD	Min	Max	5th	25th	50th	75th	95th	Fitch-Moody's	Fitch-S&P	Moody's-S&P
Industry types covered (total)	Fitch	Number	3,750	4.58	4.45	1.00	24.00	1.00	2.00	3.00	6.00	15.30	0.97	2.92***	1.75*
	Moody's		5,794	6.04	10.10	1.00	75.00	1.00	1.00	3.00	6.00	23.80			
	S&P		2,935	3.56	3.20	1.00	20.00	1.00	1.00	2.00	5.00	9.50			
Sectors covered (total)	Fitch	Number	3,750	1.60	0.97	1.00	6.00	1.00	1.00	1.00	2.00	4.00	0.02	-0.56	-0.66
	Moody's		5,794	1.87	1.61	1.00	10.00	1.00	1.00	1.00	2.00	6.00			
	S&P		2,935	1.57	0.91	1.00	5.00	1.00	1.00	1.00	2.00	4.00			
Issuers covered (total)															
As lead analyst	Fitch	Number	1,875	4.04	3.33	1.00	20.00	1.00	1.00	3.00	6.00	10.00	1.75*	0.56	1.47
	Moody's		2,895	6.35	9.32	1.00	76.00	1.00	1.50	3.00	7.00	19.00			
	S&P		2,935	4.53	4.13	1.00	23.00	1.00	1.00	3.00	6.25	13.00			
As secondary analyst	Fitch	Number	1,875	4.96	4.87	1.00	30.00	1.00	1.00	3.00	7.00	15.00	0.05	n.a.	n.a.
	Moody's		2,895	7.69	14.13	1.00	109.00	1.00	1.00	3.00	7.00	40.50			
	S&P		n.a.												
As both lead and secondary analyst	Fitch	Number	3,750	6.48	5.94	1.00	32.00	1.00	2.00	4.00	9.25	18.00	1.32	n.a.	n.a.
	Moody's		5,794	8.59	14.96	1.00	120.00	1.00	2.00	4.00	8.00	34.80			
	S&P		n.a.												
CRA analyst changes per issuer, by role															
Lead analyst (total)	Fitch	Number	1,875	1.77	1.42	0.00	7.00	0.00	1.00	2.00	2.75	4.00	3.34***	5.42***	2.16**
	Moody's		2,895	2.14	1.58	0.00	10.00	0.00	1.00	2.00	3.00	5.00			
	S&P		2,935	2.31	1.43	0.00	7.00	0.00	1.00	2.00	3.00	5.00			
Secondary analyst (total)	Fitch	Number	1,875	2.64	1.83	0.00	11.00	0.00	1.00	2.00	4.00	6.00	2.12**	n.a.	n.a.
	Moody's		2,895	2.32	1.56	0.00	7.00	0.00	1.00	2.00	3.00	5.00			
	S&P		n.a.												
Duration of CRA analyst coverage															
Lead analyst only	Fitch	Days	1,875	1487.11	1110.10	30.00	5078.00	166.90	655.00	1226.00	2022.00	3723.20	1.95*	5.56***	4.08***
	Moody's		2,895	1445.13	1186.05	25.00	5615.00	136.40	532.00	1125.00	2051.00	3888.80			
	S&P		2935	1253.78	1039.08	28.00	5627.00	89.80	425.00	975.00	1813.00	3367.40			
Secondary analyst only	Fitch	Days	1,875	1116.19	993.40	22.00	5231.00	83.40	374.50	791.00	1538.00	3278.00	5.39***	n.a.	n.a.
	Moody's		2,895	1277.12	1027.76	25.00	5586.00	167.25	510.25	1058.00	1689.00	3369.00			
	S&P		n.a.												
Total	Fitch	Days	1,875	1305.62	1101.30	22.00	5231.00	86.60	442.00	1022.00	1796.00	3660.20	2.13**	n.a.	n.a.
	Moody's		2,895	1357.76	1109.55	25.00	5615.00	149.00	519.00	1088.00	1830.00	3715.10			
	S&P		n.a.												

Table VII: Effect of CRA analyst rotation on likelihood of rating actions

The table shows coefficient estimates and standard errors of Cox proportional hazard models for estimating the hazard of rating actions. Panel A refers to the total sample including Fitch, Moody's and S&P. Panel B exhibits a subsample of investment grade issuers whereas Panel C shows the subsample of sub-investment grade issuers. Issuers are classified as investment grade when their average long-term issuer default rating is higher than "BB". The dependent variable is the time in days between downgrades and upgrades pertaining to long-term issuer ratings. The time-varying covariate "Lead analyst change" takes the value of 1 from the day a new CRA lead analyst appears on a press release or similar publication by a CRA and measures rotation. Until that day, the covariate is assigned a 0 indicating that the CRA analyst covering the respective issuer hasn't changed yet. Coverage duration is the time a CRA analyst has covered an issuer before at the time of the rating action measured in years. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Total sample									
	Fitch			Moody's			S&P		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lead analyst change	0.662***		0.564***	0.544***		0.568***	0.373***		0.391***
	(0.086)		(0.087)	(0.078)		(0.078)	(0.067)		(0.067)
Lead analyst coverage duration		-0.127***	-0.120***		-0.071***	-0.076***		-0.057***	-0.062***
		(0.014)	(0.015)		(0.010)	(0.011)		(0.011)	(0.011)
Number of firms	317	317	317	444	444	444	449	449	449

Panel B: Investment grade issuers									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lead analyst change	0.672***		0.575***	0.376***		0.414***	0.440***		0.475***
	(0.097)		(0.099)	(0.101)		(0.101)	(0.081)		(0.081)
Lead analyst coverage duration		-0.124***	-0.116***		-0.082***	-0.086***		-0.068***	-0.076***
		(0.016)	(0.017)		(0.013)	(0.013)		(0.013)	(0.014)
Number of firms	249	249	249	321	321	321	330	330	330

Panel C: Sub-investment grade issuers									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lead analyst change	0.712***		0.627***	0.793***		0.793***	0.409***		0.393***
	(0.183)		(0.184)	(0.123)		(0.124)	(0.119)		(0.120)
Lead analyst coverage duration		-0.127***	-0.120***		-0.035*	-0.036*		-0.031*	-0.028
		(0.031)	(0.032)		(0.018)	(0.018)		(0.018)	(0.018)
Number of firms	68	68	68	123	123	123	119	119	119

Table VIII: Effect of CRA analyst rotation on credit risk assessment

The table shows coefficient estimates and standard errors of fixed-effects panel regression models. Panel A refers to the total sample including Fitch, Moody's and S&P whereas Panel B exhibits each CRA separately. The dependent variable is the long-term issuer default rating mapped on a numerical scale (cf. also Table X). Lead analyst change is a dummy variable taking the value of 1 if a new CRA analysts is assigned to an issuer in a quarter and 0 if the CRA analyst has not changed and measures analyst rotation. 2_quarters and 4_quarters refers to the same dummy variable of 1 also being applied to 1 and 3 quarters after the analyst change quarter respectively. Coverage duration is the time a CRA analyst has covered an issuer before at the time of the rating action measured in quarters. Issuer-related variables controlling for financial fundamentals include leverage/ liquidity (net debt to EBITDA ratio and debt to capital ratio), firm size (market capitalization), and profit (EBITDA margin). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Total sample				Panel B: Subsamples by CRA								
	Fitch, Moody's and S&P			Fitch			Moody's			S&P		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lead analyst change_2 quarters	0.028*			0.102***			0.035			-0.003		
	(0.016)			-0.034			(0.028)			(0.024)		
Lead analyst change_4 quarters		0.049***			0.086***			0.051**			0.037**	
		(0.012)			(0.026)			(0.021)			(0.018)	
Lead analyst coverage duration			0.000			0.005***			0.001			-0.006***
			(0.001)			(0.001)			(0.001)			(0.001)
Net debt to EBITDA ratio (%)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA margin (%)	-0.008***	-0.008***	-0.008***	-0.007***	-0.007***	-0.006***	-0.007***	-0.007***	-0.007***	-0.009***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Debt to capital ratio (%)	0.017***	0.017***	0.017***	0.020***	0.020***	0.020***	0.015***	0.015***	0.015***	0.018***	0.018***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market capitalization (USD mm)	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	7.382***	7.359***	7.409***	6.644***	6.657***	6.733***	7.835***	7.817***	7.873***	7.338***	7.298***	7.334***
	(0.065)	(0.064)	(0.063)	(0.216)	(0.215)	(0.213)	(0.102)	(0.100)	(0.098)	(0.096)	(0.095)	(0.093)
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agency F.E.	Yes	Yes	Yes	-	-	-	-	-	-	-	-	-
Observations	39,328	39,328	39,328	9,760	9,760	9,760	15,183	15,183	15,183	14,401	14,401	14,401
Number of firms	1,068	1,068	1,068	269	269	269	399	399	399	399	399	399
R-squared	0.096	0.096	0.096	0.129	0.129	0.129	0.073	0.074	0.073	0.130	0.130	0.132
Adjusted R-squared	0.069	0.070	0.069	0.098	0.099	0.099	0.044	0.045	0.044	0.101	0.102	0.104

Table IX: Robustness checks - Effect on credit risk assessment

The table shows coefficient estimates and standard errors of fixed-effects panel regression models. Panel A and B refer to the total sample including Fitch, Moody's and S&P. Panel A exhibits subsamples by investment grade and sub-investment grade issuers whereas Panel B shows subsamples by time periods. Issuers are classified as investment grade when their average long-term issuer default rating is higher than "BB". The dependent variable is the long-term issuer default rating mapped on a numerical scale (cf. also Table X). Lead analyst change is a dummy variable taking the value of 1 if a new CRA analysts is assigned to an issuer in a quarter and 0 if the CRA analyst has not changed and measures analyst rotation. 2_quarters and 4_quarters refers to the same dummy variable of 1 also being applied to 1 and 3 quarters after the analyst change quarter respectively. Coverage duration is the time a CRA analyst has covered an issuer before at the time of the rating action measured in quarters. Issuer-related variables controlling for financial fundamentals include leverage/ liquidity (net debt to EBITDA ratio and debt to capital ratio), firm size (market capitalization), and profit (EBITDA margin). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Subsamples by rating level (Fitch, Moody's and S&P)						
	Investment grade issuers			Sub-investment grade issuers		
	(1)	(2)	(3)	(4)	(5)	(6)
Lead analyst change_2 quarters	0.011			0.053		
	(0.016)			(0.039)		
Lead analyst change_4 quarters		0.034***			0.065**	
		(0.012)			(0.030)	
Lead analyst coverage duration			0.000			0.001
			(0.001)			(0.002)
Net debt to EBITDA ratio (%)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA margin (%)	-0.009***	-0.009***	-0.009***	-0.010***	-0.009***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Debt to capital ratio (%)	0.013***	0.013***	0.013***	0.022***	0.022***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market capitalization (USD mm)	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	6.710***	6.687***	6.721***	10.757***	10.737***	10.817***
	(0.066)	(0.065)	(0.064)	(0.169)	(0.168)	(0.164)
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Quarter F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Agency F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,650	30,650	30,650	8,678	8,678	8,678
Number of firms	793	793	793	275	275	275
R-squared	0.099	0.099	0.099	0.257	0.257	0.257
Adjusted R-squared	0.073	0.073	0.073	0.227	0.227	0.227

Table X: Numerical reference scale for alphanumerical ratings

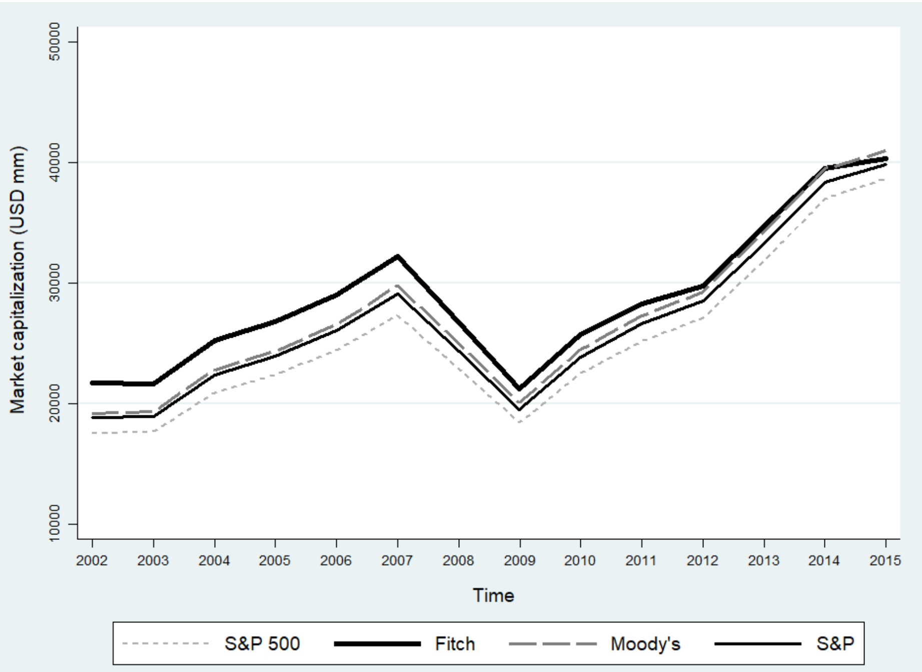
The table shows the numerical rating code corresponding to the individual rating agencies' alphanumerical rating scales. The coded ratings are used as the dependent variable for the fixed effects panel regressions.

S&P long-term rating class	Moody's long-term rating class	Fitch long-term rating class	Rating code
AAA	Aaa	AAA	1
AA+	Aa1	AA+	2
AA	Aa2	AA	3
AA-	Aa3	AA-	4
A+	A1	A+	5
A	A2	A	6
A-	A3	A-	7
BBB+	Baa1	BBB+	8
BBB	Baa2	BBB	9
BBB-	Baa3	BBB-	10
BB+	Ba1	BB+	11
BB	Ba2	BB	12
BB-	Ba3	BB-	13
B+	B1	B+	14
B	B2	B	15
B-	B3	B-	16
CCC+	Caa1	CCC+	17
CCC	Caa2	CCC	18
CCC-	Caa3	CCC-	19
CC	Ca	CC	20
C	C	C	21
D		D / DD / DDD	21

VIII. Figures

Figure I: Summary statistics

The figure shows the mean of quarterly values per year for market capitalization (measured in USD mm) and Altman Z-scores between 2002 and 2015 for S&P 500 issuers rated by Fitch (thick black line), Moody's (long dotted gray line) and S&P (thin black line). For comparison, the values for all S&P 500 constituents (short dotted gray line) is included.



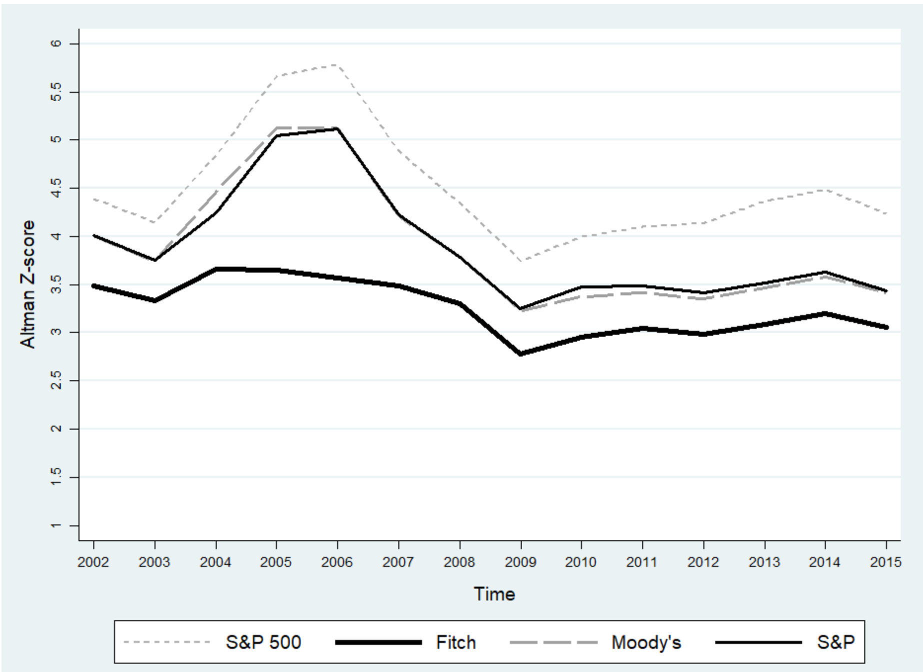
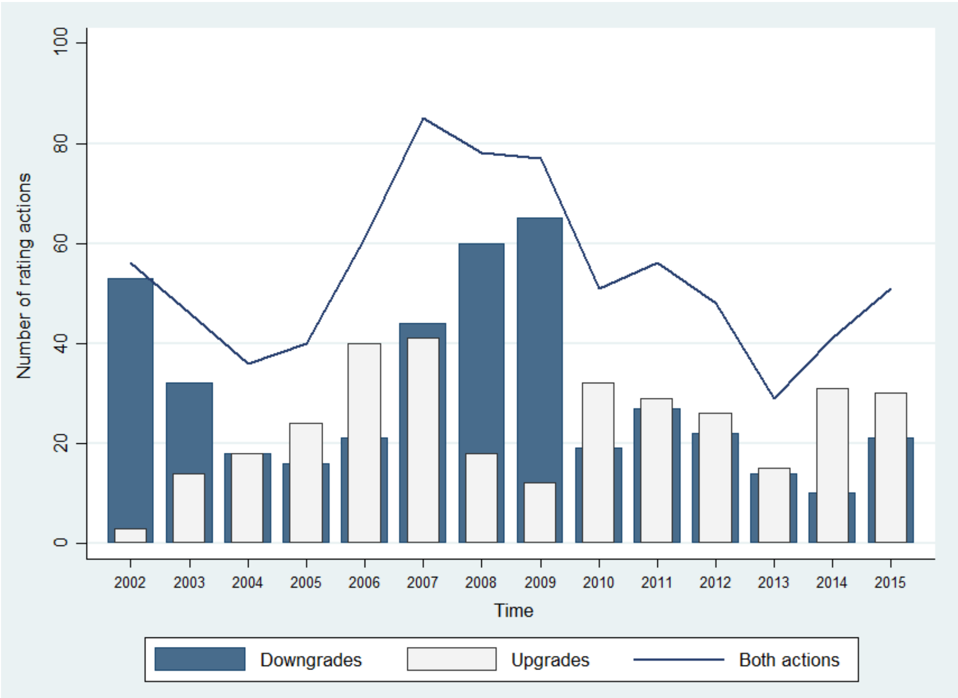


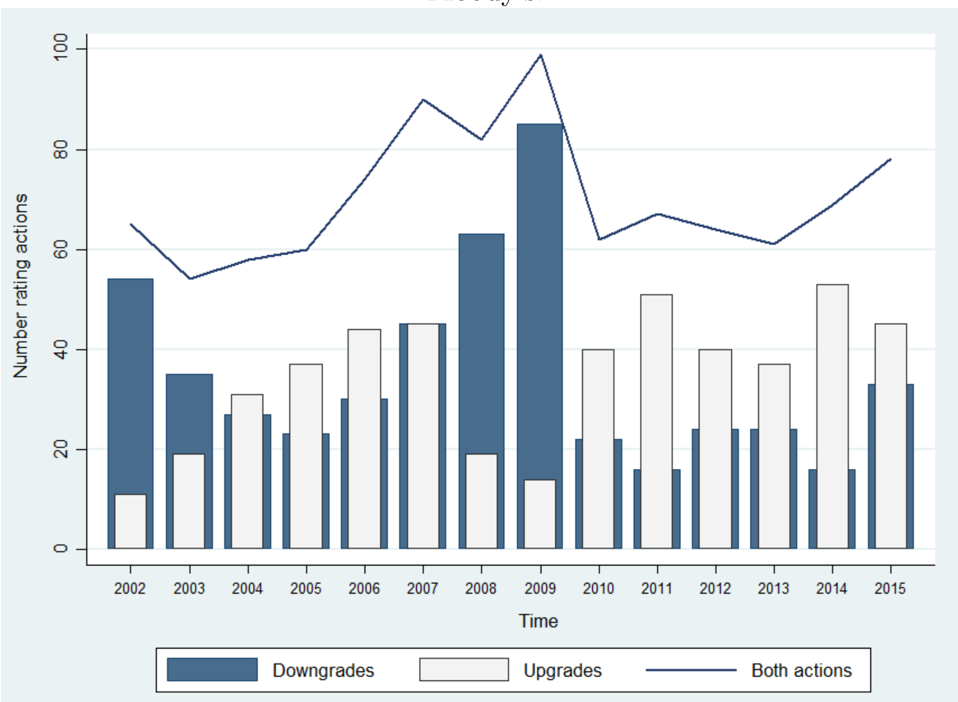
Figure II: Number of downgrades and upgrades over time

The figure shows the overall number of downgrades (dark bars) and upgrades (light gray bars) of the long-term issuer rating of S&P 500 issuers rated by Fitch, Moody's and S&P between 2002 and 2015.

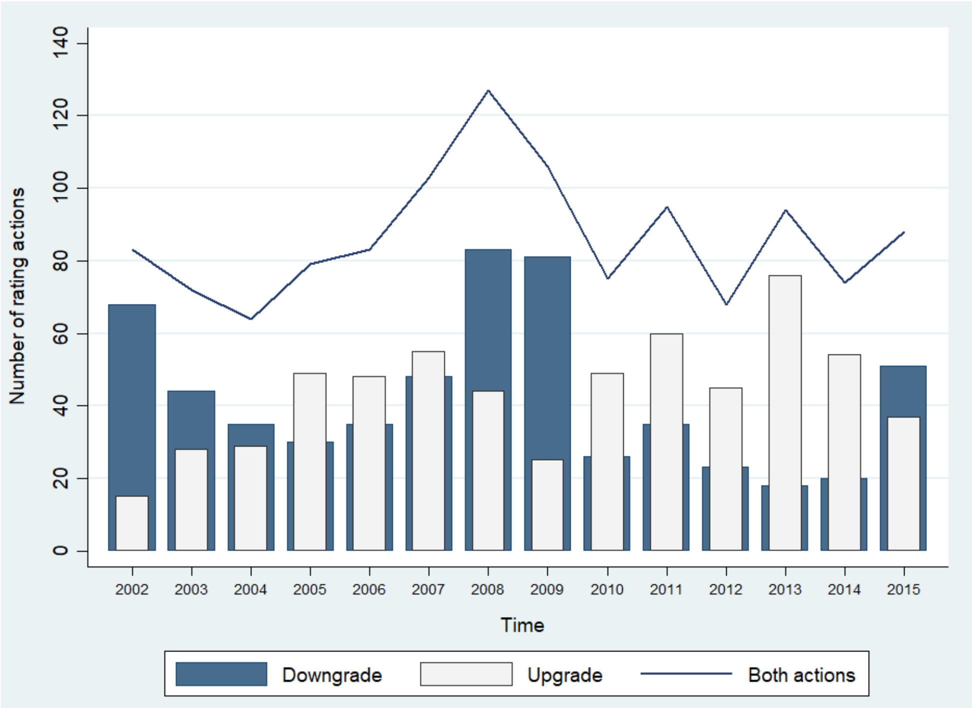
Fitch:



Moody's:



S&P:



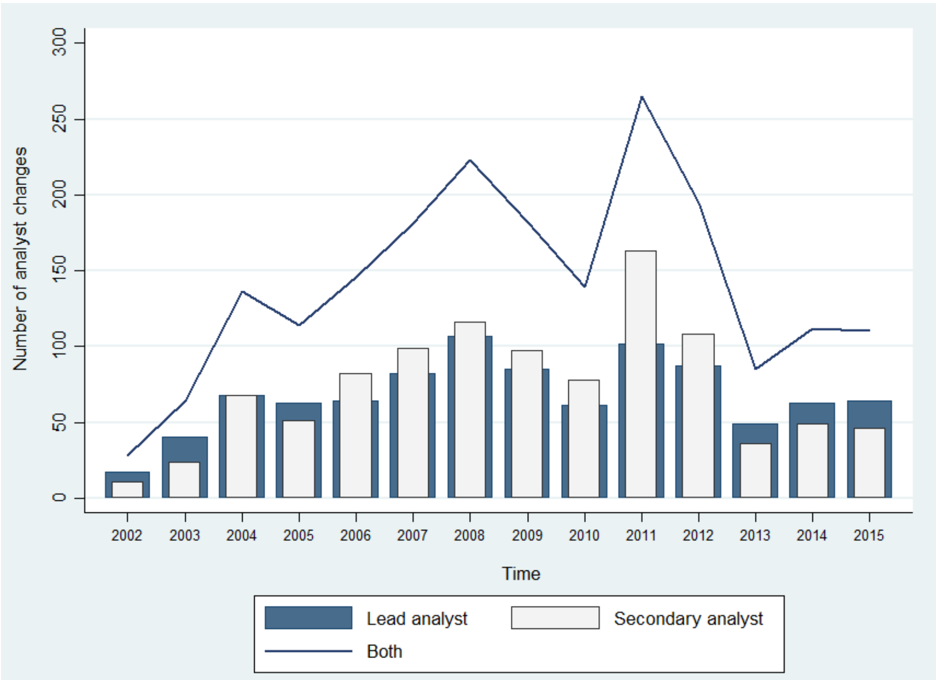
Number of rating actions
0
20
40
60
80
100
120
140
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
Time
Downgrade
Upgrade
Both actions

Figure III: CRA analyst changes over time

The figure shows the total number of credit analyst changes witnessed by S&P 500 issuers rated by Fitch, Moody's and S&P by credit analyst role and per year between 2002 and 2015. Lead analyst changes are visualized as dark bars and secondary analyst changes by light gray bars. The total number of changes is visualized as a dark line.

Fitch:

Moody's:



S&P:

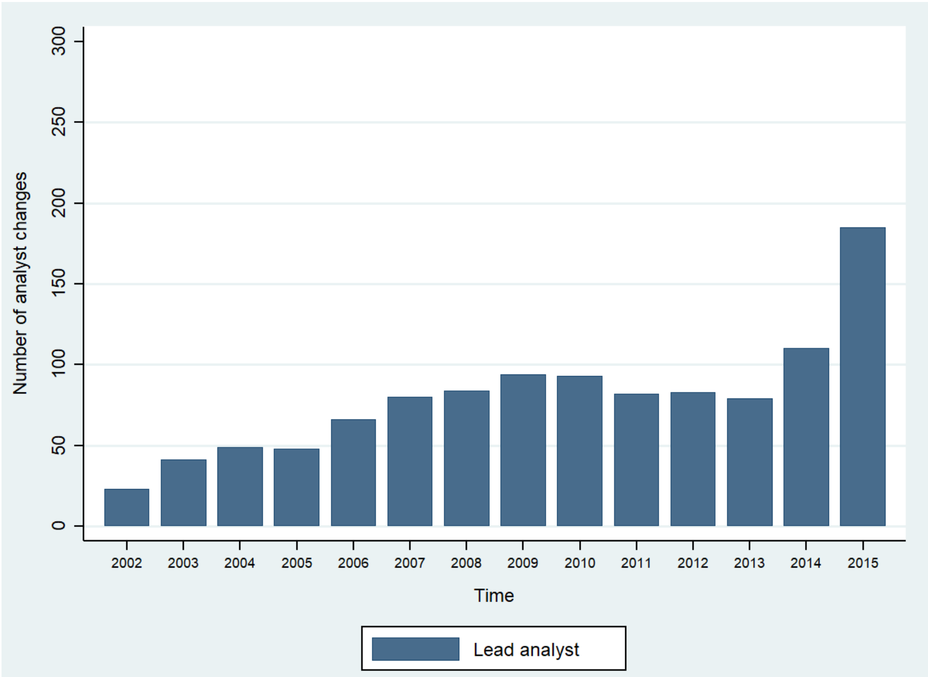

Number of analyst changes
0
50
100
150
200
250
300
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
Time
Lead analyst

Figure IV: Share of rating downgrades and upgrades by quarter

The figure shows the share of rating actions (i.e. rating downgrades and upgrades) by Fitch, Moody's and S&P documented in the quarters shortly before and after a lead analyst change. The share in percent is visualized by dark bars along the quarters in focus shown on the y-axis. Each point on the y-axis summarized two quarters. The average share of downgrades and upgrades by quarter taking all quarters in the sample into account is visualized as a dark solid line.

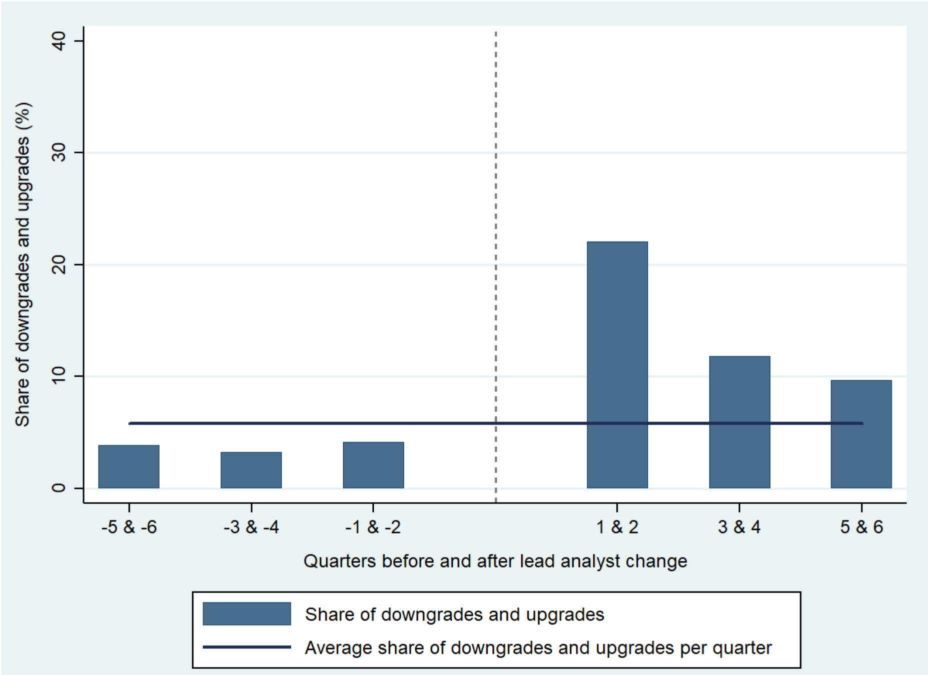


Figure V: Ratio of simultaneous CRA analyst changes at several CRAs over time

The figure shows the ratio of lead analyst changes happening in the same year at Fitch, Moody's and S&P at individual S&P 500 issuers compared to the total number of analyst changes per year between 2002 and 2015. The ratio of simultaneous lead analyst changes is visualized as dark area.