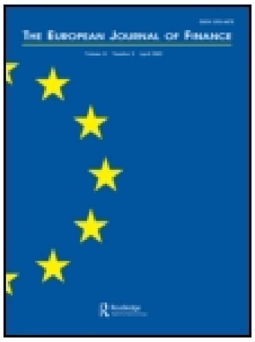

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The path to impairment: do credit-rating agencies anticipate default events of structured finance transactions?

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The global financial crisis (GFC) has led to a general discussion of the accuracy and declining standards of credit-rating agency ratings. Substantial criticism has been directed towards the securitisation market, which has been identified as one of the main sources of the crisis. This study focuses on the ability of rating agencies to adjust their ratings prior to impairments of structured finance transactions. We develop a new measure that quantifies a rating agency's performance in advance of defaults. By analysing a large number of impaired transactions rated by Moody's Investors Service, we find that rating quality deteriorated during the GFC. Furthermore, we identify tranche-specific and macroeconomic factors that explain differences in Moody's performance.

Keywords: anticipation coefficient; credit-rating agencies; rating quality; global financial crisis; structured finance rating

JEL Classification: G01, G14, G24, G28

1. Introduction

The structured finance market has become an increasingly important part of the financial system. Just a few years ago, securitisation was widely regarded as the 'instrument of the future' (Kothari 2006). The ability of structured finance to pool a large number of risky assets and to sell them to investors with various risk preferences led to a tremendous growth in the issuance of structured securities, which are also known as securitisations. Among the beneficiaries of the growing securitisation market were the credit-rating agencies (CRAs). Moody's Investors Service, for example, reported in 2006 that its structured finance earnings accounted for 44% of its revenues. A large proportion of securitisation deals received investment-grade ratings, suggesting a low risk involved in these transactions.

The global financial crisis (GFC), however, led to a general discussion of the accuracy and declining standards of CRA ratings. The Bank for International Settlements (2009) summarises as follows:

> A bank should conduct analyses of the underlying risks when investing in structured products and must not solely rely on the external credit ratings assigned to securitisation exposures by

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> the CRAs. A bank should be aware that external ratings are a useful starting point for credit analysis, but are no substitute for full and proper understanding of the underlying risk, especially where ratings for certain asset classes have a short history or have been shown to be volatile.

One striking feature of the GFC is that a large fraction of highly rated securitisations were impaired. Between 1981 and 2006, only 0.02% of investment-grade structured finance transactions defaulted. In 2008, this figure reached a historical maximum of 1.03%. Given the important role of external ratings, the question as to how well ratings are suited to serve as an indicator for impairment risk is of particular interest for investors and regulators.

The aim of this paper is to answer whether CRAs anticipate impairment events of structured finance transactions. In the context of this work, the term *rating quality* is defined by a CRA's ability to adjust its ratings in a timely manner to increased risk prior to impairment. Our first contribution is the development of the *anticipation coefficient* which quantifies a rating agency's performance in advance of defaults. This is an important contribution as this new metric incorporates the whole adjustment process before impairment. Previous research concentrates on the rating at single points in time such as the time of origination or one year prior to default in order to analyse differences in the forecasting ability of rating agencies. Important parts of the adjustment process are ignored in these contributions.

Using the anticipation coefficient, we empirically analyse ratings by Moody's Investors Service for 13,679 structured finance transactions with impairment between 2001 and 2008. Our analysis is divided into three parts. The first part looks at how credit ratings are adjusted in general. Our study shows that Moody's adjusted its ratings gradually in advance of defaults. In 2008, a significant amount of downgrading took place 180 days prior to impairment. Moreover, the analysis reveals that in the context of the GFC, Moody's carried out systematic changes to its rating models, resulting in an overall downgrading of most securitisations.

The second part addresses the question as to whether the general criticism towards CRAs of having poorly anticipated impairments during the GFC is justified. We observe a decline in Moody's rating quality during the GFC that can be explained by two main factors: first, a poorer anticipation of defaults of securities that initially received investment-grade ratings and, second, a higher proportion of defaults of initially highly rated securities.

The third part analyses the impact of tranche-specific and macroeconomic factors on a rating agency's ability to adjust its ratings in a timely manner. Previous research suggests that CRAs may assign inflated ratings due to issuer shopping (Bolton, Freixas, and Shapiro, forthcoming). Our analysis indicates that this conflict of interest is less severe for transactions with a higher deal volume. Potentially, reputational pressure is higher for these securities. Moreover, we find that Moody's ratings become more valuable over time and that they better reflect increased risk prior to impairments when other CRAs evaluate the same security. Finally, the empirical analysis suggests that rating quality in the securitisation market strongly depends on the state of the US real estate market.

The remainder of this work is organised as follows: Section 2 provides a brief overview of the relevant literature. Section 3 develops a new measure to quantify a rating agency's ability to adjust ratings in advance of impairments. Section 4 analyses how credit rating quality changes over time and which tranche-specific and macroeconomic factors influence the forecasting ability of structured finance ratings. Section 5 summarises the findings and discusses the major ramifications of the empirical results.

2. Literature review

This paper is related to several strands of literature. One part of the research deals with the pricing and the risk parameters of structured finance transactions. Duffie and Gârleanu (2001), Longstaff and Rajan (2008), and Hull and White (2004) focused on explaining the observed market prices of credit default swap indices such as the North American CDX and the European iTraxx. The central point of their research was the specification of dependency structures of portfolio assets. Relevant parameters for the risk of loan portfolios include default probabilities, loss rates given default, and dependency parameters among the portfolio's assets, such as correlations, or more general copulas. Among others, Merton (1974), Longstaff and Schwartz (1995), and Leland and Toft (1996) addressed the probabilities of default. Altman et al. (2005), Acharya, Bharath, and Srinivasan (2007), and Qi and Yang (2009) provided an analysis of the recovery rates of defaulted securities. Li (2000) and Schönbucher and Schubert (2001) focused on the dependency structures of default events. The CRAs estimate these parameters to assess the risk inherent in structured finance transactions.

With regard to the GFC, Coval, Jurek, and Stafford (2009) showed how modest imprecision in these parameter estimates can cause AAA-rated securities to default with reasonable likelihood. Porras (2008) emphasised the impact of underestimated correlation during the GFC. Rösch and Scheule (2010) and Ashcraft, Goldsmith-Pinkham, and Vickery (2010) found that structured finance ratings do not include all factors explaining securitisation impairment risk. Benmelech and Dlugosz (2009) empirically analysed the rating quality of structured debt.

One of the major critiques of the rating industry argues that CRAs have an incentive to assign inflated ratings as they receive their fees from the issuer. Support for this hypothesis was given by Griffin and Tang (forthcoming), who analysed the impact of subjectivity on collateralised debt obligation (CDO) ratings and found that rating agencies divert from their own models by assigning better ratings than a neutral risk assessment would suggest. Bolton, Freixas, and Shapiro (forthcoming) introduced a model based on microeconomic assumptions, suggesting that competition among CRAs increases the problem of issuer shopping. Löffler (2009), on the other hand, analysed Moody's stock price and argued that market discipline may be sufficient to prevent CRAs from assigning inflated ratings. Mathis, McAndrews, and Rochet (2009) examined this reputation argument and showed that its validity depends on the share of income that a CRA generates with the rating of complex products. A comprehensive discussion on the causes of the GFC was given by Crouhy, Jarrow, and Turnbull (2008), who argued that CRAs were at the centre of the crisis as many investors relied on their ratings for complex products. Likewise, a report by the Committee on the Global Financial System (2008) highlights the impact of structured finance ratings on the GFC. Finally, several studies have addressed the adequacy of external ratings in determining financial institutions' capital requirements for securitisations (Calem and LaCour-Little 2004; Rösch and Scheule, forthcoming).

Altman and Rijken (2004) and Amato and Furfine (2004) addressed the aim of CRAs to achieve rating stability (through-the-cycle approach). Löffler (2005) found that rating agencies react slowly to new information. This is explained by assuming that CRAs set different thresholds for each rating migration step. Altman and Kao (1992) detected a positive serial autocorrelation in agency ratings when the initial rating change is a downgrade. A study that analyses the adjustment of credit ratings in advance of defaults was presented by Güttler and Wahrenburg (2007). However, in contrast to our study, they examined corporate bond rather than structured finance ratings and their main focus was on how rating agencies react to rating transitions by other rating agencies. Violi (2008) analysed rating transitions of corporate and structured ratings and found significant differences in the rating mobility across structured finance products.

3. Rating quality framework and hypothesis development

3.1 *Rating quality framework*

One of the research objectives of this study is to provide insights into the adjustment process of ratings prior to impairment. This section develops a new measure that allows assessing the quality of ratings in advance of a default. In order to analyse the work of CRAs not only qualitatively but also quantitatively, it is essential to assign numerical values to ratings. Although rating agencies claim that their ratings are ordinal measures of risk, it is common practice among academics and regulatory authorities to transform ratings into a cardinal scale (Cantor and Packer 1997; Jorion, Liu, and Shi 2005). In the following, we use a mapping scale that converts Moody's rating classes into 21 integers, starting with Aaa = 1 to C = 21. A higher value consequently means that the rating agency considers a security to be more risky.

Moreover, our rating quality framework draws on the event study methodology. Fama et al. (1969) first introduced this methodology in the context of market efficiency tests. Traditionally, event studies focus on the impact of an event on the price of a firm (MacKinlay 1997). The main idea of an event study is to define a central event as day 0 and then analyse what happened before and after this day (Binder 1998). In this study, we use the impairment as our central event. According to Moody's Investors Service, an impairment event is defined by a shortfall in interest or principal payments or by a downgrade to Ca/C (Moody's Investors Service 2009). Referring to variables in event time (e.g. 20 days before impairment) allows us to compare ratings of securities with different impairment dates.

Existing research focuses on ratings at origination or at the beginning of a year to address the question as to how well ratings reflect default risk. Unfortunately, such an approach ignores important parts of the adjustment process. To illustrate this problem, Figure 1 shows the ratings of two sample securities over time relative to their impairment date.

Both securities have the same rating one year prior to default (A1 = 5). While the rating of the security on the left is gradually adjusted over time, the rating of the other security stays constant until the occurrence of impairment. Solely focusing on the rating one year prior to impairment (or similar measures, such as rating at origination or at the beginning of a year) would lead to

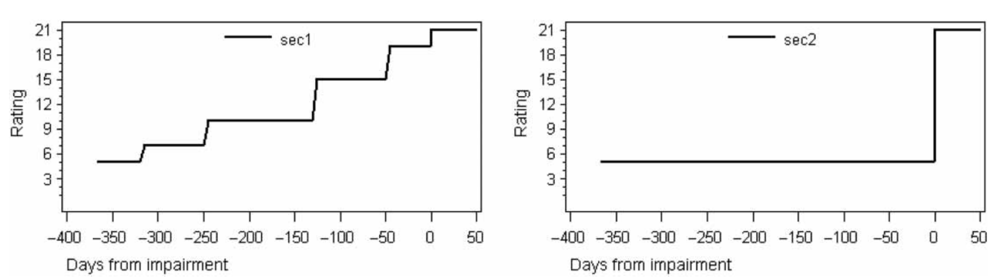

Figure 1. Adjustment processes of two sample securities.
Notes: Both transactions receive the same rating (A1 = 5) one year prior to impairment. However, the adjustment process is completely different, illustrating that solely focusing on the rating one year prior to impairment is not sufficient.

the false conclusion that the rating agency performed equally well in both cases. Obviously, the ratings for the first security are of much greater value.

To take such differences into account, we introduce a new coefficient that measures how well the CRAs anticipate the impairment of the respective (later impaired) tranche. Similar to a Gini coefficient, this 'anticipation coefficient' is defined as the ratio of two areas. Plotting the rating level over time, one can derive this coefficient by dividing the area under the rating curve (Area I) by the area under an optimal[1] rating curve (Area I + Area II) (Figure 2). The optimal rating curve is realised when the CRA assigns the lowest possible rating already one year prior to impairment. For Moody's rating classes, the lowest possible rating is Caa3 = 19 since ratings of Ca = 20 or C = 21 would have already triggered the impairment (compare with Moody's definition of impairment).

Mathematically, the anticipation coefficient (ac_i) is defined as

$$\mathrm{ac}_i = \frac{\sum_{t=-365}^{-1} (R_{i,t} - 1)}{365 \cdot (19 - 1)} = \frac{1}{6570} \cdot \sum_{t=-365}^{-1} (R_{i,t} - 1), \qquad (1)$$

where ac_i is the anticipation coefficient of security i and $R_{i,t}$ is the rating of security i at time t relative to impairment. Subtracting one from the ratings ensures that the anticipation coefficient is within an interval between zero and one ($\mathrm{ac}_i \in [0; 1]$). To understand the intuition behind this coefficient, it may be helpful to take a look at two extreme examples, an early and a late anticipation of impairment. In the former case, the rating agency anticipates the impairment one year in advance and consequently assigns the lowest rating (Caa3 = 19) for the entire observation period. This results in an anticipation coefficient of one. In the latter case, the rating agency does not anticipate the impairment prior to the event and assigns a very good rating (i.e. Aaa = 1) to the specific tranche until the occurrence of the event. Such a performance results in a very low anticipation coefficient (ac = 0) since the area under the rating curve is very small. In other words, the anticipation coefficient reflects early CRA downgrades.

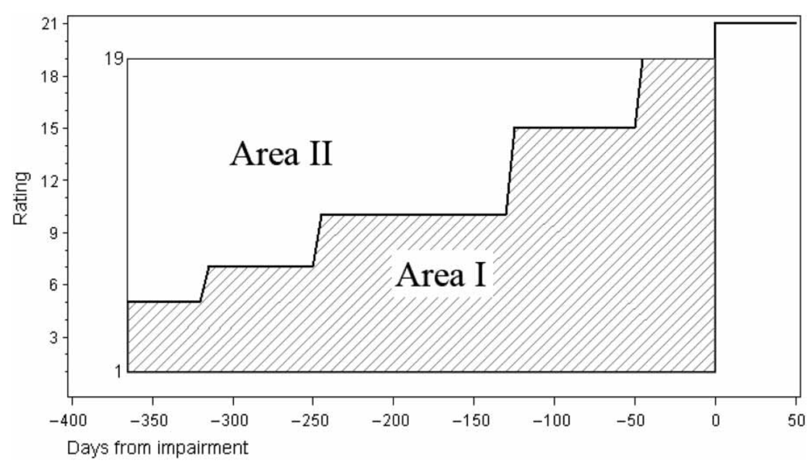

Figure 2. Graphical illustration of the anticipation coefficient.
Notes: To analyse the rating quality, we introduced an anticipation coefficient that can be calculated by dividing Area I by the combined area of Area I and Area II which reflects the best anticipation possible since a CRA would assign the lowest rating (Caa3 = 19) to a security for which it would expect an impairment already one year in advance.

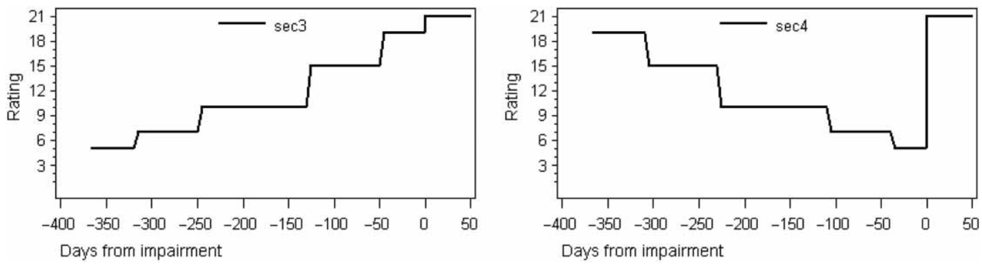

Figure 3. Adjustment processes of two sample securities with equal anticipation coefficients.
Notes: Both transactions result in the same anticipation coefficient since the areas under the rating curves are equal. Nevertheless, the performance of the rating agency is significantly better for the security on the left since the ratings of the second security falsely suggest a decreasing risk of default.

Some problems with the anticipation coefficient may relate to the equal weighting of time and may be relevant when rating agencies upgrade securities prior to impairments. Figure 3 shows two securities with identical anticipation coefficients but completely different rating histories.

The areas below both rating curves are equal and therefore both anticipation coefficients are equal. Without doubt, the ratings of the first security reflect the increased risk prior to impairment better than the ratings of the second security. One possible solution to this problem would be to attach a higher weight to ratings close to impairment. Equation (2) shows how the coefficient could be modified by adding linearly increasing weights:

$$\mathrm{ac}_i = \frac{\sum_{t=-365}^{-1} w_t (R_{i,t} - 1)}{\sum_{t=-365}^{-1} w_t (19 - 1)} \quad \text{with } w_t = \alpha + \beta \cdot t. \tag{2}$$

The parameters α and β determine how much more weight is attached to ratings close to impairment. In the following, however, we use the unweighted approach ($\alpha = 1$ and $\beta = 0$) since the data set we examine in our study does not include any rating upgrades.

3.2 *Hypothesis development*

The following hypotheses aim to answer how the rating quality for structured finance securities changes over time and which factors explain its differences. Based on changes in Moody's anticipation coefficient as a measure for rating quality, the hypotheses are as follows:[2]

- *H*1: Rating quality deteriorated during the GFC.
- *H*2*a*: Rating quality depends on the deal volume of a transaction.
- *H*2*b*: Time since origination has an influence on rating quality.
- *H*2*c*: CRAs perform better when facing competition from other rating agencies.
- *H*2*d*: The impairment type and default amount have an impact on rating quality.
- *H*3: Differences in rating quality can be explained with macroeconomic factors.

H1 is directed towards the general criticism against rating agencies in the financial crisis, H2a–d relate to the influence on the rating quality of tranche-specific factors, and H3 relates to the impact of macroeconomic factors.

H1 addresses the role of credit ratings during the GFC. A substantial amount of criticism has been directed towards CRAs, accusing them of having poorly anticipated the increase in the impairment rate. Coval, Jurek, and Stafford (2009), for example, argued that CRAs have assigned high ratings to very risky assets in the crisis. The hypothesis, therefore, aims to analyse whether empirical data confirm this criticism and show that CRAs performed poorly during the GFC.

H2a addresses a potential conflict of interest of rating agencies. Crouhy, Jarrow, and Turnbull (2008) argued that CRA fees are paid by issuers and that this mismatch could serve as an incentive for rating agencies to assign more issuer-friendly ratings than an independent risk assessment would suggest. Given that rating agencies typically receive a certain proportion of the deal volume, the deal balance may have an influence on overall rating quality. A small deal volume implies low fee revenues and thereby reduces the incentive to distort the rating. In contrast, higher deal volumes are related to higher fee revenues and, possibly, also to a higher willingness to assign issuer-friendly ratings. Conversely, higher fees can also lead to more accurate ratings for two reasons. First, assigning biased ratings to transactions with higher deal volumes can severely damage a rating agency's reputation. Second, higher fee revenues allow CRAs to allocate larger resources (e.g. more financial analysts) to these transactions. As a result, ratings for larger deals may better reflect increased risk in advance of impairments.

H2b addresses the impact of the time since origination on rating quality. The CRAs may be able to accumulate deal-specific knowledge that helps in identifying potential risks in a timelier manner. Furthermore, the risk assessment may become less biased the longer a security has been rated. Rösch and Scheule (2010) showed that an origination rating generates approximately 5.7 times more fee revenues for CRAs than monitoring a rating for one year does. Consequently, credit ratings may be more distorted close to origination.

H2c addresses the degree to which competition with other rating agencies increases overall rating quality. Facing competition from other CRAs can serve as an incentive to perform better to increase the market share. The better a rating agency anticipates impairment, the higher the value of the ratings for investors is. Issuers of securities are interested in having their products rated by a reputable CRA. Another advantage that comes with competition is an increased amount of available information. Rating changes made by other CRAs can, for example, alert a CRA to revise its own assessment of a security (Güttler and Wahrenburg 2007).

H2d analyses the impact of the impairment type and the impairment severity on rating quality. Over 97% of observed impairments are principal impairments, defined as shortfalls in principal payments. The rating agencies aware of this issue may be more careful with their assessments prior to principal payments than in advance of interest payments. Thus, the type of impairment can have an influence on rating quality. Another factor that we analyse in this context is the impact of the severity of impairments. Severe shortfalls in interest payments or principal payments may be easier to anticipate than just minor shortfalls.

H3 identifies the degree to which macroeconomic factors help in explaining differences in the rating quality. Based on the nature of structured finance transactions, one would expect close links to risk parameters of the underlying assets. Identifying such factors not only would be helpful in explaining past differences, but could also contribute to a better understanding as to how reliable future ratings are.

4. Empirical analysis

4.1 *The data set*

This paper analyses a data set provided by Moody's Investors Service covering all Moody's-rated securitisations until 2008. The data contain characteristics of transactions, characteristics of tranches, and ratings of tranches over time, as well as realisations of impairment events. Unfortunately, rating data from other CRAs are not available for this study. However, we hand-collected ratings by Standard & Poor's (S&P) and Fitch for 1000 randomly selected transactions and found very high Spearman correlation coefficients (93.4% between Moody's and S&P, 95.8% between Moody's and Fitch, and 98.5% between S&P and Fitch). Moreover, most of the rating differences are related to a deviation of a single notch. These findings suggest that our results based on Moody's data can be generalised to other major CRAs.

As outlined in the previous section, we first translated Moody's rating classes into 21 numerical values (Aaa = 1, Aa1 = 2, …, C = 21). In addition to the ratings, watchlist entries are available. A watchlist entry indicates that a rating change in the near future is highly probable but that the rating agency has not finished the formal rating review process yet. A rating may be put on review for possible upgrade, downgrade, or change with uncertain direction. Previous studies suggest that the inclusion of the watchlist status significantly improves the accuracy of default predictions (Hamilton and Cantor 2004). Sy (2004) and Güttler and Wahrenburg (2007) made use of the watchlist information by adding (subtracting) a constant to the numerical rating for a negative (positive) watchlist entry. The magnitude of this adjustment factor is, however, subject to discussion. Assuming that a watchlist entry is a weaker statement than an actual rating change suggests that the factor should be less than one. Bannier and Hirsch (2010), however, showed that securities with a negative watchlist entry are, on average, downgraded by 1.65 notches. Given that approximately 65% of the securities placed on review for downgrade are subsequently downgraded, we believe that the adjustment factor should lie somewhere between 0.5 and 1.5. In our study, we used a conservative value of 0.8, which is similar to the adjustment factors used in previous studies.[3]

The second step is inspired by the event study methodology. Following this methodology and defining the day of impairment as the central event allowed us to analyse securitisations over time, independent of their impairment date. In the next step, we extracted for all impaired tranches the daily ratings from 365 days before until 365 days after the impairment. We thereby created a data set with information on ratings from one year before until one year after the impairment.

Finally, deal- and tranche-specific information was combined and merged with the rating file. In addition to the impairment date and the daily ratings before and after the impairment, the final data set includes the following information:

- deal category: asset-backed security (ABS), CDO, residential mortgage-backed security (RMBS), home equity loan (HEL), or commercial mortgage-backed security (CMBS);
- deal balance and tranche balance;
- closing date and date of maturity;
- impairment type (two types exist: shortfalls in principal payments, defined as principal impairments, and shortfalls in interest payments, defined as interest impairments);
- default amount.

Structured finance transactions are very heterogeneous by definition. Various filter rules are aimed at generating a homogeneous data set. The following observations were deleted:

- Transaction observations that cannot be placed into the categories ABS, CDO, RMBS, HEL, and CMBS. These are mainly asset-backed commercial paper, structured covered bonds, catastrophe bonds, and derivative product companies.

- Transaction observations with an impairment date before 2001 due to a limited number of impairment events. Those of the years after 2008 were unavailable at the time of writing this paper.
- Transaction observations not denominated in US dollars and those that did not originate in the USA.
- Transaction observations that had missing ratings for one or more days of the observation period.

The resulting data set comprises 13,679 impaired tranche observations. Table 1 shows the total number of observed impairments over time and the frequency of deal characteristics, as well as the relative impairment rate. The number of observed impairments fluctuated between 90 and 252 for the period 2001–2006. Most observations had impairments in 2007 (1254) and 2008 (11,454), illustrating the severity of the financial turmoil in the securitisation market. Likewise, the impairment rate rose sharply in 2007 and 2008, with RMBSs and HELs especially experiencing a large increase in impairments.

4.2 *Average ratings prior to impairment*

The first question we address is how ratings generally adjust prior to impairments. Do CRA ratings reflect increased default risk prior to the impairment event itself? To shed some light on the adjustment process, we first calculated the means of Moody's ratings at different times in advance of impairments. The results are presented in Table 2.

As expected, ratings were adjusted for the increased risk close to an impairment event. In all the years, we observed a similar upward trend over time, which illustrates that, on average, Moody's has downgraded tranches before impairments. However, differences become evident by separately focusing on three parts of the adjustment process: (i) the rating level at the beginning of the observation period (i.e. 365 days prior to impairment), (ii) the rating adjustment on the impairment day, and (iii) the speed of adjustment in advance of the impairment event.

On focusing on the initial rating level one year prior to impairment, significant differences over time are apparent. In 2006, for example, the average rating was 15.58 (corresponding to a rating between B2 and B3), whereas in 2008 the average rating was 7.65 (corresponding to an investment-grade rating of Baa1). This finding is consistent with the observation that during the GFC, a high number of tranches with investment-grade ratings experienced impairments. A higher proportion of defaults of initially A-rated (Aaa–A3) securities causes the average rating to start at a lower level.

Another striking feature is that the average rating on the impairment day changes over time. In 2001, securities had an average B1 rating (14.27) on day 0. This may seem puzzling at first sight since Moody's defines an impairment event by a shortfall in interest or principal payments or by a downgrade to Ca/C. According to this definition, one would, therefore, expect an average rating that is close to 20 on the impairment day. However, by more closely analysing the adjustment process of randomly selected tranches, we found that, especially in the first few years of the observation period, Moody's did not adjust all ratings immediately on the impairment day. In many cases, the downgrading or the complete withdrawal of ratings did not happen until several weeks after the actual impairment.

Furthermore, we observed differences in the adjustment process. While ratings were adjusted gradually over time in most years, in 2008, significant downgrading took place approximately 180 days prior to impairment (see the upper curve in Figure 4). A reasonable explanation for this

Table 1. Distribution of impairments over time and impairment type.

	Distribution of impairments								
	2001	2002	2003	2004	2005	2006	2007	2008	Total
ABS	29	107	96	137	18	32	27	31	477
CDO	52	111	47	49	23	17	209	2073	2581
RMBS	4	3	3	7	8	6	97	2942	307
HEL	13	14	30	13	21	25	912	6313	7341
CMBS	5	17	23	19	20	22	9	95	210
Total	103	252	199	225	90	102	1254	11,454	13,679
Impairment rate	(0.63%)	(1.34%)	(0.93%)	(0.99%)	(0.32%)	(0.25%)	(2.17%)	(17.26%)	(5.01%)
No. of rated tranches	16,309	18,814	21,416	22,728	28,302	41,247	57,661	66,374	272.851

	Rating one year prior to default							
	2001	2002	2003	2004	2005	2006	2007	2008
Aaa–A3	8 (0.06%)	25 (0.16%)	16 (0.09%)	70 (0.40%)	3 (0.01%)	0 (0.00%)	163 (0.37%)	5388 (10.68%)
Baa1–B3	91 (3.76%)	221 (6.94%)	170 (4.13%)	126 (2.55%)	71 (1.10%)	54 (0.59%)	1,057 (8.20%)	5969 (39.56%)
Caa1–C	4 (12.50%)	6 (26.10%)	13 (23.14%)	29 (28.97%)	16 (13.06%)	48 (17.29%)	34 (16.74%)	97 (77.82%)
Total	103	252	199	225	90	102	1254	11,454
Impairment rate	(0.63%)	(1.34%)	(0.93%)	(0.99%)	(0.32%)	(0.25%)	(2.17%)	(17.26%)
No. of rated tranches	16,309	18,814	21,416	22,728	28,302	41,247	57,661	66,374

Notes: The distribution of impairments in the final data set is given. In the upper part of the table, the distribution of impairments over time and by asset category of the underlying portfolio is given. In the lower part of the table, the rating of impaired securities one year prior to default is given. Especially in 2007 and 2008, a high proportion of transactions with impairment had an initial A rating (Aaa–A3) one year before default. The figures within brackets show relative impairment rates that can be interpreted as an empirical probability of default.

Table 2. Average ratings at different times surrounding the impairment event.

Days relative to impairment	2001	2002	2003	2004	2005	2006	2007	2008
−365	11.99	11.30	11.50	10.30	12.71	15.58	10.10	7.65
−300	12.06	11.45	11.93	10.50	13.18	15.73	10.17	8.04
−240	12.21	11.66	12.18	11.38	13.51	15.95	10.27	8.36
−180	12.23	12.02	12.37	11.91	14.58	16.12	10.39	11.40
−120	12.60	12.61	12.99	12.49	15.30	16.53	10.70	13.26
−90	12.84	12.91	13.22	12.67	15.78	16.67	12.36	13.73
−60	12.98	13.18	13.39	12.85	16.13	16.87	12.80	14.45
−30	13.28	13.88	13.69	12.91	16.39	17.05	13.10	14.69
−5	13.39	14.88	13.79	13.09	16.55	17.14	13.29	14.82
0	14.27	16.39	16.92	18.38	18.23	18.84	18.93	19.76
30	14.27	16.39	16.94	18.38	18.24	18.84	18.93	19.77
90	14.98	17.40	17.28	18.90	18.79	19.05	19.37	20.11

Notes: A heterogeneous adjustment process is given. Differences in the rating level one year prior to impairment as well as differences in adjustment levels can be observed, while ratings decline in all the years over time.

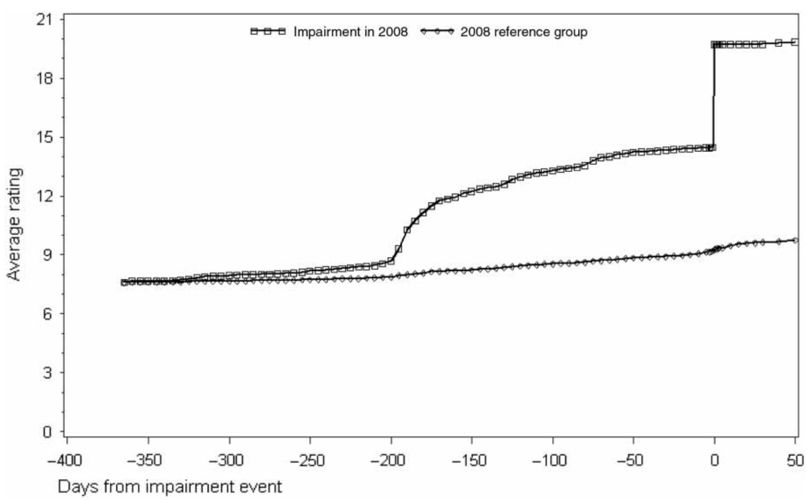

Figure 4. Average ratings of impaired and non-impaired tranches in 2008.
Notes: In contrast to other years, in 2008, securities without impairment were also downgraded.

feature is that in the context of the GFC, rating agencies carried out some systematic adjustments. The sudden increase in the impairment rate, especially for mortgage-backed securities (MBSs), may have raised questions regarding some assumptions (e.g. an underestimation of the correlation between the default risks of MBSs) in the models that CRAs employed. If this is the case, one would expect that not only defaulting tranches but also securities that never experienced impairments would have been downgraded in 2008. To test whether this is the case, we extended the data set by including securities that did not experience any shortfalls in interest or principal payments. Obviously, it is impossible to extract daily ratings relative to an impairment event given that such

Table 3. Average ratings in 2008.

2008	January	February	March	April	May	June	July	August	September	October	November	December
Average rating	11.82	11.71	11.8	**11.99**	12.84	**12.98**	13.62	13.79	13.9	**14.08**	15.02	15.35
Change (%)	−0.93	0.77	1.61	**7.09**	1.09	**4.93**	1.25	0.80	1.29	**6.68**	2.20	0.13

Notes: The average ratings for tranches without impairment in 2008 are given. Significant downgrading took place in April (7.09%), June (4.93%), and October (6.68%).

an event does not exist. We solved this problem by randomly selecting five securities without impairment for every tranche that defaulted. The impaired tranche thereby serves as a reference tranche for the five other securities, which allowed us to use the impairment date of the reference tranche as an imaginary impairment date for the sample securities. Several filters ensure that the securities in the new data set are of the same type (i.e. ABS, CDO, RMBS, HEL, and CMBS) and have the same rating 365 days prior to impairment as their respective reference tranches. The new data set was then used to analyse how ratings changed for products without impairment. Figure 4 shows the adjustment process for impaired tranches in 2008, as well as the rating curves for a group of sample securities without impairment. In contrast to those of the previous years, the rating curve of the 2008 reference group features an upward slope that reveals that not only transactions with impairment but also transactions without impairment were downgraded in that year.

The high density of downgrades over time indicates that rating agencies also revised their models. The analysis of the rating changes in calendar time reveals that a high proportion of downgrades in 2008 took place in April, June, and October (compare Table 3). This finding supports the hypothesis that a revision in the rating models also contributed to the downgrading trend in 2008.

4.3 *Rating quality over time*

4.3.1 H1: Rating quality deteriorates during the GFC

To test the hypothesis of whether rating quality was significantly worse during the GFC, we analysed changes in the anticipation coefficient, introduced in the previous section, over time. The results are shown in Figure 5.

Figure 5 reveals that overall rating quality changed over time. From 2001 to mid-2004, the anticipation coefficient fluctuated between 0.5 and 0.7. In the next two years, the graph followed an upward trend, which indicates that Moody's performed better in that period. However, in 2007, forecasting power fell significantly, reaching a minimum in the beginning of 2008. This finding supports the hypothesis that ratings for securitisations were less predictive during the GFC. It is important to note that the low anticipation coefficients in 2007 and 2008 do not necessarily imply a critique of CRAs. The poor anticipation of impairments may have also been caused by the more turbulent economic environment which made it difficult to predict defaults.

Another aim associated with H1 is to find out what kinds of securities contributed to the observed decline in rating quality. To do so, we analysed which groups of transactions were most affected. The observed impairments can be divided into two groups: transactions with an investment-grade rating (Aaa–Baa3) 365 days before impairment and transactions with a speculative-grade rating (Ba1–C) 365 days before impairment. While the average anticipation coefficients of both groups followed the same overall trend, results are more pronounced for securities that initially received

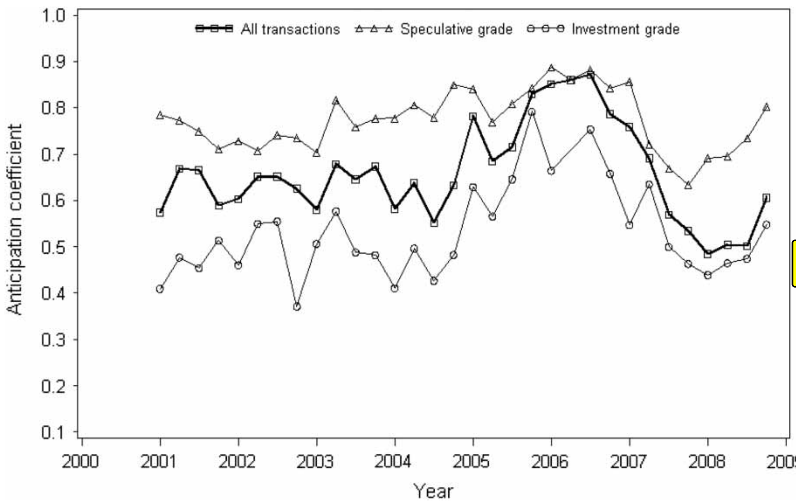

Figure 5. Average anticipation coefficient over time.
Notes: The bold line represents the average anticipation coefficient of all impaired securities. Moreover, the graph shows the changes in the anticipation coefficient separately for securities based on their rating one year prior to default.

an investment-grade rating (Figure 5). Another factor that contributes to the differences in overall rating quality is the composition of impairments. Table 1 (rating one year prior to default) shows that during the GFC, the proportion of highly rated transactions (Aaa–Aa3) with impairment increased. As a result, the overall anticipation coefficient also reflects the changed composition of the impairments.

In summary, the decline in rating quality during the GFC can be explained by two main factors: first, the poorer anticipation of defaults of senior securities and, second, the higher proportion of defaults of initially highly rated securities.

4.4 *Influence of tranche-specific factors on rating quality*

Structured finance transactions are very heterogeneous by definition. Apart from the deal type (ABS, CDO, MBS, etc.), securities vary in many other aspects, such as the deal volume, the subordination level, and the impairment type. H2a–d address the influence of such tranche-specific factors on rating quality. To test the impact of these factors, we used a regression model of the form

$$\phi^{-1}(\mathrm{ac}_i) = \beta' * x_i + \varepsilon_i \tag{3}$$

where Φ^{-1} is the inverse of the normal cumulative distribution function (CDF), x_i is a vector of observable and thus known variables, ac_i is the unweighted anticipation coefficient as described in Section 3, β' is the vector of sensitivities, and ε_i is a normally distributed random error with expectation zero. Transforming the anticipation coefficient with the inverse of the normal CDF accounts for the fact the coefficient is always within an interval between zero and one.

The vector x_i includes the following variables: $x_1 - x_5$ are dummy variables (0 or 1) for the various asset types (ABS, CDO, RMBS, HEL, and CMBS); x_6 is the log of the deal volume in US dollars; x_7 is the years since origination; x_8 is the years to maturity; x_9 is a dummy variable that equals one if at least three CRAs rated this transaction and zero otherwise;[4] x_{10} is a dummy variable that equals one if principal is impaired and zero if interest is impaired; and x_{11} is the log of the default amount in US dollars.

The regression coefficients and significance levels (using heteroskedasticity-robust standard errors) are presented in Table 4. In years with a higher number of impairments, results tend to be statistically more significant as a greater sample size implies lower standard errors.

4.4.1 H2a: Rating quality depends on the deal volume of a transaction

The sensitivity of the anticipation coefficient towards the deal balance is positive in all the years. Consequently, all other things being equal, the ratings of transactions with a higher deal volume reflect increased risk prior to impairment better than ratings for securities with a small volume. The coefficients are statistically significant for the years 2001, 2003, 2004, 2006, 2007, and 2008. The data, therefore, support the assumption that a higher deal volume increases rating quality. One interpretation may be that the risk of severely damaging its reputation seems to outweigh the possible short-term gains a rating agency can achieve by assigning issuer-friendly ratings. Another factor that may contribute to the better anticipation of impairments of high-volume deals is that for such deals typically more information is available. For example, Hung, Lee, and Pai (2009) showed that markets for small-cap stocks are less efficient than those for high-cap stocks. This pattern may also be valid for structured finance securities.

4.4.2 H2b: The time since origination has an influence on rating quality

The variable 'years since closing' is positively correlated with the anticipation coefficient in all the eight observation periods. Thus, Moody's seems to improve its ratings the longer a security exists. A possible explanation for this positive impact on the forecasting quality could be a learning effect. The rating agencies accumulate information about the transactions they rate. Such information on past performance can be helpful in identifying deal-specific risk factors. In addition, the conflict of interest that rating agencies face is weaker in the years after origination. For new ratings, CRAs may tend to assign more issuer-friendly ratings to increase their revenues. Issuers have an incentive to get their securities rated by a CRA that offers high ratings since such ratings facilitate capital access. Bolton, Freixas, and Shapiro (forthcoming), for example, argued that competition between CRAs leads to better initial ratings. Although rating agencies also receive fees for the monitoring of ratings, these fees are considerably lower than those charged for origination ratings (Rösch and Scheule 2010).

4.4.3 H2c: Rating agencies perform better when facing competition from other CRAs

Various authors, including Bolton, Freixas, and Shapiro (forthcoming) and Fons (2008), argued that more competition increases the conflict of interest and thereby exacerbates the problem of issuer shopping. On the other side, Hörner (2002) provided an alternative prediction about the effect of increased competition and argued that greater competition enhances reputational risk and thereby improves the quality of ratings. The latter argument is often used in policy arguments (Becker and Milbourn 2011). Our regression model adds the dummy variable 'number of ratings' to examine the effect of increased competition on rating quality. The variable is zero if a certain transaction is only rated by one or two major CRAs and one if the transaction has three or four ratings. The statistically significant sensitivities in 2002 and 2004 are positive, indicating that Moody's performance was better when facing competition from other CRAs.

However, it is important to distinguish between two different types of competition: an *a priori* competition and an *a posteriori* competition. *A priori* competition relates to the competition

Table 4. Regression results of tranche-specific determinants of the anticipation coefficient.

Variable	2001	2002	2003	2004	2005	2006	2007	2008	All
ABS	0.052	1.265	−0.986	−0.208	1.453	−1.064	0.041	0.022	−0.017
CDO	0.53	1.555	−0.817	0.263	0.919	−1.45	−0.670**	−0.698***	−0.034**
RMBS	−0.549	0.601	−0.892	−0.293	0.736	−1.725*	−0.610*	−0.623***	−0.034**
HEL	0.105	1.287	−1.113	−0.183	0.982	−1.720*	−0.38	−0.184	0.04
CMBS	0.553	1.539	−0.517	0.631	1.478	−1.398	−0.284	−0.092	0.334**
Deal balance	0.213**	0.033	0.077*	0.142*	0.06	0.150**	0.153***	0.167***	0.146***
Years since closing	0.169***	0.116***	0.091***	0.115***	0.090***	0.155***	0.149***	0.062***	0.086***
Years to maturity	0.001	0.002	−0.019***	−0.025	0.001	0.010*	−0.005*	−0.003**	−0.011***
Number of ratings	−0.02	0.227**	−0.059	0.201*	0.019	0.129	−0.002	0.012	0.008
Principal impairment	0.583*	0.165	0.561***	−0.165	−0.07	−0.238	−0.11	0.015	0.125***
Default amount	−0.319***	−0.143***	−0.041	−0.140**	−0.123**	−0.085*	−0.176***	−0.183***	−0.167***
F-statistic	12.6***	14.7***	20.1***	11.4***	32.7***	63.5***	114.7***	607.3***	687.9***
Adjusted R^2	0.579	0.408	0.531	0.352	0.802	0.895	0.507	0.375	0.367
Observations	103	252	199	225	90	102	1254	11,454	13,679

Notes: The results of the regression model using robust standard errors are given. The dependent variable is the unweighted anticipation coefficient discussed in Section 3. Independent variables are dummies for the different transaction types (ABS, CDO, RMBS, HEL, and CMBS) that take on the value of 1 if the security belongs to the respective group and the value of zero otherwise. The deal balance and the default amount are given in their logarithmic forms. Years since closing is the time since origination and years to maturity is the time to legal maturity. Number of ratings is another dummy variable that takes on the value of 1 if at least three major CRAs rated the tranche and the value of zero otherwise. The variable principal impairment is one if the impairment is due to a shortfall in principal payments.

*Two-sided significance levels representing 10%.

**Two-sided significance levels representing 5%.

***Two-sided significance levels representing 1%.

between CRAs before an issuer has selected a rating agency by which the transaction shall be rated. *A posteriori* competition refers to the competition between CRAs that rate the same transactions. The problem of issuer shopping is more relevant for *a priori* competition since rating agencies have an incentive to outbid each other to get the rating job. By contrast, our regression analysis focuses on *a posteriori* competition, that is, on the influence on rating quality of a higher number of CRAs that rate the same transaction.

4.4.4 H2d: The impairment type and default amount have an influence on rating quality

To analyse the influence of the impairment type on rating quality, we added the dummy variable 'principal impairment' to our regression model. The variable takes the value of one for principal impairments and zero for interest impairments. Table 4 shows that the sensitivity of this variable is positive overall. Therefore, transactions with principal impairments generally have higher anticipation coefficients than transactions with shortfalls in interest payments. Given that most impairments belong to the first group (principal impairments), rating agencies may be more careful in assigning ratings in advance of principal payments than in advance of interest payments.

Table 4 also reveals that Moody's ratings better reflected increased risk prior to impairments of securities with a lower default amount. The default amount is negatively correlated with the anticipation coefficient in all the years. One explanation for this behaviour could be that smaller default amounts are typically caused by shortfalls in payments from individual assets, whereas higher default amounts are caused by more general economic downturns that affect a higher proportion of assets. This especially affects highly rated (A region) securities as they require correlated defaults in large numbers to lead to impairment due to over-collateralisation. Possibly, the through-the-cycle approach that most rating agencies use amplifies this effect.

Table 4 also offers information on how the type of underlying asset portfolio influences rating quality. However, the impact was not constant for the whole observation period. Overall, CDO ratings performed poorly. Given that CDOs typically have very broad asset portfolios and in many cases were even restructured from other CDOs (known as CDO-squared transactions), it seems plausible that it was more difficult for CRAs to identify changes in risk for these transactions than for other transaction types.

4.5 *Influence of macroeconomic factors on rating quality*

4.5.1 H3: Differences in rating quality can be explained with macroeconomic factors

After having analysed how tranche-specific factors affect rating quality, this hypothesis addresses the question as to how macroeconomic factors can be used to explain changes in the anticipation coefficient. To do so, we focused on aggregate data (annual average anticipation coefficients) and not on individual tranches. Figure 5 shows that the average anticipation coefficient changed over time. Since the value of a structured finance transaction depends on the value and cash flows of the underlying assets, macroeconomic variables might also affect the predictability of impairments.

To test the impact of macroeconomic factors, we regressed the anticipation coefficient on numerous explanatory variables. These variables include the Case–Shiller US National House Price Index provided by S&P. The Case–Shiller Index serves as a proxy for the housing market. For the calculation of the correlation coefficients, the natural logarithms of the growth rate were used. Furthermore, we added the seasonally adjusted GDP growth rate and the national unemployment rate as reported by the US Bureau of Economic Analysis and the US Bureau of Labor Statistics.

While examining the effect of macroeconomic variables on the anticipation coefficient, it is important to keep in mind that the anticipation coefficient describes the rating adjustments for a

Table 5. Regression of the anticipation coefficient on macroeconomic variables.

Variable	(1)	(2)	(3)
Intercept	0.963***	0.816***	0.625***
Case–Shiller	0.632		
Case–Shiller (lagged by 180 days)		1.565**	
Case–Shiller (lagged by 360 days)			2.602***
GDP growth	0.004		
GDP growth (lagged by 180 days)		0.004	
GDP growth (lagged by 360 days)			0.01
Unemployment level	−0.059		
Unemployment level (lagged by 180 days)		−0.036	
Unemployment level (lagged by 360 days)			−0.002
F-statistic	2.75*	1.9	5.04**
Adjusted R^2	0.145	0.079	0.227
Observations	32	32	32

Notes: The results of the regression models using robust standard errors are given. The dependent variable is the quarterly average anticipation coefficient. Independent variables are the natural logarithms of the Case–Shiller US National House Price Index, the seasonaly adjusted US GDP growth rate, and the US national unemployment rate. All independent variables are additionally specified with a 180-day and a 360-day lag to take into account that the anticipation coefficient describes the rating adjustments for a one-year period.
*Two-sided significance levels representing 10%.
**Two-sided significance levels representing 5%.
***Two-sided significance levels representing 1%.

one-year period and not for a specific point in time. For example, the anticipation coefficient of a security with impairment on 1 July 2007 describes the rating adjustments from 1 July 2006 to 30 June 2007. Consequently, the explanatory variables may better explain changes in the coefficient with a certain lag. In our example, it may be more appropriate to use economic indicators from the end of 2006 rather than from June 2007 (when the impairment eventually occurred). To allow for this effect, the independent variables are specified with a 180-day and a 360-day lag. Table 5 shows the estimated regression coefficients.

The model with the best fit uses the variables lagged by one year. The regression coefficients reveal that the Case–Shiller House Price Index positively affects the anticipation coefficient. A high Pearson correlation coefficient of $\rho = 0.58$ implies that the anticipation coefficient moves in line with the growth of the Case–Shiller Index of the year before. Figure 6 presents both curves: the anticipation coefficient and the logs of the Case–Shiller Index growth rate with a one-year lag.

The positive correlation can be explained by the asset portfolios of structured finance securities that are, in many cases, closely related to the housing market. In the case of a significant downturn in the housing market, many assets will lose their value in a short time, which does not allow CRAs to adjust their ratings in a timely manner. As a result, the average anticipation coefficient falls. However, the positive correlation also suggests that the anticipation coefficient increases if the housing market is in good condition. The explanation for this is straightforward: in a boom period, fewer securities default and those very few that still experience shortfalls in payments very likely belong to the more risky tranches that typically receive a lower rating from CRAs. In good years, the average anticipation coefficient is consequently dominated by risky securities with low ratings. As a result, the anticipation coefficient rises. This effect has already been illustrated in Table 1, which shows the composition of impairments.

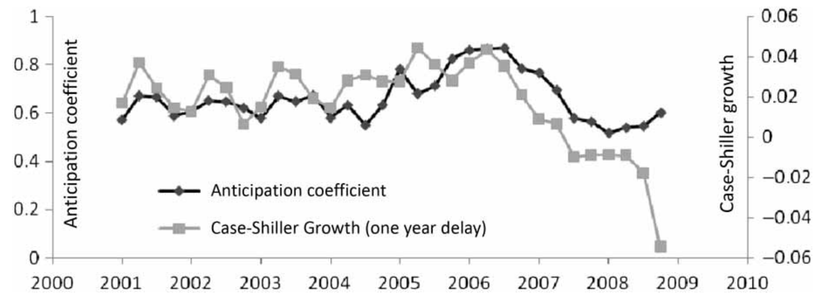

Figure 6. Anticipation coefficient and Case–Shiller growth over time.
Notes: The anticipation coefficient (black) and the logs of the Case–Shiller growth (grey) with a one-year lag are shown. Both curves move in line, which illustrates the high correlation between both the variables.

5. Discussion and outlook

To date, no empirical evidence exists on the information content of ratings for structured finance securities prior to impairment. The main objective of this paper was to analyse rating adjustments prior to impairment events and to reveal and explain differences in rating agency performance along this dimension. Based on an empirical study of 13,679 impairments rated by Moody's, we showed that ratings are generally adjusted prior to default.

This paper developed a new measure that quantifies a CRA's performance in advance of impairments. In contrast to existing research, this new measure, the anticipation coefficient, includes rating information of a whole one-year period. The literature thus far has focused on the rating at origination or the beginning of a year. A high anticipation coefficient signals that ratings were adjusted in a timely manner prior to shortfalls in interest or principal payments and therefore allowed investors to adapt to the increased portfolio risk. The anticipation coefficient may be applied for the analysis of other rating applications.

The anticipation coefficient reveals that the Moody's ability to identify higher levels of impairment risk deteriorated significantly during the GFC. This is consistent with the general criticism put forward against CRAs. However, for the time prior to the crisis, we observed an improvement in rating quality. The low level of the anticipation coefficient during the GFC can be ascribed to the over-proportional increase in impairments of highly rated tranches and the relatively late adjustments for securities that initially received investment-grade ratings. These findings may not be interpreted as a critique of the valuable work CRAs provide. It is reasonable to argue that the forecasting of such a severe downturn is difficult.

Using the anticipation coefficient, we found that differences in Moody's performance can be partially explained by deal-specific and macroeconomic factors. The ratings of securities with a higher deal volume are typically of higher value for investors. Furthermore, ratings better reflect increased risk prior to impairments the longer they have existed, so that CRAs can accumulate deal-specific information over time that they then use to improve their ratings. Another factor that influences rating quality is the competition CRAs face after origination. Transactions that are rated by several CRAs tend to have better risk assessments prior to defaults. Surprisingly, Moody's performed better in anticipating impairments with low default amounts. One possible explanation for this behaviour is that, in their assessments, rating agencies allow for the risk that some of the portfolios' assets will experience shortfalls in payments but do not expect economic downturns that will affect a higher number of assets.

With respect to macroeconomic factors, a significant impact of the housing market on rating quality in the structured finance market became evident. For example, the forecasting quality of ratings highly correlates with the Case–Shiller US National House Price Index.

Unfortunately, our empirical analysis only assesses data from Moody's Investors Service. While previous research suggests that ratings of several CRAs show a high level of agreement, comparing Moody's performance with those of other rating agencies offers potential for further research. In addition, a more thorough analysis as to how to take the watchlist status of a transaction into account may yield further insights.

Overall, the analysis shows that ratings do not consistently reflect increased risk prior to impairments. Investors and regulators should consider further information next to ratings, such as deal volume, asset type, time since origination, and the overall economic situation.

Acknowledgements

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Notes

1. Optimal means that the rating agency (in our case Moody's) anticipated the impairment one year prior to impairment and therefore assigned the lowest possible rating (Caa3 = 19) at that time.
2. Section 4.1 shows empirical evidence that the findings may be generalised to other CRAs.
3. Note that our findings are robust with regard to alternative values. Güttler and Wahrenburg (2007) and Sy (2004) used adjustment factors of 1.0 and 0.67, respectively.
4. This variable is based on information about ratings from Moody's, S&P, Fitch Ratings, and the Dominion Bond Rating Service and collected from Bloomberg/Datastream.

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