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SECURITIZATION RATING PERFORMANCE AND AGENCY INCENTIVES

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Securitization Rating Performance and Agency Incentives

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Abstract

This paper provides an empirical study, which assesses the historical performance of credit rating agency (CRA) ratings for securitizations before and during the financial crisis. The paper finds that CRAs do not sufficiently address the systematic risk of the underlying collateral pools as well as characteristics of the deal and tranche structure in their ratings. The paper also finds that impairment risk is understated during origination years and years with high securitization volumes when CRA fee revenue is high.

The mismatch between credit ratings of securitizations and their underlying risks has been suggested as one source of the Global Financial Crisis, which resulted in the criticism of models and techniques applied by CRAs and misaligned incentives due to the fees paid by originators.

Keywords: Asset-backed Security, Credit Rating Agency, Collateralized Debt Obligation, Economic Downturn, Fee Revenue, Forecasting, Global Financial Crisis, Home Equity Loans, Impairment, Mortgage-backed Security, Rating, Securitization

JEL Classification: G20, G28, C51

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1. Introduction

This paper compares and analyzes cross-sectional and time-series characteristics of credit rating agency (CRA) ratings, implied impairment rate estimates and realized impairment rates of asset portfolio securitizations. Two distinct hypotheses are analyzed, which provide empirical evidence on the role of ratings for securitizations during the Global Financial Crisis (GFC).[1] This is of highest importance as shortcomings may have been instrumental to past, current and future loss rates of investors in relation to structured finance transactions, which are generally called securitizations. Structured finance ratings and associated fee revenue have experienced an unprecedented growth in past years and until the GFC were the dominant rating category – both in terms of numbers of ratings issued as well as CRA fee revenue.[2]

The Global Financial Crisis led to an unprecedented and unexpected increase of impairment rates for securitizations. The disappointment of investors resulted in the criticism of models applied by credit rating agencies. Examples are VECTOR from Fitch rating agency (see Fitch Ratings, 2006), CDOROM from Moody's rating agency (see Moody's Investors Service, 2006) and CDO Evaluator from Standard and Poor's rating agency (see Standard & Poor's, 2005). A similar critique was ventured after the South East Asian Crisis of 1997 in relation to corporate bond issuer and bond issue credit ratings. For example, Leot *et al.* (2008) find that ratings follow rather than predict the crisis as systematic downgrades occurred subsequent to the crisis.

Securitizations involve the sale of asset portfolios to bankruptcy-remote special purpose vehicles, which are funded by investors of different seniorities (tranches). Based on the nature of the securitized asset portfolios, important transaction types include asset-backed securities (ABSs), collateralized debt obligations (CDOs), home equity loan-backed securities (HELs) and mortgage-backed securities (MBSs). Securitizations are generally over-the-counter instruments. Information is available to measure the risk of securitizations and includes credit ratings, impairment histories and proxies for the asset portfolio risk, such as asset value indices or cash flow indices. The evaluation of individual risks, their dependence structure and derivatives is complicated by the low liquidity of the underlying assets, the unavailability of secondary markets and the recent origination of such transactions.

Various streams exist in literature on the measurement of financial risks of securitizations and – with regard to the risk exposure – similar credit derivatives. A first stream focuses on the pricing, where the central issue is to explain observed prices such as credit spreads of credit default swap indices. The most

[1] Namely, the Impairment Risk and Agency Incentive hypotheses, compare Section 2.

[2] Rating fee revenue peaked in 2007. According to Table 1, CRA Moody's Investors Services has generated in 2007 a fee revenue of $873 million for structured finance ratings, $412 million for corporate issuer and issue ratings, $274 million for financial institution issuer and issue ratings and $221 million for public project and infrastructure ratings. The relative fee revenues in 2007 (1998) were 49% (32%) for structured finance ratings, 23% (33%) for corporate issuer and issue ratings, 15% (20%) for financial institution issuer and issue ratings and 12% (15%) for public project and infrastructure ratings.

prominent examples are the CDX North America and iTraxx Europe indices, which reference the default events in relation to bond portfolios. These indices were originated in 2003 and 2004. Credit spreads for the indices as well as tranches are generally available daily. Longstaff and Rajan (2008) and Hull and White (2004) apply a risk-neutral pricing framework to develop pricing techniques for these spreads. A central point of these risk models is the specification of the dependence structure for the portfolio assets.

Another stream is concerned with the modeling and estimation of risk characteristics of the underlying asset portfolio without relying on market prices. The focus is on the derivation of the distribution of future asset values (or losses) based on individual risk parameters. In the case of a loan portfolio, the relevant parameters are default probabilities, loss rates given default, exposures at default and dependence parameters such as correlations or more general copulas. Merton (1974), Leland (1994), Jarrow and Turnbull (1995), Longstaff and Schwartz (1995), Madan and Unal (1995), Leland and Toft (1996), Jarrow *et al.* (1997), Duffie and Singleton (1999), Shumway (2001), Carey and Hrycay (2001), Crouhy *et al.* (2001), Koopman *et al.* (2005), McNeil and Wendin (2007) and Duffie *et al.* (2007) address the default likelihood. Dietsch and Petey (2004) and McNeil and Wendin (2007) model the correlations between default events. Carey (1998), Acharya *et al.* (2007), Pan and Singleton (2008), Qi and Yang (2009), Grunert and Weber (2009) and Bruche and Gonzalez-Aguado (2010) develop economically motivated empirical models for recoveries using explanatory co-variables. Altman *et al.* (2005) model correlations between default events and loss rates given default.

Within this stream, credit ratings are often used to explain credit risk. Ratings aim to measure the credit risk of corporate bond issuers, corporate bond issues, sovereigns and structured finance issues. In the contemporary climate of the Global Financial Crisis, the role and importance of ratings to all market participants (e.g., issuers, investors and regulators), while controversial, is acknowledged. Previous research focuses on the degree to which corporate credit rating changes introduce new information. For example, Radelet and Sachs (1998) find that rating changes are pro-cyclical. This suggests that they provide only a limited amount of new information to the market. Ederington and Goh (1993), Dichev and Piotroski (2001) and Purda (2007) find that corporate credit rating downgrades provide news to the market. Loeffler (2004) finds that the default prediction power of ratings is low. Poon *et al.* (2009) analyze solicited and unsolicited bank credit ratings and show that solicitation is a significant explanatory variable between both groups. Jorion *et al.* (2005) show that after Regulation Fair Disclosure, the market impact of both downgrades and upgrades is significant and of greater magnitude compared to that observed in the pre-Regulation Fair Disclosure period. The relative roles of different CRAs have also been studied. For example, Miu and Ozdemir (2002) examine the effect of divergent Moody's and S&P's ratings of banks and Becker and Milbourn (2008) analyze the link between information efficiency of ratings and competition after the market entry of CRA Fitch. Guettler and Wahrenburg (2007) find that bond ratings by Moody's and Standard & Poor's are highly correlated and Livingston *et al.* (2010) find that the impact of Moody's ratings on market reactions is stronger compared to Standard & Poor's.

With regard to the GFC, Demyanyk *et al.* (2010) find that updated credit score next to credit score at origination is an important predictor of mortgage default. Rajan *et al.* (2008) show that the omission of soft information in ratings can lead to substantial model risk. Mayer *et al.* (2008) find that the decline of housing prices was responsible for increasing sub-prime mortgage delinquency rates. Benmelech and Dlugosz (2009) show empirically that rating inflation was an issue in the GFC and they argue that one of the causes of the crisis was overconfidence in statistical models. The authors use rating migration statistics and analyze up- and downgrades around the crisis. Ashcraft *et al.* (2009) find that CRA ratings for mortgage-backed securities provide useful information for investors, show significant time variation and become less conservative prior to the GFC. Griffin and Tang (2009) compare CRA model methodologies with CRA ratings for collateralized debt obligations and find that the models are more accurate than the ratings. Coval *et al.* (2009) argue that model risk and the exposure to systemic risk of securitization may explain the increase of impairment rates during the GFC. Crouhy *et al.* (2008) point out that CRAs' fee revenues depend on the number of ratings and may be linked to ratings quality. Similarly, Franke and Krahnen (2008) argue that incentive effects in relation to rating shopping have played an important role in the GFC, particularly associated with the allocation of equity tranches of securitizations. Hull (2009) and Hellwig (2008) identify deficient CRA models as a cause of the GFC. Bolton *et al.* (2009) show that the fraction of naive investors is higher, and the reputation risk for CRAs of getting caught understating credit risk is lower during economic booms, which gives CRAs the incentive to understate credit risk in booms. Dokko *et al.* (2009) analyze the role of monetary policy in the housing bubble prior to the crisis.

Other authors focus on strategic mortgage default.[3] Krainer *et al.* (2009) develop an equilibrium valuation model that incorporates optimal default to show how mortgage yields and lender recovery rates on defaulted mortgages depend on initial loan-to-value ratios. Their empirical findings confirms the presence of strategic default. Bajari *et al.* (2008) model the drivers of traditional and strategic default and find that the US decrease in home prices as well as deterioration in loan quality led to increases in mortgage default rates. Guiso *et al.* (2009) use survey data to analyze the likelihood for strategic default if the debt value exceeds the value of the collateralized house value. Important drivers of this likelihood are relocation costs, moral and social considerations as well as the proportion of foreclosures in the same region.[4]

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3 A strategic default is the decision by a borrower to default despite having the financial ability to make loan payments. In relation to the recent financial crisis, strategic default may have been encouraged by large drops in real estate (collateral) values and interest rates.

4 There is a related literature which focuses on the mortgage asset class, the GFC and lending standards. Demyanyk and Hemert (2009) and Dell'Ariccia *et al.* (2008) analyze US loan-level data and find that the quality of loans deteriorated for six consecutive years before the GFC. These findings are consistent with Rajan *et al.* (2008) who argue that lenders have an incentive to originate loans that rate high based on characteristics that are reported to investors which may lead to a deterioration of loan quality.

This paper identifies two gaps in the existing literature. Firstly, important contributions analyze rating migrations with regard to informativeness of securitization credit ratings.[5] This paper extends the literature by analyzing the ability of credit ratings to reflect impairment risk and collects a unique database of 13,072 impairment events and fee revenue for a CRA. The analysis of impairment events as the realization of impairment risk provides new insights. The analysis of rating changes is important but partially limited as it assumes the accuracy of credit ratings which is the main testable hypotheses.

Secondly, this paper finds new evidence on incentive miss-alignments and extends the above theoretical literature empirically. The paper is first of its kind to show that CRAs collect the majority of fee revenue at origination. Following this observation, the paper compares ratings at origination with ratings at monitoring years as well as total securitization volume at origination. The paper finds that ratings under-reflect risk in periods when CRA fee revenue is high and offers an alternative theoretical explanation for the observation by Bolton *et al.* (2009) who relate rating inflation (i.e., the underestimation of risk by ratings) to the fraction of naive investors.

Please note, that this paper does not argue that CRA fee revenue has led to inaccurate ratings but rather argues that current incentive structures may give rise to inaccurate credit ratings and that the elimination of such incentives may support more meaningful external ratings for securitizations in the future. To date, investors and prudential regulators assume the existence of a link between impairment risk and credit ratings by acknowledging CRAs and assigning credit spreads and regulatory capital risk weights to CRA rating categories.

The remainder of this paper is organized as follows. Section 2 develops the main hypotheses, consistent with the current literature in relation to the risk and uncertainty of CRA assessments. A framework to test the hypotheses is presented. Section 3 describes the data used in the study and analyzes the hypotheses. Various robustness checks are conducted. Section 4 discusses the major ramifications of the empirical results for securitization risk models and provides suggestions in relation to a new stability framework for financial markets, institutions and instruments.

2. Hypotheses and Testing Approach

2.1 Development of Hypotheses

Rating agencies have been charged for the failure to measure the impairment risk of securitizations i.e., the risk that investors may experience losses. The papers aims to provide empirical insights into CRA securitization ratings and their information content relative to the inherent risks.

[5] Examples are Benmelech and Dlugosz (2009) and Ashcraft *et al.* (2009).

CRAs address various elements of the asset and liability side of securitizations when designing and implementing a securitization rating model. Rajan *et al.* (2008) find that securitization risk models omit ‘soft’ information. This implies that CRA ratings, relying on such incomplete models omit important risk factors and hence misevaluate the average credit quality of the asset portfolio. Crouhy *et al.* (2008) suggest that CRAs did not monitor raw data and were tardy in recognizing the implications of the declining state of the sub-prime market and support the argument by Rajan *et al.* (2008) that other asset portfolio characteristics, such as soft facts, may be important drivers of asset portfolio risk.

Our *Impairment Risk Hypotheses* distinguish missing information on the asset (H1a) and liability side (H1b) of securitizations. H1a addresses characteristics of the asset portfolio and is stated as follows:

H1a: Ratings contain all information about the average asset quality of the asset portfolio relevant for impairment risk such as asset class, resecuritization status and transaction size.

H1b addresses the tranching structure of securitizations and the discussion on the appropriate specification of the dependence structure of the asset portfolio (compare Hull, 2009; Hellwig, 2008). The probability distribution and hence the percentiles of losses associated with the pool are particularly sensitive to the correlations in the underlying asset pool (compare Gibson, 2004; Coval *et al.*, 2009). Thus, the level of subordination may be a key driver and should explain tranche impairments after controlling for credit ratings if correlations are mis-specified in the CRA model. H1b is therefore:

H1b: Ratings contain all information about the characteristics of securitizations relevant for impairment risk, such as subordination level and tranche thickness.

Furthermore, the rating agencies may have an incentive to bias the measures of impairment risk. Crouhy *et al.* (2008) argue generally that CRA fees are paid by issuers and that CRA competition is limited by regulation. This may imply that the credit quality measured by a CRA and CRA fee revenue are positively correlated. However, CRAs publish default and rating migration tables, which are used to calibrate ratings to metric risk measures. Thus, a systematic ‘rating for fee’ policy would be noticed and priced by investors when analyzing the financial risk in relation to ratings. Two *Agency Incentive Hypotheses* address two potential ways in which rating agencies may ‘circumvent’ this rating-performance mechanism.

The first incentive problem (H2a) relates to the assumption that investors do not differentiate the risk with regard to origination and monitoring years. Rating performance measures are generally calculated as an average per rating class and/or observation year. The fee revenue of rating agencies is high when the first rating is generated (origination year) and low in later years when ratings are revisited (monitoring years). Figure 1 shows the origination volume and outstanding volume of the analyzed tranches as well as the CRA fee revenue.[6] It is apparent and insightful that despite the fact that CRAs provide origination and monitoring ratings, CRA fee revenue corresponds with the origination volume rather than the outstanding volume.[7] Thus, H2a is:

H2a: Rating-implied impairment risk and time since origination are positively correlated.

The reason for this finding is that origination fees exceed the monitoring fees in absolute terms.[8] In addition, the fees in relation to origination and monitoring years are often paid upfront despite their lagged recognition as accounting income. As a result, CRAs may have an incentive to assign i) too low risk ratings in origination years to increase fee revenue and ii) too high risk ratings in monitoring years to maintain stable default and rating migration performance measures. In other words, this hypothesis tests whether the underestimation of risk decreases over time since origination.

The second incentive problem (H2b) relates to a critique by Bolton *et al.* (2009) who suggest that the fraction of naive investors is higher, and the reputation risk for CRAs of getting caught understating credit risk is lower during economic booms, which gives CRAs the incentive to understate credit risk in economic booms. Figure 1 supports this argument visually by showing that the origination volume and thus fee volume is high in economic booms. Hence, H2b tests whether impairment risk is underestimated during periods of high securitization activity at origination:

H2b: Rating-implied impairment risk and rating intensity at origination are negatively correlated.

2.2 Empirical Testing Approach

This section develops a simple model for impairment risk of securitizations from which the empirical testing approach of the later sections is derived. First we propose a default model for the assets in the pool which forms the basis for the impairment model for securitized tranches. Following the credit risk models in Gordy (2000), Gordy (2003), McNeil and Wendin (2007), and Gupton *et al.* (1997), let R_{kt} denote the asset return of borrower k in time period t ($k=1,...,K;t=1,...,T$) which is generated by the following process

$$R_{kt}=\sqrt{\rho}\cdot X_t+\sqrt{1-\rho}\cdot\varepsilon_{kt} \tag{1}$$

[6] Please note that outstanding volume as well as fee revenue relate to origination years and monitoring years while the origination volume relates to origination years only.

[7] A similar conclusion can be drawn for count data instead of volume data.

[8] In financial year 2007, CRA Moody's Investors Service generated 77% of fee revenue for origination of ratings and 23% for monitoring of ratings. The empirical data suggests that 37% of structured finance ratings relate to an origination year and 63% of structured finance ratings relate to a monitoring year. These numbers imply that an origination rating generates approximately 5.7 times more fee revenue than monitoring a rating for one year.

where X_t and ε_{kt} are standard normally distributed systematic and idiosyncratic risk factors and ρ is a parameter denoting the correlation between asset returns which measures the strength of association between borrowers. The factors are assumed to be serially and cross-sectionally independent.

A default event occurs if the asset return R_{kt} falls below a threshold c_{kt}, that is

$$D_{kt} = 1 \Leftrightarrow R_{kt} < c_{kt} \tag{2}$$

where D_{kt} is an indicator variable with

$$D_{kt} = \begin{cases} 1 & \text{borrower } k \text{ defaults in } t \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Under the normality assumption of the model the probability of default is $\pi_{kt} = \Phi(c_{kt})$ where $\Phi(.)$ is the standard normal cumulative distribution function. Now, assume that K assets are pooled to an asset portfolio j.[9] The default rate of the pool is the average over the default indicators of its assets and defined as

$$P_{jt} = \frac{1}{K}\sum_{k}^{K} D_{kt} \tag{4}$$

A common approximation of the probability density $f(p_{jt})$ of the default rate of the pool uses the assumptions of an infinite large number and homogeneity of assets with $c_{kt} = c_{jt}$ for all k. The density converges against the 'Vasicek'-density under these assumptions (see Vasicek, 1987, 1991; Gordy, 2000, 2003):

$$f(p_{jt}) = \frac{\sqrt{1-\rho}}{\sqrt{\rho}} \cdot \exp\left(\frac{1}{2}(\Phi^{-1}(p_{jt}))^2 - \frac{1}{2\rho}(c_{jt} - \sqrt{1-\rho} \cdot \Phi^{-1}(p_{jt}))^2 \right) \tag{5}$$

where $\Phi^{-1}(.)$ is the inverse standard normal cumulative distribution function. The default rate has the

9 Please note that it is common to refer to the asset portfolio with terms such as deal or transaction.

cumulative distribution function (see e.g. Bluhm *et al.*, 2003)

$$F(p_{jt}) = P(P_{jt} < p_{jt}) = \Phi\left(\frac{\sqrt{1-\rho}\,\Phi^{-1}(p_{jt}) - c_{jt}}{\sqrt{\rho}}\right) \tag{6}$$

P_{jt} in Equation (5) and Equation (6) can also be interpreted as the loss rate (rather than the default rate) of the portfolio when loss rates given default are deterministic and equal to unity.

Next, consider the structuring of a pool (or transaction) into several tranches. A tranche i ($i = 1,...,I_j$) of pool j experiences a loss and therefore an impairment if the default rate P_{jt} in the portfolio exceeds the relative subordination level (or attachment level) AL_{ijt}

$$D_{ijt} = 1 \Leftrightarrow P_{jt} > AL_{ijt} \tag{7}$$

where D_{ijt} is an indicator variable with

$$D_{ijt} = \begin{cases} 1 & \text{tranche } i \text{ of asset pool } j \text{ is impaired in } t \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

The relative attachment level is calculated by the ratio of the attachment level (in \$) and the deal principal (in \$) of period t. As a result of this definition, impaired tranches of previous years have reduced both the attachment level as well as the deal principal. The probability of a tranche impairment is thus

$$P(D_{ijt} = 1) = P(P_{jt} > AL_{ijt}) \tag{9}$$

The attachment probability (i.e., the propensity of being exposed to a loss in the underlying asset pool) for a tranche i of asset pool j in period t ($i = 1,...,I_j; j = 1,...,J; t = 1,...,T$) is based on the Vasicek-distribution is then given as

$$P(D_{ijt} = 1) = 1 - F(AL_{ijt}) = 1 - \Phi\left(\frac{\sqrt{1-\rho}\,\Phi^{-1}(AL_{ijt}) - \Phi^{-1}(\pi_{jt})}{\sqrt{\rho}}\right) \tag{10}$$

$$= \Phi\left(\frac{-\sqrt{1-\rho}\,\Phi^{-1}(AL_{ijt}) + \Phi^{-1}(\pi_{jt})}{\sqrt{\rho}} \right)$$
$$= \Phi\left(\eta_{ijt}\right)$$

which implies that the tranche impairment probability is a function of the

- Average portfolio asset quality π_{jt};
- Asset correlation ρ;
- Attachment level of a tranche relative to the total deal principal AL_{ijt}.

Please note that $\eta_{ijt} \equiv \frac{-\sqrt{1-\rho}\,\Phi^{-1}(AL_{ijt}) + \Phi^{-1}(\pi_{jt})}{\sqrt{\rho}}$; $i = 1,...,I_j;\ j = 1,...,J; t = 1,...,T$. Moreover, note that this probability is *unconditional* with respect to the systematic risk factor X_t. This implies that the probability does not assume that the realization of X_t is known ex ante.

All hypotheses test whether CRAs capture impairment risk accurately ex ante. If a CRA correctly assesses the impairment risk of a tranche, i.e., correctly derives the above parameters, calculates the tranche impairment probabilities and assigns ratings accordingly, then the tranche impairment probability should solely be explained by the ratings.

More formally, the impairment of tranche i ($i = 1,...,I_j$) of asset pool j ($j = 1,...,J$) in time t ($t = 1,...,T$) is linked with observable information by the Probit regression.[10]

$$P\left(D_{ijt} = 1\right) = \Phi\left(\beta' x_{ijt}\right) \tag{11}$$

where x_{ijt} is a vector of tranche ratings at the beginning of an observation period. β is the respective vector of sensitivities and includes an intercept. Note that the left hand side is the same probability as in Equation (10). If ratings fully explain the impairment probability, then no other variable besides the ratings should be significant in the model. In other words, if ratings reflect the tranche impairment probability accurately, they should include the information as specified in Equation (10).

[10] The models were also estimated for robustness using only one tranche per pool to analyze the dependence between multiple tranches in relation to a single asset portfolio. The results are similar to the ones presented and shown in Section 3.4.1.

However, if a rating omits information, then additional information besides the rating may explain the tranche impairment probability. Examples may relate to the asset portfolio quality, the securitization structure as well as observable information with regard to the business cycle as stated in our hypotheses. Consider an error in assigning one or more of the pool parameters made by the CRA resulting in $\tilde{\eta}_{ijt} \neq \eta_{ijt}$. Using $\tilde{\eta}_{ijt}$ instead of η_{ijt} will provide erroneous impairment probability assessments $\tilde{P}(D_{ijt} = 1) = \Phi(\tilde{\eta}_{ijt}) \neq P(D_{ijt} = 1)$ and therefore misclassification into wrong rating grades. The true impairment probability can then be written as

$$P(D_{ijt} = 1) = \Phi(\tilde{\eta}_{ijt} + \Delta_{ijt}) \tag{12}$$

with $\Delta_{ijt} \equiv \eta_{ijt} - \tilde{\eta}_{ijt}$ denoting the measurement error in variables which may refer to characteristics of the pool, the tranche or time. Model (12) will provide the basis for the empirical tests in the following section.[11]

Please note that this paper focuses on the ability of ratings and other risk factors to explain the binary impairment risk. Thus, the above probit analysis is appropriate to compare ratings and impairment events as it links the probability of impairment with explanatory variables. Krahnen and Weber (2001) argue that such a link is a necessity under generally accepted rating principles. These types of models have also been employed in other studies for analyzing corporate bond issue and issuer ratings or a bank's loan credit ratings (compare e.g. Grunert *et al.,* 2005).[12] However, it may be argued that the above model is oversimplified and therefore the empirical approach is not valid and robust with respect to model mis-specification. For example, the above model in Equation (10) assumes homogeneity, large pools, and normally distributed risk factors whereas literature has found that Student's t-distributions or copulas explain credit spreads of CDOs better than Gaussian copulas (compare e.g. Hull and White, 2004). We analyze the impact of the assumptions and the robustness of results in Section 3.4.

11 This approach is consistent with Ashcraft *et al.* (2009) who distinguish between the case that ratings partially explain risk (Informativeness) and the case where other variable are additionally significant (Information Efficency).

12 The research question is slightly different to the analysis of rating standard dynamics. One important study in this area is by Blume *et al.* (1998) who analyze corporate rating standards and find that such rating standards have become more stringent from 1978 to 1995. Rating standard is defined in this study as the propensity to assign a certain rating category and thus an ordered Probit models is estimated where the ratings grades are the dependent variables. Another example for such an approach is Becker and Milbourn (2008).

3. Empirical Analysis

3.1 Structured Finance Data

This paper analyzes a comprehensive panel data set of structured finance transactions rated by CRA Moody's Investors Service. The data covers characteristics of asset portfolios (which are also known as collateral portfolios), characteristics of tranches, ratings of tranches as well as occurrences of impairment events for tranches.

This paper focuses on the CRA Moody's as Moody's unique corporate structure implies that fee revenues are published. Please note that Standard & Poor's is a subsidiary of McGraw-Hill and FitchRatings is a subsidiary of Fimalac. Both parent firms do not publish fee revenues for securitizations. We have checked the consistency of structured finance ratings[13] across three CRAs. We hand-collect the initial ratings of 1,000 randomly selected tranches and assigned numbers from 1 (rating Aaa for Moody's and rating AAA for Standard & Poor's and Fitch respectively) to 21 (rating C). Of the 1,000 tranches rated by Moody's, 680 are rated by Standard & Poor's and 356 are rated by Fitch. We find extremely high Spearman correlations[14] coefficients in excess of 90%: between Moody's and Standard & Poor's: 0.9339, between Moody's and Fitch: 0.9584 and between Standard & Poor's and Fitch: 0.9855. Moody's and Standard & Poor's differ in 88 of 680 cases. Moody's and Fitch differ in 49 of 356 cases and Standard & Poor's and Fitch differ in 11 of 163 cases. This implies that the empirical likelihood of a rating deviation is between 6.7% and 13.8%. Please note that the majority of ratings difference relates to a single notch. These findings suggest that results based on Moody's can be generalized to other major rating agencies.

This is also consistent with Guettler and Wahrenburg (2007), who find that bond ratings by Moody's and Standard & Poor's are highly correlated. Our empirical findings, industry experience and interviews with employees of the three CRAs support our conjecture that the ability to predict default or impairment risk is similar for the three major CRAs. In addition, Livingston *et al.* (2010) find that the impact of Moody's ratings on market reactions is somewhat stronger compared to Standard & Poor's and supports the use of Moody's ratings further.

The focus of the present study is on the performance of CRA ratings, which involves a comparison of CRA ratings with the likelihood of occurrence of impairment events. An impairment event is defined as (compare Moody's Investors Service, 2008):

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13 Please note that starting August 2010 such ratings require the 'SF' designation to be differentiated from bond another ratings.

14 We chose to report this measure for the relationship as ratings are ordinal in nature. We obtain similar results for Bravais-Pearson correlation coefficients.

> "[...] one of two categories, principal impairments and interest impairments. Principal impairments include securities that have suffered principal write-downs or principal losses at maturity and securities that have been downgraded to Ca/C, even if they have not yet experienced an interest shortfall or principal write-down. Interest impairments, or interest-impaired securities, include securities that are not principal impaired and have experienced only interest shortfalls."

Our model suggests that impairment risk is measured by CRAs ex ante and unconditional on the macroeconomic factor. However, the *realization* of impairments is measured conditional on the economy. To control for the unanticipated realization of the economy we include rating years, or alternatively, proxies for the economy in the regression models. Moreover, to check for structural breaks and to control for the increasing number of defaults we additionally divide our data into the sub-periods before and during the GFC.

Alternative measures for rating performance have been proposed in literature (compare Section 1). Firstly, ratings may be compared to the performance of the asset portfolios. The approach may be reasonable for asset portfolios such as mortgage-backed securities where information on the default rates of the underlying portfolios is available. We chose not to follow this approach for two reasons: i) we focus on the securitization market rather than mortgage-backed securities only and find distinct differences between various asset portfolios; and ii) credit ratings are issued for individual securities (tranches) and a key element in credit ratings is the credit enhancement (subordination) of these securities.

Secondly, ratings may be compared to the propensity of occurrence of rating downgrades. We chose not to follow this approach as our research question aims to analyze the accuracy of credit ratings with regard to the ex ante prediction of impairment risk. Analyzing rating downgrades limits the interpretation of results as the link between downgrades and losses to investors is less transparent as it assumes the accuracy of credit ratings which is the main testable hypotheses.

Structured finance transactions are very heterogeneous by definition. The authors are aware of potential prudential policy implications of this study. Seven filter rules to generate a homogeneous data set are applied and the following observations are deleted:

1. Transaction observations which can not be placed into the categories ABS, CDO, CMBS, HEL or RMBS. These are mainly asset-backed commercial paper, structured covered bonds, catastrophe bonds, and derivative product companies. 22.0% of the original number of observations are deleted;
2. Transaction observations where the monetary volume and therefore relative credit enhancement and thickness of individual tranches could not be determined without setting additional assumptions due to i) multiple currency tranches and ii) missing senior unfunded tranche characteristics. 13.5% of the original number of observations are deleted after the application of Filter Rule (1);

3. Transaction observations which are not based on the currency USD or transaction observations which are not originated in the USA. 5.0% of the original number of observations are deleted after the application of Filter Rule (1) and Filter Rule (2);
4. The time horizon is 1997-2008. Tranche observations which relate to years prior to 1997 due to a limited number of impairment events. Impairment events are the focus of this paper and years prior to 1997 have experienced few impairment events. Years after 2008 are not yet available at the time of writing this paper. 7.3% of the original number of observations are deleted after the application of Filter Rule (1) to Filter Rule (3);
5. Tranche observations which have experienced an impairment event in prior years. 0.2% of the original number of observations are deleted after the application of Filter Rule (1) to Filter Rule (4).

The resulting data comprises 325,443 annual tranche observations. The number of impaired tranche observations is 13,072.[15] The data set is one of the most comprehensive data sets on securitization collected and analyzed to date.

Table 1 shows various proxies for origination[16] and outstanding volume of the data: number of tranches, number of deals and volume. The variables cover CRA ratings at origination and the beginning of a year, asset pool and securitization characteristics, impairment events as well as systematic variables. In addition, rating fee revenues of the CRA Moody's Investors Service is shown. The outstanding number relates to issues which are rated at the beginning of the year and hence originated in prior years. Outstanding volume has increased during the whole observation period. Origination volume and structured finance fee revenues have increased prior to the GFC and decreased during the GFC. Therefore, structured finance fees coincide more with the origination volume which is in line with the recognition of the majority of fee revenue at or shortly after origination by the CRA.[17]

Table 2 describes the co-variables used in the empirical analysis. The table is consistent with Figure 1.

Table 3 and Table 4 describe the number of observations over time. The overall number of rated securitizations has increased at an increasing rate over time.[18]

Table 3 shows the relative frequency of rating categories at origination (Panel A) and at the beginning of the observation year (Panel B). In both Panels, the average rating quality deteriorates over time as the relative frequency of the rating category Aaa declined. This may reflect i) a deterioration of the average

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[15] The original data set included 15,083 impairment events before the application of filtering rules.

[16] Origination volume relates to the year starting from the time that a rating was first assigned.

[17] Compare Footnote 2.

[18] All tables weight individual transactions equally and the findings are robust for the value of securitizations.

asset portfolio quality, ii) a higher average risk level induced by the securitization structure (e.g., subordination or thickness), or iii) a change of the CRA rating methodology.[19]

Table 4 shows the relative frequency of asset portfolio (Panel A) and securitization characteristics (Panel B). Asset portfolio characteristics are the asset portfolio category, the resecuritization status and the asset portfolio size. The asset portfolio categories are asset backed security (ABS), collateralized debt obligation (CDO), commercial mortgage-backed security (CMBS), home equity loan security (HEL) and residential mortgage-backed security (RMBS). The asset portfolio size is categorized into Small (asset portfolio size less than or equal to $500 million), Medium (asset portfolio size greater than $500 million and less than or equal to $1,000 million) and Big (asset portfolio size greater than $1,000 million).

The number of rated tranches has increased at an increasing rate. The relative frequency of CDO and HEL has increased. The relative frequency of resecuritizations has generally decreased. The inflation-adjusted asset portfolio size has increased.

Securitization characteristics are the subordination level, thickness and origination year. The subordination level Junior indicates that a tranche attaches between 0% and 5%, Mezzanine indicates that a tranche attaches between 5% and 30% and Senior indicates that a tranche attaches between 30% and 100%.

The relative frequency of mezzanine and thin tranches has increased while the relative frequency of the various origination years (OY) depends on the origination as well as the maturity and impairment of securitizations.

Generally speaking, the validation of credit ratings is complicated as the use of ratings involves two steps: firstly the ordinal assessments of the financial risk of issuers or issues by CRAs and secondly the calibration of these ordinal ratings to metric credit risk measures such as default rates, loss rates given default or unconditional loss rates. This calibration step is generally opaque and investors rely on impairment rate tables which are periodically updated by CRAs. These tables are generally univariate and aggregate over various dimensions. The data set enables the estimation of impairment risk based on the most detailed information level, i.e., the individual transaction in a given observation year. Table 5 and Table 6 show the impairment rates over time for all tranches as well as per rating category, asset portfolio and securitization characteristics.

US securitizations have experienced two economic downturns during the observation period: the first one in 2002 subsequent to the US terrorist attacks (a period characterized by large bankruptcies such as Enron, WorldCom and various US airlines) and the Global Financial Crisis. With regard to the GFC, the

19 This finding is consistent with Ashcraft *et al.* (2009) who analyze AAA fractions for MBS and HEL securities over time.

impairment rate has increased by a factor of approximately 80 within two years between 2006 and 2008. Approximately 81% of all impairment events relate to 2008.[20]

Table 5 shows the impairment rates for rating categories at origination (Panel A) and at the beginning of the observation year (Panel B). In both Panels, the impairment rate increases for lower rating categories (i.e., from rating Aaa-A to rating Caa) and fluctuates over time with a dramatic increase during the GFC for all rating classes. The relative increase decreases during the GFC with the rating quality (i.e., from rating Caa to rating Aaa-A).[21] Ironically, investors were most surprised by the increase of impairment rates of highly rated securitizations.

Table 6 shows the impairment rates for asset portfolio (Panel A) and securitization characteristics (Panel B). Impairment rates are high in 2002 and 2007/2008. Impairment rates per rating category fluctuate over time. Impairment rates per asset portfolio type increased in 2002 for CDOs and in 2008 especially for CDOs, MBSs and HELs. HELs include sub-prime mortgage loans and the impairment risk increased to a larger degree than the one of MBSs. It can also be seen that HELs and MBSs did not experience an economic downturn in 2002. The asset classes CMBS and RMBS are aggregated to the category MBS due to the limited number of impairment events in earlier years. The impairment rate has increased in 2008 especially for resecuritizations. The levels of the impairment rates are fundamentally different between the various asset portfolio categories. Impairment rates of junior tranches increased to a greater degree than impairment rates of senior tranches. Impairment rates of thin tranches increased more than impairment rates of thick tranches and the ones of more recent vintage (with regard to the GFC) more so than the ones of older vintage. This result is consistent with findings by Demyanyk and Hemert (2009) for securitized sub-prime mortgage loans and Ashcraft *et al.* (2009) for mortgage-backed securities.

3.2 H1 - Impairment Risk Hypotheses

Table 7 presents Probit models linking the impairment events with CRA ratings. Model 1 takes the dummy-coded ratings (reference category: Aaa-A) into account. As measures for in-sample accuracy of the models the Pseudo-R^2, re-scaled R^2, and the area under the receiver operating characteristic curve (AUROC) are calculated (see Agresti,1984).[22] The parameter estimates increase from rating Aaa-A to

[20] This number underlines the severity of the GFC and the importance of this study. However, it also raises the concern of imbalances in the data set. We address the issue of robustness by i) controlling for rating years, ii) analyzing the data for the period prior to the GFC and the GFC and iii) focusing on relative differences within these controlled environments.

[21] Please note that inconsistencies may reflect the accuracy as well as the stochastic nature of impairment events. The latter is particularly relevant if the number of observations is low for a given category. One example is the impairment rate for the rating classes Ba (16.49%) and B (4.68%) in 2007 in Panel B of Table 5 as one would expect the impairment rate of rating Ba to be lower than rating B. These inconsistencies are in line with reports by the data-providing CRA (compare Moody's Investors Service, 2008).

[22] All measures are bounded between zero (lowest fit) and one (highest fit).

rating Caa and are significant. This demonstrates that the ratings imply higher impairment risk from Aaa to Caa as one would expect. Model 1 shows that CRA ratings explain the credit risk.

Model 2 includes the ratings as well as the dummy-coded rating years (reference category: 1997). The rating years are significant which implies that the realized impairment rates differ between the years. This has been pointed out by previous studies on corporate ratings (compare e.g., Loeffler, 2004) which conclude that ratings average the risk over the business cycle.[23] In other words, Model 2 shows that CRA ratings do not explain the increased level of impairment risk especially during economic downturns. This might be due to omitted macroeconomic factors in the credit rating or due to unexpected and unpredictable systematic random shocks in the year following the rating. If an explanatory variable is correlated with the systematic risk, it might be possible to obtain results, which are spuriously significant and capture the economy in the observation year partially. Therefore, we include rating year fixed effects in all subsequent models.

In addition, we include various macroeconomic variables and find that the results are robust with regard to these control variables. Therefore, Model 3 includes the growth rate of real GDP as a proxy for the US economy. The impact is highly significant and and GDP growth and impairment risk are negatively related.

In Table 8 we additionally include asset portfolio characteristics (Model 4, 6, 7 and 8) such as the information as to whether the deal is a CDO, HEL, MBS or ABS (which is measured by the intercept), a resecuritization (such as a CDO squared or CDO cube) or not (i.e. a ‘plain vanilla' deal), and the deal size, as well as year fixed effects to control for systematic risks. All variables are significant, which implies that the securitizations are different in their risks from the level implied by credit ratings. In other words, after controlling for credit ratings there are asset portfolio specific variables which add explanatory power to securitization risks. In particular, for the whole time series (Model 4 and 6), CDOs and HELs are more risky than stated by the CRA, a resecuritization is more risky than a plain vanilla transaction, and the risk increases with deal size after controlling for ratings.

Model 5, 6, 7 and 8 include securitization characteristics (subordination level and thickness of a tranche). These variables add to the explanation of impairment risk after controlling for ratings and observation year specific effects. Especially, tranche risk given the rating decreases with higher subordination and higher thickness.[24] We ran the Model 4 to Model 8 by replacing the observation year dummies by the growth rate of real GDP and obtained similar results.[25]

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[23] Such models are also known as through-the-cycle models.

[24] One argument is that the additional explanation of these variables may be provided by the ordinal scaling of ratings. That is, the number of rating grades is finite and the additional variables may explain variations within a rating grade. This argument confirms that a rating is not enough to explain the inherent risk. In other words, tranches within the same rating grade might then have different risks which is also in support of our hypotheses.

[25] The only noticeable difference was the parameter change for the MBS dummy to 0.0579 and a p-value of 0.0119. Generally speaking, the growth rate of real GDP is less powerful in explaining time-varying risk characteristics than rating year dummies.

The ramifications are that CRA ratings do not sufficiently account for the average impairment risk stipulated by asset portfolio and securitization characteristics over time.

The split of the data into pre-GFC and GFC (Model 7 and Model 8) years shows that the asset portfolio characteristics (asset portfolio category, resecuritization status and deal size) are cyclical as the parameter sign changes while the securitization characteristics are not cyclical. Impairment risk is significantly lower (higher) for CDO, HEL, MBS, resecuritization and big deals before (during) the GFC than during (before) the GFC. Likewise, subordination and tranche thickness are negatively related to impairment risk and ratings are not able to explain this.

In summary, we reject the hypothesis H1a that ratings contain all information about the average asset quality of the asset portfolio relevant for impairment risk. In addition, we reject hypothesis H1b that ratings contain all information about the characteristics of securitizations relevant for impairment risk. CRAs do not take all available asset portfolio and securitization information into account, which is relevant for explaining impairment risk. Important ramifications are that i) CRAs may have to include such characteristics into the rating models or ii) users such as investors or prudential regulators should apply asset portfolio specific impairment rates to ratings when interpreting CRA ratings.

3.3 H2 - Agency Incentive Hypotheses

Figure 1 provides empirical evidence that CRAs collect the majority of fee revenue at origination. Commercial CRAs may have a monetary incentive to bias the measures of impairment risk to generate fee revenue, which is tied to the origination rather than the monitoring process of securitizations. Following this argumentation, the paper compares ratings at origination with ratings at monitoring years as well as other macroeconomic conditions represented by the securitization volume at origination. The analyzed incentive hypotheses test whether a CRA may underestimate the risk in general at origination (as fee revenue is high at origination) or during economic booms (as origination volumes and therefore fee revenue is high during economic booms).[26]

Please note that the panel data set looks at origination and monitoring years, i.e., years between origination and maturity of securitizations. The impact of the vintage, i.e., the year of origination is shown in Table 9. Model 9 shows the same parameter estimates as Model 2. Model 10 shows that the origination years (also known as vintages) differ in risk and that ratings are unable to explain the risk of the different vintages.

Model 11 includes two variables which capture the strategic default of borrowers due to the relation between outstanding loan amounts and loan repayment/service rates. The results show that ratings do

[26] Please note that Bolton *et al.* (2009) provide the complementary argument that investors are naive and reputation risk is low.

not reflect vintage risk (i.e., origination year dummies) in general and strategic default characteristics in particular.

The two variables are constructed following Demyanyk *et al.* (2010) for every securitization, origination and observation period.[27] Firstly, the principal collateral adjustment ratio (PCR) is calculated, which accounts for changes in the outstanding loan amount as well as collateral under the assumption of a fixed-rate asset portfolio:

$$PCR_t = \frac{PVR_t}{CVR_t} \tag{13}$$

PVR_t is the principal value ratio of current to origination principal value:[28]

$$PVR_t = \frac{1-\left(\frac{1}{1+r_0}\right)^{T-t}}{1-\left(\frac{1}{1+r_0}\right)^{T}} \tag{14}$$

With 0 as the origination date, t the observation date and T the loan maturity date. The loan maturity date is approximated by the median maturity of the respective loan portfolio. r_0 is the interest rate at origination and is approximated by the federal funds rate.[29]

CVR_t is the collateral value ratio of current to origination real estate value proxied by the Standard & Poor's Case-Shiller 10 index (SPCS10):

$$CVR_t = \frac{CS_t}{CS_0} \tag{15}$$

27 Please note that by including PVR (see below) we extend the approach by Demyanyk *et al.* (2010) by accounting for the loan amortization.

28 As we have only access to legal maturities which are significantly longer than real maturity, we assume a loan maturity of 10 years. The results are robust with regard to variations in this parameter.

29 Please note that we also modeled the discount rate by the federal fund rate plus a lending spread and confirmed the robustness of the results.

SPCS10 is a composite index of the top 10 US metropolitan statistical areas. Other proxies (asset indices) for the collateral value may exist. We chose the the Standard & Poor's Case-Shiller 10 index as the majority of securitizations are backed by mortgage portfolios.

In addition, we construct an interest rate ratio (IRR) to measure the serviceability of the asset portfolio. IRR indicates the degree to which new or floating rate loans become more serviceable due to interest changes:

$$IRR_t = \frac{r_t}{r_0} \tag{16}$$

PCR and IRR reflect changes in the underlying loans since origination which may change the incentives of borrowers to strategically default on their loans in relation to the outstanding loan amount to collateral value and the serviceability.

In order to test the hypotheses H2a and H2b, we replace the origination year fixed effects by the time since origination (TSO) and the securitization volume at origination (SVO). TSO is equal to one in the origination year and greater than one in monitoring years.[30]

Table 10 shows that the negative parameter estimate (panel for all years) for the time since origination (TSO) implies that the level of impairment risk (given the rating) decreases over time. The relative fee revenue is high at origination and low thereafter. The implication is that the impairment risk given ratings (i.e., which is not explained by ratings) decreases over time. This confirms that CRAs may have an incentive to assign i) too low risk ratings in origination years to increase fee revenue and ii) too high risk ratings in monitoring years to maintain stable default and rating migration performance measures. The second and third panel show that this effect is mainly driven by the occurrence of the GFC. In summary, we reject the hypothesis H2a that rating-implied impairment risk and time since origination are positively correlated.

In addition, a high securitization volume at origination (when absolute fee revenue is high) implies high impairment risk after controlling for rating. This result holds for the years before and during the GFC. Thus we reject the hypothesis H2b that rating-implied impairment risk and rating intensity at origination are negatively correlated.[31]

30 High SVO indicates that a tranche was originated in a high securitization volume year (i.e., especially 2002 and later). Low SVO indicates that a tranche was originated in a low securitization volume year (i.e., especially before 2002).

31 High securitization volume (SVO) may coincide with periods of high collateral value and therefore reflect strategic default rather than inaccuracies due to securitization volumes. We have re-estimated the models controlling for PCR and IIR and obtained similar results for this parameter.

Both hypothesis tests suggest that impairment risk is under-represented by ratings when fee revenue is high, which is the case at origination and during an economic boom when origination volume is high.

3.4 Robustness Tests

3.4.1 Dependence across Tranches within a Deal

The empirical Probit regression model assumes independence of the tranches. However, the impairment events may exhibit dependence between the tranches of the same deal.[32]

Therefore, we repeat the model estimations using only one tranche per deal. The tranches are selected randomly per deal. The reduced data set contains 60,360 observations. We show the modified results for the key results of Table 8 in Table 11 and of Table 10 in Table 12 respectively.

In summary, the results are consistent. Very few variables become insignificant in the models for data before GFC while the variables stay significant for GFC data. The implication is that the findings remain but at a slightly lower statistical confidence level.

3.4.2 Regression Link Function

The Probit regression is based on the assumption of a Probit link function in the regression. Other assumptions are homogeneity, large pool size and normality of risk factors.[33]

We test the robustness of our approach in relation to violations of these assumptions.[34] We conduct several Monte-Carlo simulation studies which are carried out as follows:

1. For the simulations we specify the unconditional default probability $\pi = \Phi(c)$ and the asset return correlation ρ.
2. K borrowers are pooled and each pool is tranched into five tranches (with attachment levels 1%, 3%, 5%, 10%, and 30%). According to the decreasing tranche risk we assign five dummy coded rating grades A, B, C, D, and E.[35]

32 We would like to thank our conference discussants of the paper for raising this concern.

33 The large pool size assumption is checked for robustness in Section 3.4.3. The normality assumption is checked for robustness in Section 3.4.4. The impact of heterogeneity is analyzed by the inclusion of an instrument (distortion) variable throughout these sections.

34 Please note that the regression results may be spurious, biased, or inconsistent if the approach is not robust with respect to these types of mis-specification.

35 Please note that these thresholds were chosen in line with standard subordination levels of securitizations.

3. We randomly draw a time series of macroeconomic fixed ('distortion' or 'instrument') effects $\tilde{\xi}_t$ from a normal distribution with mean zero and standard deviation 0.1.[36]
4. We randomly draw pool specific fixed ('distortion' or 'instrument') effects $\tilde{\varphi}_j$ from a standard normal distribution.[37]
5. We generate default events for the assets in the pool from which the impairment of a tranche is derived in the following way:

(a) Firstly we randomly draw time series of realizations for the common risk factors X_{jt} for the pools.[38] The conditional probability of default (CPD) of each borrower within asset pool j is computed as

$$CPD_{jt}(X_{jt}) = \Phi\left(\frac{\tilde{c}_{jt} - \sqrt{\rho}X_{jt}}{\sqrt{1-\rho}}\right) \quad (17)$$

$\tilde{c}_{jt}$ is the default threshold. This threshold would equal a constant c in the case where the model is correctly specified by the rating agency, i.e., when there is no other effect present besides the one measured by the rating according to the attachment level. To control for macroeconomic fixed time effects we add the $\tilde{\xi}_t$ to the constant c such that $\tilde{c}_{jt} = c + \tilde{\xi}_t$. Hence, the default probabilities of the pools simultaneously change over time via the fixed effects by which a co-movement of the pools is introduced. The results are reported in Table 13. In Table 14, we also include pool specific heterogeneity by adding the 'distortion' or 'instrument' variable $\tilde{\varphi}_j$ leading to $\tilde{c}_{jt} = c + \tilde{\varphi}_j + \tilde{\xi}_t$.

(b) The number of defaults in pool j $(j = 1,..., J)$ is randomly drawn from a (conditional) binomial distribution with K assets and probability equal to the CPD. The default rate is computed by dividing the number of defaults by the number of assets in the pool.

(c) For the realized default rate of each pool we note if a tranche in a pool is impaired.

6. We run the Probit regression of tranche impairments on ratings, fixed year effects (which act as controls for the effects $\tilde{\xi}_t$), and the additional variables $\tilde{\varphi}_j$.

[36] The standard deviation was chosen to match empirical data. Other values were tested with similar results.

[37] The standard deviation was chosen to match empirical data. Other values were tested with similar results.

[38] Please note that X_{jt} are independent over pools and time. Serial co-movement is introduced through $\tilde{\xi}_t$.

7. Steps 5 and 6 are repeated 1,000 times for varying pool sizes, varying numbers of pools, and various parameter settings. The parameter estimates are summarized and reported.

The default probabilities of the assets in the pool are set to $\pi = 5\%$ and the asset return correlation is set to $\rho = 0.2$. Unless noted otherwise, the number of portfolio assets in each pool is $K = 10{,}000$. The number of pools is $J = 1{,}000$ and number of years is $T = 10$ per simulation run.

The empirical analysis is based on a Probit link function between impairment probabilities and explanatory variables. A frequently used alternative to the Probit function is the Logit function which exhibits wider tails. We therefore run the simulations generated under the above model and estimate the model i) under the default generating Probit link function and ii) under a mis-specified logistic regression with Logit function.

The results from the Monte-Carlo simulation with 1,000 iterations is shown in Table 13 where only the time effects are included in the data generating process (and *not* the pool specific effects), that is, $\tilde{c}_{jt} = c + \tilde{\xi}_t$. The left part contains in Column 1 the averages of the 1,000 estimates for the intercept, fixed effects for year 2 to 10 (denoted t2 to t10), and rating grades B to E for the Probit specification. The intercept measures the reference category which is year 1 and rating grade A. In addition, we include a randomly generated distortion or instrumental variables $\tilde{\varphi}_j$ in the *regression* to test whether an effect which should not be significant is detected to be significant under our model mis-specifications. Column 2 provides the empirical standard deviation of the simulated sample of the 1,000 estimates. Column 3 shows the average of the 1,000 estimated standard deviations for each parameter estimate. Column 4 gives the fraction of rejections of the null hypothesis that the respective parameter equals zero at a significance level of 5%. Thus, we expect the true null hypothesis to be rejected in about 5% of all iterations.

The table shows that most of the year fixed effects are significant (rejection rates between 20% and 100%). The coefficients for the ratings are increasing with decreasing credit quality. The average coefficient for the instrument is close to zero as expected and the true null is rejected in about 5% of all cases. From comparing columns 2 and 3 we see that the averages of the standard deviations of the estimates (in column 3) are close to their 'true' standard deviations which are measured by their empirical standard deviation (in column 2). The right hand side of the table contains in Columns 1 to 4 the analogous estimation results if a Logit specification is used in the estimation. The coefficients and the standard deviations of the Logit model are on an absolute scale larger throughout. However, the percentages of rejections of the null hypotheses are quite similar to the Probit model. We therefore conclude that the specification of the linking function of the regression model does not alter the results. This is particularly important for the instrumental variable which is included as it should be significantly different from zero in less than 5% of all cases. Thus, a true null is not rejected in more cases than given by the size of the test. A variable which does not explain the risk of the tranches is not spuriously identified to do so by the test as it does not enter the default generating process of Equation (17).

The previous examples considered significance of the instrumental variable when it does not have an effect on the 'true' risk, i.e., it is included in the empirical regression model but not in the model which generated the defaults according to Equation (17). To check the power of the test (i.e., to see whether a variable is detected to be significant when it *should* be significant because it is also present in the default generating process) we include the pool specific distortions $\tilde{\varphi}_j$ in the regressions *and* in Equation (17), that is, $\tilde{c}_{jt} = c + \tilde{\varphi}_j + \tilde{\xi}_t$. That is, it should empirically be detected to explain default risk in addition to the ratings as it now enters the default generating process. Table 14 shows the results for this case. While the coefficients for the time and the rating effects show similar behavior as before, the instrumental variable is now different from zero in 100% of all regressions with an average coefficient of -2.41 (Probit) and -3.99 (Logit). This shows that a variable which is driving defaults in addition to ratings is detected to be significant with a large probability (e.g., subordination in our empirical analysis). This holds for the true model (Probit) and for a mis-specified model (Logit).

3.4.3 Mis-Specification of Number of Portfolio Assets

Earlier in the paper we used the assumption of an infinite number of assets within a pool which leads together with the homogeneity assumption to the closed form solution for the tranche attachment probability in Equation (10). We additionally simulate the defaults for asset pool sizes of 100 and 1,000 respectively, where we assume again that pools are homogeneous. The pool distortion parameter $\tilde{\varphi}_j$ enters only the regression model and not the 'true' risk model. Table 15 shows the results for the Probit model (1,000 asset in the left part, 100 assets in the right part). As a result, the estimates for the coefficients and the standard deviation differ only slightly whereas the rejection rates for the instrumental variable are around 5%. A variable which does not drive defaults will not be detected to be significantly different from zero in the regression with higher probability than given by the size of the test, even if the pool is smaller than assumed in the large homogeneous model. This supports the robustness of the empirical approach with regard to the assumption of an infinite large pool which was used to derive the Probit model.

3.4.4 Mis-Specification of Dependence Assumptions in the Pool

Another potential criticism concerns the distributional assumptions of our model, particularly the dependence between assets in the pools. For deriving the probability of a tranche default we applied a standard Gaussian copula model with normally distributed risk factors which might be oversimplified.

Particularly, it may be argued that there is evidence that copulas other than the Gaussian describe credit risk, credit spreads and dependencies more accurately (compare e.g., Hull and White, 2004). A mis-specification of model assumptions might create spurious results in our Probit regression which assumes normality. We analyze this criticism by using a double T copula as a representative for other models. This copula exhibits strong tail dependence in contrast to the Gaussian copula. We therefore generate asset returns by

$$\tilde{R}_{kt} = \sqrt{\frac{\nu}{\psi_{t,\nu}}}\left(\sqrt{\rho}X_t + \sqrt{1-\rho}\varepsilon_{kt}\right) \tag{18}$$

where ν is an integer denoting the degrees of freedom, and $\psi_{t,\nu}$ is a random variable which is χ^2-distributed with ν degrees of freedom. A borrower k defaults when his asset return crosses a threshold $T_\nu^{-1}(\pi)$ where T_ν^{-1} denotes the inverse of the Student-T cumulative distribution function with ν degrees of freedom. Hence, asset returns follow a Student-T copula. Defaults in the pools are then generated as above (but using the Student-T copula) and the simple (mis-specified) Probit model (or Logit model, respectively) is estimated. The parameter ν is set to 5 in order to produce high tail dependence.

Table 16 and 17 show the results for the base case where the instrumental variable does not enter the 'true' risk (i.e., the default generating process) of the pools, and the case where it influences pools risk, respectively. We also show the Probit and the Logit specification to contrast the result. The results are very similar to the former ones with correct specification of the distributional assumption (normality). In the first case the instrument is significant in about 5% of all cases, in the second case it is significant in 100% of all cases. Hence, we conclude that the presented approach is robust with regard to the mis-specification of the dependence structure of the assets.

4. Discussion and Outlook

To date, empirical evidence on the accuracy of ratings and risk models for securitizations is limited. The article's main objective is to analyze the impact of idiosyncratic and systematic risk characteristics on impairment risk of securitizations using a large empirical dataset.

The most substantial findings are that CRA ratings for securitizations do not fully account for the average credit quality in asset portfolios and the structure of asset securitizations. Asset portfolios follow specific business cycles and similar ratings which relate to different asset classes at a given point in time may relate to different stages of the business cycle and therefore risk. The results are robust with regard to tranche dependencies (within a given transaction), number of portfolio assets and distributional assumptions.

In addition, credit ratings measure a too low impairment risk level at origination when fee revenue is high and if a securitization was originated in a high securitization activity year. Generally speaking, this underestimation of risk coincides with periods of high fee revenue.

In the broader context, CRA ratings as well as many other commercial vendor solutions may have to be interpreted in relation to the invested resources. Please note that the major CRAs cover a large number of rated debt issuers and issues per year[39] with a limited number of financial analysts[40]. Despite this criticism, this paper has also shown that ratings are informative with regard to the average idiosyncratic impairment risk over the business cycle.

Consequences from the findings of the papers relate to establishment of rating standards for CRA's and higher transparency of their employed approaches, models and parameters, along with more prudential supervision. This paper has shown that the 'paid-by-originator' approach is a source for misaligned incentives. This may be addressed i) ex ante by switching to a 'paid-by-investors' approach or ii) ex post by a tax for risk under-representation.

CRAs publish histories of their financial risk measures as well as the respective realizations. Little is known of the quality of models of other vendors as well as financial institution internal models as the respective information is kept private. However, recent negative earnings announcements of financial institutions suggest that other models applied in industry share similar properties to CRA assessments. Model outputs should be used with caution and a formal validation of such models is important.

[39] For instance, in 2007, Moody's Investors Service rated 100 sovereigns; 12,000 corporate issuers; 29,000 public finance issues; and 96,000 structured finance obligations.

[40] For instance, in 2007, Moody's Investors Service employed approximately 1,000 analysts.

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Table 1. Origination Volume, Outstanding Volume and CRA Structured Finance Fee Revenue, Various Categories

This table shows the Origination volume, outstanding volume and structured finance fee revenue of the CRA Moody's Investors Service. Origination numbers relate to the year starting from the time that a rating was first assigned. Origination numbers have increased prior to the GFC and decreased during the GFC. Outstanding numbers relate to issues which are rated at the beginning of the year and hence originated in prior years. Outstanding numbers have increased during the whole observation period. SF stands for structured finance (securitization) rating revenues and PPI stand for Public, Project & Infrastructure rating revenues. SF rating fee revenues have increased prior to the GFC and decreased during the GFC.

	Origination volume			Outstanding volume			CRA fee revenue (in $ m)			
Year	Tranches	Deals	Volume (in $ bn)	Tranches	Deals	Volume (in $ bn)	SF	Corporate	Financials	PPI
1997	2,704	582	243	10,957	2,958	959				
1998	2,501	559	269	12,839	3,360	1,130	143	144	90	65
1999	2,665	574	271	13,855	3,702	1,298	172	166	105	60
2000	2,674	582	302	14,941	3,944	1,441	199	163	112	46
2001	4,533	761	402	16,309	4,193	1,579	274	226	131	64
2002	5,727	855	477	18,814	4,536	1,782	384	228	155	81
2003	6,783	1,014	537	21,416	4,888	2,012	475	267	181	87
2004	9,599	1,189	781	22,728	5,065	2,202	553	300	209	82
2005	16,597	1,617	1,301	28,302	5,438	2,565	709	277	214	185
2006	19,929	1,827	1,491	41,247	6,312	3,401	873	336	233	198
2007	12,958	1,405	1,126	57,661	7,511	4,380	873	412	274	221
2008	1,014	231	199	66,374	8,453	5,067	411	301	263	230
Total	87,684	11,196	7,399	325,443	60,360	27,816	5,066	2,817	1,967	1,319

Table 2. Variables, Values and Definitions of Empirical Analysis

This table shows the variables, values and definitions used in the empirical analysis.

Variable	Values	Definition
Impairment	1: impairment, 0: no impairment	Indicates whether a tranche is impaired in the observation year;
Rating 1	Aaa, Aa, A, Baa, Ba, B, Caa	Rating at the origination of the transaction reflects the risk of a tranche and is measured at origination of the respective tranche.
Rating 2	Aaa, Aa, A, Baa, Ba, B, Caa	Rating at the beginning of the respective year reflects the risk of a tranche and is measured at the beginning of an observation year.
Deal category	ABS: asset backed security, CDO: collateralized debt obligation, CMBS: commercial mortgage-backed security, HEL: home equity loan security, RMBS: residential mortgage-backed	Indicates the nature of underlying asset portfolios. In the empirical analysis, the categories RMBS and CMBS are aggregated to category MBS due to the limited number of past impairment events in these categories.
Resecuritization	1: resecuritization, 0: no resecuritization	Indicates whether a transaction is a resecuritization of previous transactions. These transactions are often called 'squared' (e.g., CDO-squared). The database allows for the identification of resecuritizations for CDO and MBS transactions.
Deal size:	Metric	Indicates the inflation-adjusted logarithm of the size of the underlying asset portfolio;
Subordination	Metric, between zero and one	Indicates the relative size (in relation to the deal size) of the tranches that are subordinated to the respective tranche.
Thickness	Metric, between zero and one	Indicates the relative size (in relation to the deal size) of the respective tranche;
Origination year	Integer, 1997-2008	Year in which a tranche was first rated which coincides with the year in which transaction was closed.
TSO	Integer, positive	Time since origination indicates the time in years since a tranche was first rated;
SVO	Metric	Securitization volume at origination indicates logarithm of the volume of rated tranches for a given year. Alternative indicators of origination volumes such as the number of originated tranches or transactions were tested for robustness and resulted in similar results.
GDP	Metric	Growth rate of real GDP
PCR	Metric	Principal change to collateral change ratio. Compare Equation (13). Changes relate to origination.
IRR	Metric	Interest rate change ratio. Compare Equation (16). Changes relate to origination.

Table 3. Total Number of Observations, Relative Frequencies of Ratings at Origination and Ratings at the Beginning of the Year

This table shows the total number of observations and the relative frequencies of ratings at origination and at the beginning of the year. The panel data is based on securitizations rated by CRA Moody's Investors Service. The following observations were excluded: i) transaction observations which can not be placed into the categories asset-backed security, collateralized debt obligation, commercial mortgage-backed security, residential mortgage-backed security or home equity loan security; ii) transaction observations where the monetary volume and therefore relative credit enhancement and thickness of individual tranches could not be determined without setting additional assumptions; iii) transaction observations which are not based on the currency USD or transaction observations which are not originated in the USA; iv) tranche observations which relate to years prior to 1997 due to a limited number of observations, v) tranche observations which have experienced an impairment event in prior years. The number of rated tranches has increased at an increasing rate. The rating quality of rated tranches has generally decreased over time as a smaller fraction of tranches are rated Aaa.

Panel A: Rating at Origination								
Year	All	Aaa	Aa	A	Baa	Ba	B	Caa
1997	10,957	69.66%	16.72%	6.20%	5.04%	1.58%	0.80%	0.00%
1998	12,839	69.41%	15.02%	6.82%	5.97%	1.79%	0.97%	0.01%
1999	13,855	67.10%	13.95%	7.87%	7.28%	2.41%	1.34%	0.04%
2000	14,941	64.86%	12.76%	8.96%	8.49%	3.00%	1.84%	0.09%
2001	16,309	62.50%	12.17%	9.91%	9.67%	3.59%	2.06%	0.10%
2002	18,814	60.31%	11.45%	10.73%	11.04%	4.26%	2.10%	0.10%
2003	21,416	57.49%	11.26%	11.95%	12.16%	4.70%	2.32%	0.11%
2004	22,728	53.78%	11.39%	13.38%	13.89%	4.90%	2.55%	0.11%
2005	28,302	51.08%	12.06%	14.12%	15.21%	4.98%	2.47%	0.07%
2006	41,247	50.04%	13.48%	13.88%	15.43%	5.14%	1.99%	0.04%
2007	57,661	47.43%	15.07%	14.48%	15.86%	5.46%	1.66%	0.03%
2008	66,374	47.25%	16.18%	14.38%	14.89%	4.99%	2.02%	0.29%
Total	325,443	58.41%	13.46%	11.06%	11.25%	3.90%	1.84%	0.08%

Panel B: Rating at the beginning of a year								
Year	All	Aaa	Aa	A	Baa	Ba	B	Caa
1997	10,957	72.09%	13.50%	6.74%	4.74%	1.93%	1.00%	0.00%
1998	12,839	72.57%	11.37%	7.24%	5.76%	1.94%	1.11%	0.01%
1999	13,855	70.70%	10.04%	8.05%	6.79%	2.79%	1.52%	0.10%
2000	14,941	68.04%	9.46%	9.02%	8.33%	2.94%	1.93%	0.28%
2001	16,309	65.95%	9.01%	9.97%	8.92%	3.78%	2.13%	0.25%
2002	18,814	63.03%	9.00%	10.76%	10.28%	4.44%	2.21%	0.27%
2003	21,416	58.92%	9.51%	11.88%	11.67%	4.89%	2.68%	0.44%
2004	22,728	53.96%	10.35%	13.20%	13.21%	5.31%	3.24%	0.74%
2005	28,302	51.24%	11.25%	13.86%	14.39%	5.34%	3.05%	0.87%
2006	41,247	50.70%	12.81%	13.56%	14.66%	5.31%	2.34%	0.62%
2007	57,661	48.61%	14.61%	14.00%	14.91%	5.51%	1.93%	0.44%
2008	66,374	48.23%	15.63%	12.12%	12.68%	6.16%	3.89%	1.29%
Total	325,443	60.34%	11.38%	10.87%	10.53%	4.19%	2.25%	0.44%

Table 4. Total Number of Observations, Relative Frequencies of Asset Portfolio and Securitization Characteristics

This table shows the total number of observations and the relative frequencies of asset portfolio and securitization characteristics. Asset portfolio characteristics are the asset portfolio category, the resecuritization status and the asset portfolio size. The asset portfolio categories are asset backed security (ABS), collateralized debt obligation (CDO), commercial mortgage-backed security (CMBS), home equity loan security (HEL) and residential mortgage-backed security (RMBS). The resecuritization status indicates whether a transaction is a resecuritization of previous transactions or a primary securitization. The asset portfolio size is categorized into Small (inflation-adjusted asset portfolio size less than or equal to $500 million), Medium (asset portfolio size greater than $500 million and less than or equal to $1,000 million) and Big (asset portfolio size greater than $1,000 million). The number of rated tranches has increased at an increasing rate. The relative frequency of CDO and HEL has increased. The relative frequency of resecuritizations has generally decreased. The asset portfolio size has increased.

Securitization characteristics are the subordination level, the thickness and the origination year. The subordination level Junior indicates that a tranche attaches between 0 and 5%, Mezzanine indicates that a tranche attaches between 5% and 30% and Senior indicates that a tranche attaches between 30% and 100%. The relative frequency of mezzanine and thin tranches has increased.

Panel A: Asset portfolio characteristics

Year	All	ABS	CDO	CMBS	HEL	RMBS	Sec.	Re-Sec.	Small	Medium	Big
1997	10,957	17.03%	0.77%	2.92%	14.88%	64.41%	93.01%	6.99%	79.55%	15.80%	4.65%
1998	12,839	20.05%	1.16%	4.15%	18.70%	55.94%	94.34%	5.66%	75.91%	18.40%	5.69%
1999	13,855	22.29%	2.36%	6.05%	21.52%	47.78%	95.51%	4.49%	72.39%	20.27%	7.34%
2000	14,941	23.97%	4.69%	8.28%	22.07%	40.99%	96.31%	3.69%	69.47%	22.46%	8.07%
2001	16,309	24.29%	6.97%	9.60%	21.94%	37.19%	96.87%	3.13%	68.61%	22.92%	8.47%
2002	18,814	21.95%	8.77%	11.43%	20.75%	37.11%	97.47%	2.53%	64.87%	25.76%	9.37%
2003	21,416	19.91%	9.96%	12.49%	20.83%	36.81%	97.87%	2.13%	61.16%	28.52%	10.32%
2004	22,728	18.73%	11.83%	13.24%	24.17%	32.03%	97.95%	2.05%	55.39%	31.34%	13.27%
2005	28,302	14.17%	12.14%	13.20%	28.26%	32.23%	98.32%	1.68%	49.68%	33.31%	17.02%
2006	41,247	9.53%	11.00%	11.35%	30.42%	37.69%	98.85%	1.15%	43.58%	35.66%	20.76%
2007	57,661	6.75%	11.40%	10.38%	31.80%	39.67%	98.97%	1.03%	39.99%	37.45%	22.56%
2008	66,374	6.11%	12.10%	10.70%	29.76%	41.33%	98.85%	1.15%	39.65%	37.29%	23.07%
Total	325,443	17.06%	7.76%	9.48%	23.76%	41.93%	97.03%	2.97%	60.02%	27.43%	12.55%

Panel B: Securitization characteristics

Year	All	Junior	Mezzanine	Senior	Thin	Thick	OY <= 2004	OY 2005	OY 2006	OY 2007
1997	10,957	30.51%	38.49%	31.00%	35.43%	64.57%	100.00%	0.00%	0.00%	0.00%
1998	12,839	28.23%	39.82%	31.95%	34.88%	65.12%	100.00%	0.00%	0.00%	0.00%
1999	13,855	27.82%	42.24%	29.94%	35.22%	64.78%	100.00%	0.00%	0.00%	0.00%
2000	14,941	26.56%	44.85%	28.59%	36.51%	63.49%	100.00%	0.00%	0.00%	0.00%
2001	16,309	25.19%	47.05%	27.76%	38.18%	61.82%	100.00%	0.00%	0.00%	0.00%
2002	18,814	24.26%	48.86%	26.87%	42.18%	57.82%	100.00%	0.00%	0.00%	0.00%
2003	21,416	24.47%	49.61%	25.92%	45.60%	54.40%	100.00%	0.00%	0.00%	0.00%
2004	22,728	24.98%	49.50%	25.52%	46.44%	53.56%	100.00%	0.00%	0.00%	0.00%
2005	28,302	24.24%	50.58%	25.19%	51.09%	48.91%	100.00%	0.00%	0.00%	0.00%
2006	41,247	22.10%	51.01%	26.89%	57.52%	42.48%	59.76%	40.24%	0.00%	0.00%
2007	57,661	22.47%	51.28%	26.25%	61.73%	38.27%	37.35%	28.09%	34.56%	0.00%
2008	66,374	21.28%	52.27%	26.44%	62.16%	37.84%	29.14%	23.29%	28.04%	19.52%
Total	325,443	25.18%	47.13%	27.69%	45.58%	54.42%	85.52%	7.64%	5.22%	1.63%

Table 5. Impairment Rates for All Observations, Per Rating at Origination and Rating at the Beginning of the Year

This table shows impairment rates for all observations, per rating at origination and at the beginning of the year. The impairment rate is the ratio between the number of impairment events and the total number of observations in a given category and observation year. Impairment events '[...]fall into one of two categories, principal impairments and interest impairments. Principal impairments include securities that have suffered principal write-downs or principal losses at maturity and securities that have been downgraded to Ca/C, even if they have not yet experienced an interest shortfall or principal write-down. Interest impairments, or interest-impaired securities, include securities that are not principal impaired and have experienced only interest shortfalls.' (compare Moody's Investors Service, 2008).

Impairment rates are high in 2002 and 2007/2008. Impairment rates increase from rating category Aaa to C and fluctuate over time. The rating categories Aaa, Aa and A are aggregated into one category Aaa-A due to the limited number of impairment events.

Panel A: Rating at Origination

Year	All	Aaa-A	Baa	Ba	B	Caa
1997	0.27%	0.00%	2.17%	4.62%	11.36%	0.00%
1998	0.19%	0.03%	1.83%	1.74%	2.40%	0.00%
1999	0.35%	0.15%	1.88%	2.40%	1.08%	0.00%
2000	0.31%	0.08%	0.95%	3.79%	2.55%	0.00%
2001	0.58%	0.07%	2.47%	2.74%	8.63%	5.88%
2002	1.08%	0.10%	4.77%	7.61%	7.09%	0.00%
2003	0.85%	0.19%	3.88%	2.88%	3.02%	20.83%
2004	0.94%	0.61%	1.55%	2.70%	3.11%	26.92%
2005	0.27%	0.07%	0.95%	0.43%	1.86%	5.00%
2006	0.20%	0.07%	0.41%	0.57%	2.68%	0.00%
2007	2.49%	0.48%	7.37%	16.80%	1.77%	0.00%
2008	16.02%	9.88%	38.05%	36.96%	28.07%	90.63%
Total	1.96%	0.17%	2.57%	4.21%	4.14%	5.33%

Panel B: Rating at the beginning of a year

Year	All	Aaa-A	Baa	Ba	B	Caa
1997	0.27%	0.00%	0.39%	6.64%	12.73%	0.00%
1998	0.19%	0.03%	1.08%	4.42%	2.10%	0.00%
1999	0.35%	0.06%	1.70%	2.84%	5.21%	21.43%
2000	0.31%	0.02%	0.56%	2.96%	3.13%	35.71%
2001	0.58%	0.06%	2.13%	3.57%	8.36%	12.50%
2002	1.08%	0.06%	2.43%	11.72%	8.89%	26.00%
2003	0.85%	0.05%	2.16%	4.96%	8.00%	23.16%
2004	0.94%	0.27%	1.37%	3.07%	5.30%	28.99%
2005	0.27%	0.00%	0.17%	0.79%	2.89%	13.06%
2006	0.20%	0.00%	0.12%	0.50%	2.07%	17.25%
2007	2.49%	0.44%	7.20%	16.49%	4.68%	16.73%
2008	16.02%	7.53%	34.11%	45.93%	55.16%	77.84%
Total	1.96%	0.09%	1.75%	5.27%	5.76%	17.71%

Table 6. Impairment Rates for All Observations as Well as Asset Portfolio and Securitization Characteristics

This table shows the impairment rates for all observations, per deal and tranche characteristics. Impairment rates are high in 2002 and 2007/2008. Impairment rates per rating category fluctuate over time. Impairment rates per asset portfolio type increase in 2002 for CDOs and in 2008 for CDOs, HELs and MBSs. The asset classes CMBS and RMBS are aggregated to the category MBS due to the limited number of impairment events. The impairment rate has increased in 2008 especially for resecuritizations, all subordination levels and tranches originated in years prior to the GFC.

Panel A: Asset portfolio characteristics

Year	All	ABS	CDO	HEL	MBS	Sec.	Re-Sec.	Small	Medium	Big
1997	10,957	0.00%	0.00%	1.41%	0.09%	0.29%	0.00%	0.34%	0.00%	0.00%
1998	12,839	0.16%	0.00%	0.79%	0.03%	0.20%	0.14%	0.26%	0.00%	0.00%
1999	13,855	0.36%	0.61%	0.97%	0.08%	0.36%	0.00%	0.47%	0.04%	0.00%
2000	14,941	0.42%	1.43%	0.49%	0.07%	0.30%	0.54%	0.41%	0.03%	0.17%
2001	16,309	0.73%	3.96%	0.34%	0.12%	0.60%	0.20%	0.71%	0.27%	0.43%
2002	18,814	2.15%	4.91%	0.36%	0.22%	1.11%	0.00%	1.36%	0.62%	0.45%
2003	21,416	2.18%	1.97%	0.58%	0.21%	0.87%	0.22%	0.94%	0.72%	0.72%
2004	22,728	3.27%	1.56%	0.20%	0.20%	0.95%	0.21%	1.28%	0.55%	0.43%
2005	28,302	0.45%	0.58%	0.21%	0.17%	0.28%	0.00%	0.37%	0.16%	0.21%
2006	41,247	0.69%	0.26%	0.16%	0.11%	0.20%	0.00%	0.25%	0.21%	0.07%
2007	57,661	0.46%	4.67%	5.53%	0.33%	2.51%	0.17%	2.74%	2.44%	2.12%
2008	66,374	0.17%	24.93%	29.00%	8.39%	15.98%	19.40%	13.50%	18.65%	16.11%
Total	325,443	0.92%	3.74%	3.34%	0.83%	1.97%	1.74%	1.89%	1.97%	1.73%

Panel B: Securitization characteristics

Year	All	Junior	Mezzanine	Senior	Thin	Thick	OY <= 2004	OY 2005	OY 2006	OY 2007
1997	10,957	0.90%	0.00%	0.00%	0.46%	0.17%	0.27%			
1998	12,839	0.52%	0.12%	0.00%	0.33%	0.12%	0.19%			
1999	13,855	0.73%	0.32%	0.02%	0.41%	0.31%	0.35%			
2000	14,941	0.96%	0.12%	0.00%	0.33%	0.30%	0.31%			
2001	16,309	1.53%	0.42%	0.00%	0.75%	0.48%	0.58%			
2002	18,814	3.40%	0.50%	0.06%	1.68%	0.65%	1.08%			
2003	21,416	1.95%	0.75%	0.02%	1.23%	0.54%	0.85%			
2004	22,728	1.60%	0.97%	0.22%	1.14%	0.76%	0.94%			
2005	28,302	0.73%	0.18%	0.01%	0.41%	0.12%	0.27%			
2006	41,247	0.61%	0.11%	0.02%	0.21%	0.18%	0.32%	0.01%		
2007	57,661	8.56%	1.09%	0.03%	3.80%	0.37%	0.83%	0.62%	5.79%	
2008	66,374	40.08%	13.55%	1.54%	22.97%	4.62%	2.92%	11.55%	26.50%	25.88%
Total	325,443	5.13%	1.51%	0.16%	2.81%	0.72%	0.74%	4.06%	16.14%	25.88%

Table 7. The Link between Impairment Risk, CRA Ratings and Rating Year

This table shows parameter estimates for the Probit models Model 1 to Model 2. The model specification is $P(D_{ijt} = 1) = \Phi(\beta' x_{ijt})$. Standard errors are given below the parameter estimates. The significance is indicated as follows: ***: significant at 1%, **: significant at 5%, *: significant at 10%. AUROC is the area under the receiver operating characteristic curve (see Agresti,1984).

Model 1 shows that CRA ratings explain the credit risk over time. Model 2 and Model 3 show that CRA ratings do not fully include time varying (e.g., macro economic information).

Variable	Model 1	Model 2	Model 3
Intercept	-2.1517***	-3.2346***	-1.3178***
	0.0062	0.0741	0.0126
Baa	0.8351***	1.0397***	0.83093***
	0.0107	0.0133	0.01119
Ba	1.1900***	1.4301***	1.19363***
	0.0133	0.0163	0.01385
B	1.3276***	1.5209***	1.37058***
	0.0167	0.0202	0.0174
Caa	2.0038***	2.2803***	2.05554***
	0.0287	0.0344	0.02942
1998		-0.1159	
		0.1051	
1999		0.0142	
		0.0933	
2000		-0.1526	
		0.0955	
2001		0.1083	
		0.0855	
2002		0.3217***	
		0.0804	
2003		0.1596**	
		0.0807	
2004		0.1622**	
		0.0796	
2005		-0.4408***	
		0.087	
2006		-0.5317***	
		0.0859	
2007		0.6662***	
		0.0749	
2008		1.7862***	
		0.0741	
GDP			-38.1515***
			0.5727
Pseudo R-square	0.0520	0.1220	0.0680
R-square rescaled	0.1818	0.4265	0.2376
AUROC	0.7688	0.9231	0.81262

Table 8. The Link between Impairment Risk, CRA Ratings, Asset Portfolio and Securitization Characteristics, with Rating Year Fixed Effects

This table shows parameter estimates for the Probit model Model 4 to Model 8. The model specification is $P(D_{ijt} = 1) = \Phi(\beta' x_{ijt})$. Standard errors are given below the parameter estimates. The significance is indicated as follows: ***: significant at 1%, **: significant at 5%, *: significant at 10%. AUROC is the area under the receiver operating characteristic curve (see Agresti, 1984).

The inclusion of asset portfolio (Model 4 and 6) and securitization (Model 5 and 6) characteristics after controlling for credit rating and rating year explains impairment risk. The ramifications are that CRA ratings do not sufficiently account for the impairment risk stipulated by asset portfolio and securitization characteristics for given rating years. The division of the data into pre-GFC and GFC years shows that the asset portfolio characteristics (asset portfolio category, resecuritization status and deal size) are cyclical as the parameter sign changes while the securitization characteristics are not cyclical. CRAs are unable to measure both relationships.

Variable	Model 4	Model 5	Model 6	Model 7 (prior GFC)	Model 8 (GFC)
Intercept	-5.6417***	-2.8000***	-4.5874***	0.2176***	-7.0547***
	0.1575	0.0750	0.1694	0.3047	0.2006
Baa	0.9849***	0.6949***	0.5668***	0.8263***	0.5472***
	0.0138	0.0143	0.0152	0.0481	0.0169
Ba	1.4267***	1.0748***	0.9934***	1.4125***	0.9244***
	0.0170	0.0172	0.0183	0.0510	0.0208
B	1.6326***	1.1510***	1.2224***	1.8561***	1.0900***
	0.0216	0.0212	0.0228	0.0558	0.0268
Caa	2.3478***	1.9833***	1.9779***	2.5822***	1.7801***
	0.0365	0.0356	0.0382	0.0665	0.0495
CDO	0.5059***		0.5925***	-0.3066***	2.1625***
	0.0263		0.0274	0.0428	0.0801
HEL	0.5885***		0.4660***	-0.4728***	1.9970***
	0.0245		0.0252	0.0419	0.0789
MBS	-0.2606***		-0.4380***	-1.1824***	1.0394***
	0.0253		0.0262	0.0475	0.0791
Resecuritisation	0.2355***		0.3450***	-0.0909	0.3954***
	0.0528		0.0561	0.1530	0.0634
Deal size	0.1220***		0.0994***	-0.1383***	0.1657***
	0.0071		0.0077	0.0151	0.0090
Subordination		-2.6234***	-3.4892***	-1.4095***	-4.0653***
		0.0602	0.0792	0.1708	0.0935
Thickness		-0.5138***	-0.6260***	-0.5851***	-0.5317***
		0.0388	0.0454	0.0893	0.0538
Year Dummies	Yes	Yes	Yes	Yes	Yes
Pseudo R-square	0.1355	0.1328	0.1476	0.0246	0.2231
R-square rescaled	0.4735	0.4643	0.5159	0.4048	0.4729
AUROC	0.9427	0.9416	0.9540	0.9507	0.9171

Table 9. The Link between Impairment Risk, CRA Ratings and Origination Year

This table shows parameter estimates for the Probit model Model 9 to Model 11. The model specification is $P(D_{ijt} = 1) = \Phi(\beta' x_{ijt})$. Standard errors are given below the parameter estimates. The significance is indicated as follows: ***: significant at 1%, **: significant at 5%, *: significant at 10%. AUROC is the area under the receiver operating characteristic curve (see Agresti,1984).

The risk of securitization differs for each origination year (OY) and CRAs are unable to measure this element. PCR is the ratio of changes in principal to changes in collateral of the underlying loans and IRR is the change of interest. All changes relate to the period from origination to observation.

Variable	Model 9	Model 10	Model 11
Intercept	-3.2346***	-3.3453***	-4.3966***
	0.0741	0.0770	0.0879
Baa	1.0397***	1.1717***	1.1329***
	0.0133	0.0146	0.0142
Ba	1.4301***	1.5794***	1.5525***
	0.0163	0.0178	0.0174
B	1.5209***	1.7628***	1.7611***
	0.0202	0.0224	0.0220
Caa	2.2803***	2.7181***	2.7570***
	0.0344	0.0394	0.0395
OY 1998		0.1171***	
		0.0477	
OY 1999		0.1160***	
		0.0469	
OY 2000		0.0866*	
		0.0474	
OY 2001		-0.0878*	
		0.0488	
OY 2002		0.0282	
		0.0490	
OY 2003		-0.0233	
		0.0521	
OY 2004		0.1029**	
		0.0497	
OY 2005		0.8465***	
		0.0445	
OY 2006		1.5317***	
		0.0435	
OY 2007		1.5700***	
		0.0447	
PCR			1.5902***
			0.0371
IRR			-0.2879***
			0.0106
Year Dummies	Yes	Yes	Yes
Pseudo R-square	0.1220	0.1440	0.1399
R-square rescaled	0.4265	0.5035	0.4883
AUROC	0.9231	0.9479	0.9431

Table 10. The Link between Impairment Risk, CRA Ratings and Incentive Characteristics (Cont.)

This table shows parameter estimates for the Probit model Model 12 to Model 20. The model specification is $P(D_{ijt} = 1) = \Phi(\beta' x_{ijt})$. Standard errors are given below the parameter estimates. The significance is indicated as follows: ***: significant at 1%, **: significant at 5%, *: significant at 10%. AUROC is the area under the receiver operating characteristic curve (see Agresti, 1984).

The first panel (all years) shows that the impairment risk given ratings (i.e., which is not explained by ratings) decreases with time since origination. This confirms that CRAs may have an incentive to assign i) too low risk ratings in origination years to increase fee revenue and ii) too high risk ratings in monitoring years to maintain stable default and rating migration performance measures. The second and third panel show that this effect is mainly driven by the occurrence of the GFC. In addition, impairment risk given ratings increases with the securitization activity at origination. This result holds for all years, the years before and during the GFC.

		All years			prior GFC			GFC	
Variable	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20
Intercept	-2.6666***	-20.5275***	-14.5172***	-3.3839***	-8.3009***	-10.6136***	-1.9064***	-25.7527***	-15.6255***
	0.0781	0.2852	0.3355	0.0824	0.5122	0.5702	0.0176	0.3568	0.4297
Baa	1.0849***	1.1121***	1.1182***	1.0418***	1.0367***	1.1168***	1.1585***	1.1516***	1.1845***
	0.0139	0.0138	0.0140	0.0421	0.0417	0.0432	0.0154	0.0151	0.0155
Ba	1.5241***	1.5944***	1.5976***	1.5260***	1.5595***	1.6511***	1.5786***	1.6101***	1.6337***
	0.0170	0.0173	0.0175	0.0430	0.0432	0.0454	0.0197	0.0197	0.0202
B	1.7323***	1.8604***	1.8897***	1.7317***	1.8248***	1.9094***	1.7911***	1.8360***	1.9216***
	0.0215	0.0225	0.0228	0.0458	0.0474	0.0491	0.0264	0.0266	0.0279
Caa	3.0060***	2.8240***	3.1527***	2.6315***	2.8019***	2.7880***	3.1612***	2.7189***	3.3976***
	0.0417	0.0397	0.0437	0.0604	0.0628	0.0629	0.0612	0.0518	0.0688
TSO	-0.2554***		-0.1692***	0.0274***		0.0644***	-0.3807***		-0.2996***
	0.0042		0.0049	0.0057		0.0062	0.0055		0.0063
SVO		0.7006***	0.4759***		0.2062***	0.2901***		0.8718***	0.5094***
		0.0109	0.0129		0.0206	0.0224		0.0133	0.0159
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-square	0.1360	0.1364	0.1400	0.0195	0.0200	0.0204	0.2031	0.1933	0.2103
R-square rescaled	0.4755	0.4767	0.4895	0.3213	0.3285	0.3362	0.4305	0.4098	0.4458
AUROC	0.9399	0.9376	0.9424	0.9184	0.9181	0.9187	0.8953	0.8790	0.9008

Table 11. Robustness Test for the Link between Impairment Risk, CRA Ratings, Asset Portfolio and Securitization Characteristics, with Rating Year Fixed Effects

This table shows parameter estimates for the Probit model Model 4 to Model 8. Only one randomly selected tranche per deal is included to control for dependence between tranches. The model specification is $P(D_{ijt} = 1) = \Phi(\beta' x_{ijt})$. Standard errors are given below the parameter estimates. The significance is indicated as follows: ***: significant at 1%, **: significant at 5%, *: significant at 10%. AUROC is the area under the receiver operating characteristic curve (see Agresti, 1984).

The inclusion of asset portfolio (Model 4 and 6) and securitization (Model 5 and 6) characteristics after controlling for credit rating and rating year explains impairment risk. The ramifications are that CRA ratings do not sufficiently account for the impairment risk stipulated by asset portfolio and securitization characteristics for given rating years. The division of the data into pre-GFC and GFC years shows that the asset portfolio characteristics (asset portfolio category, resecuritization status and deal size) are cyclical as the parameter sign changes while the securitization characteristics are not cyclical. CRAs are unable to measure both relationships.

Variable	Model 4	Model 5	Model 6	Model 7 (prior GFC)	Model 8 (GFC)
Intercept	-7.0316***	-2.8732***	-5.6843***	-1.7997***	-8.7709***
	0.3535	0.1645	0.3890	0.6256	0.4989
Baa	0.9381***	0.7271***	0.6587***	1.1967***	0.5727***
	0.0380	0.0383	0.0406	0.1028	0.0489
Ba	1.4119***	1.1809***	1.1323***	1.7434***	0.9840***
	0.0463	0.0458	0.0488	0.1112	0.0604
B	1.6333***	1.3177***	1.3888***	2.1168***	1.2445***
	0.0575	0.0560	0.0594	0.1227	0.0791
Caa	2.1581***	1.9367***	1.9867***	2.7284***	1.7406***
	0.0762	0.0744	0.0789	0.1340	0.1126
CDO	0.6431***		0.6762***	-0.1155	1.9106***
	0.0542		0.0555	0.0834	0.1445
HEL	0.6314***		0.5211***	-0.1457*	1.7066***
	0.0521		0.0527	0.0838	0.1426
MBS	-0.1163**		-0.2406***	-0.9734***	0.9063***
	0.0567		0.0581	0.1044	0.1448
Resecuritisation	0.2307**		0.2944***	-0.1536	0.4634***
	0.0987		0.1020	0.2786	0.1192
Deal size	0.1889***		0.1442***	-0.0601**	0.2523 ***
	0.0162		0.0178	0.0305	0.0230
Subordination		-1.5296***	-1.9999***	-0.9157***	-2.3570***
		0.1248	0.1545	0.3168	0.1877
Thickness		-0.7323***	-0.5970***	-0.3828***	-0.6537***
		0.0615	0.0701	0.1185	0.0927
Year Dummies	Yes	Yes	Yes	Yes	Yes
Pseudo R-square	0.0932	0.0895	0.0986	0.0277	0.1851
R-square rescaled	0.4498	0.4317	0.4759	0.4129	0.4386
AUROC	0.9490	0.9460	0.9540	0.9460	0.9120

Table 12. Robustness Test for the Link between Impairment Risk, CRA Ratings and Incentive Characteristics

This table shows parameter estimates for the Probit model Model 12 to Model 20. Only one randomly selected tranche per deal is included to control for dependence between tranches. The model specification is $P(D_{ijt}=1)=\Phi(\beta' x_{ijt})$. Standard errors are given below the parameter estimates. The significance is indicated as follows: ***: significant at 1%, **: significant at 5%, *: significant at 10%. AUROC is the area under the receiver operating characteristic curve (see Agresti, 1984).

The first panel (all years) shows that the impairment risk given ratings (i.e., which is not explained by ratings) decreases with time since origination. This confirms that CRAs may have an incentive to assign i) too low risk ratings in origination years to increase fee revenue and ii) too high risk ratings in monitoring years to maintain stable default and rating migration performance measures. The second and third panel show that this effect is mainly driven by occurrence of the GFC. In addition, impairment risk given ratings increases with the securitization activity at origination. This result holds for all years, the years before and during the GFC.

		All years			prior GFC			GFC	
Variable	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20
Intercept	-2.7695***	-16.8314***	-10.9480***	-3.5097***	-6.1942***	-6.4569***	-1.8889***	-25.7616***	-14.7603***
	0.1694	0.6352	0.7887	0.1913	0.8705	1.0051	0.0517	0.9420	1.2060
Baa	0.9605***	1.0082***	0.9933***	1.2990***	1.3226***	1.3309***	0.9593***	0.9786***	0.9860***
	0.0378	0.0376	0.0381	0.0925	0.0920	0.0934	0.0453	0.0452	0.0458
Ba	1.4578***	1.5151***	1.5039***	1.7804***	1.8230***	1.8314***	1.4051***	1.4197***	1.4263***
	0.0460	0.0464	0.0468	0.0977	0.0984	0.1000	0.0581	0.0580	0.0590
B	1.7701***	1.8030***	1.8565***	1.9924***	2.0497***	2.0544***	1.8243***	1.7369***	1.8874***
	0.0585	0.0591	0.0602	0.1050	0.1074	0.1078	0.0817	0.0795	0.0842
Caa	2.6612***	2.4474***	2.6958***	2.7356***	2.7905***	2.7850***	2.7892***	2.3359***	2.8239***
	0.0847	0.0793	0.0856	0.1257	0.1272	0.1275	0.1292	0.1123	0.1337
TSO	-0.1960***		-0.1272***	-0.0122		0.0071	-0.3194***		-0.2163***
	0.0087		0.0104	0.0113		0.0127	0.0130		0.0159
SVO		0.5496***	0.3270***		0.1090***	0.1186***		0.8762***	0.4775***
		0.0244	0.0304		0.0349	0.0394		0.0352	0.0447
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-square	0.0942	0.0936	0.0961	0.0242	0.0244	0.0244	0.1742	0.1701	0.1805
R-square rescaled	0.4547	0.4519	0.4639	0.3617	0.3648	0.3648	0.4128	0.4030	0.4277
AUROC	0.9460	0.9440	0.9490	0.9390	0.9400	0.9400	0.8980	0.8930	0.9090

Table 13. Robustness Test 2a: Mis-Specification of Probit Function, without Pool-Specific Distortion

This table shows results from a Monte-Carlo simulation with 1,000 iterations. The left panel shows results from the Probit models, the right panel shows the results from the Logit models. Column 1 contains the averages of the 1,000 parameter estimates. Column 2 shows their empirical standard deviation over the 1,000 samples. Column 3 contains the averages of the 1,000 estimates for the standard deviations. Column 4 gives the fraction of rejection of the Null hypothesis that the respective parameter equals zero. t2 to t10 denote the coefficients for the time dummies, B to E are the coefficients for the rating grades B to E. Year 1 and rating grade A is the reference category represented by the intercept. 'Instrument' is an additional randomly drawn regressor or distortion.

	K=10,000 assets							
	Probit				Logit			
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
Intercept	-2.7446	0.1305	0.1265	1.0000	-5.6050	0.3644	0.3494	1.0000
t2	0.0569	0.0675	0.0690	0.1260	0.0963	0.1151	0.1174	0.1210
t3	0.2455	0.0697	0.0687	0.9300	0.4165	0.1181	0.1171	0.9300
t4	-0.0149	0.0662	0.0691	0.0480	-0.0256	0.1131	0.1177	0.0480
t5	0.2518	0.0695	0.0687	0.9540	0.4265	0.1174	0.1171	0.9520
t6	0.4095	0.0691	0.0688	1.0000	0.6949	0.1183	0.1174	1.0000
t7	-0.0204	0.0686	0.0691	0.0620	-0.0346	0.1166	0.1177	0.0570
t8	-0.0102	0.0698	0.0691	0.0530	-0.0174	0.1185	0.1177	0.0530
t9	-0.1156	0.0675	0.0694	0.3790	-0.1959	0.1153	0.1183	0.3740
t10	0.1779	0.0703	0.0688	0.7240	0.3013	0.1190	0.1171	0.7240
B	1.5416	0.1256	0.1218	1.0000	3.5765	0.3596	0.3461	1.0000
C	2.2699	0.1237	0.1202	1.0000	4.8311	0.3557	0.3431	1.0000
D	2.7420	0.1241	0.1201	1.0000	5.5924	0.3571	0.3429	1.0000
E	3.6339	0.1238	0.1216	1.0000	7.0864	0.3560	0.3454	1.0000
Instrument	-0.0002	0.0155	0.0150	0.0470	-0.0003	0.0259	0.0256	0.0520

Table 14. Robustness Test 2b: Mis-Specification of Probit Function, with Pool-Specific Distortion

This table shows results from a Monte-Carlo simulation with 1,000 iterations. The left panel shows results from the Probit models, the right panel shows the results from the Logit models. Column 1 contains the averages of the 1,000 parameter estimates. Column 2 shows their empirical standard deviation over the 1,000 samples. Column 3 contains the averages of the 1,000 estimates for the standard deviations. Column 4 gives the fraction of rejection of the Null hypothesis that the respective parameter equals zero. t2 to t10 denote the coefficients for the time dummies, B to E are the coefficients for the rating grades B to E. Year 1 and rating grade A is the reference category represented by the intercept. 'Instrument' is an additional randomly drawn regressor or distortion.

	K=10,000 assets							
	Probit				Logit			
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
Intercept	-2.9112	0.0951	0.0952	1.0000	-5.1959	0.1730	0.1771	1.0000
t2	0.2619	0.0880	0.0890	0.8400	0.4663	0.1581	0.1586	0.8380
t3	0.0770	0.0911	0.0893	0.1380	0.1365	0.1641	0.1591	0.1460
t4	0.2963	0.0888	0.0890	0.9190	0.5276	0.1597	0.1586	0.9150
t5	-0.0272	0.0897	0.0895	0.0650	-0.0490	0.1605	0.1595	0.0630
t6	-0.1514	0.0887	0.0899	0.3870	-0.2697	0.159	0.1602	0.3970
t7	0.2577	0.0896	0.0890	0.8260	0.4592	0.1615	0.1586	0.8280
t8	0.3320	0.0900	0.0889	0.9670	0.5906	0.1619	0.1585	0.9670
t9	-0.16983	0.0844	0.0899	0.4590	-0.3033	0.1516	0.1602	0.4610
t10	0.5260	0.0891	0.0890	1.0000	0.9366	0.1609	0.1587	1.0000
B	1.5176	0.0772	0.0762	1.0000	2.7199	0.1396	0.1391	1.0000
C	2.2464	0.0815	0.0794	1.0000	4.01029	0.1482	0.1468	1.0000
D	2.7212	0.0852	0.0829	1.0000	4.8523	0.1549	0.1549	1.0000
E	3.6159	0.0933	0.0919	1.0000	6.4576	0.1722	0.1758	1.0000
Instrument	-2.241	0.0438	0.0447	1.0000	-3.9945	0.0826	0.0883	1.0000

Table 15. Robustness Test 3: Large Pool Assumption

This table shows results from a Monte-Carlo simulation with 1,000 iterations. The left panel shows results from the Probit models for pool size with K=1,000 assets, the right panel shows the results from the Probit models for pool size with K=100 assets. Column 1 contains the averages of the 1,000 parameter estimates, Column 2 shows their empirical standard deviation over the 1,000 iterations. Column 3 contains the averages of the 1,000 estimates for the standard deviations. Column 4 gives the fraction of rejection of the Null hypothesis that the respective parameter equals zero. t2 to t10 denote the coefficients for the time dummies, B to E are the coefficients for the rating grades B to E. Year 1 and rating grade A is the reference category represented by the intercept. 'Instrument' is an additional randomly drawn regressor or distortion.

	K=1,000 assets					K=100 assets			
	Probit					Probit			
	[1]	[2]	[3]	[4]		[1]	[2]	[3]	[4]
Intercept	-2.7080	0.1973	0.2056	0.9980	Intercept	-2.4957	0.1123	0.1125	1.0000
t2	-0.0993	0.0718	0.0692	0.2960	t2	0.1318	0.0669	0.0680	0.4800
t3	-0.3177	0.0695	0.0701	0.9930	t3	-0.0378	0.0677	0.0681	0.0830
t4	-0.0288	0.0687	0.0690	0.0620	t4	-0.2373	0.0685	0.0685	0.9290
t5	0.2390	0.0709	0.0686	0.9340	t5	0.0397	0.0676	0.0680	0.0890
t6	-0.2060	0.0705	0.0695	0.8220	t6	0.1750	0.0665	0.0680	0.7350
t7	-0.0890	0.0710	0.0691	0.2550	t7	-0.2615	0.0693	0.0685	0.9670
t8	-0.0373	0.0710	0.0690	0.0980	t8	-0.1343	0.0654	0.0682	0.4940
t9	0.1624	0.0692	0.0686	0.6510	t9	-0.2996	0.0690	0.0687	0.9910
t10	-0.2792	0.0718	0.0699	0.9770	t10	0.1832	0.0666	0.0680	0.7760
B	1.5475	0.1925	0.2029	0.9980	B	1.5212	0.1095	0.1083	1.0000
C	2.2756	0.1947	0.2011	0.9980	C	2.2482	0.1096	0.1067	1.0000
D	2.7470	0.1934	0.2008	0.9980	D	2.7158	0.1087	0.1067	1.0000
E	3.6381	0.1952	0.2019	0.9980	E	3.5602	0.1109	0.1085	1.0000
Instrument	-0.0008	0.0153	0.0157	0.0490	Instrument	0.0004	0.0148	0.0150	0.0510

Table 16. Robustness Test 4a: Dependence Assumption

This table shows results from a Monte-Carlo simulation with 1,000 iterations where the dependence assumptions of the model are violated. The true default generating process applies a Student-T copula while the empirical model assumes either a Probit (normality) or a Logit model. The left panel shows results for the Probit specification, the right panel shows the results for the Logit specification. Column 1 contains the averages of the 1,000 parameter estimates. Column 2 shows their empirical standard deviation over the 1,000 samples. Column 3 contains the averages of the 1,000 estimates for the standard deviations. Column 4 gives the fraction of rejection of the Null hypothesis that the respective parameter equals zero. t2 to t10 denote the coefficients for the time dummies, B to E are the coefficients for the rating grades B to E. Year 1 and rating grade A is the reference category represented by the intercept. 'Instrument' is an additional randomly drawn regressor or distortion.

	K=10,000 assets							
	Probit				Logit			
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
Intercept	-2.2011	0.0767	0.0765	1.0000	-4.0574	0.1643	0.1641	1.0000
t2	-0.0059	0.0681	0.0676	0.0490	-0.0099	0.1158	0.1152	0.0450
t3	0.2715	0.0660	0.0660	0.9840	0.4552	0.1117	0.1116	0.9840
t4	0.2507	0.0681	0.0661	0.9670	0.4203	0.1147	0.1118	0.9670
t5	0.4176	0.0670	0.0654	1.0000	0.6991	0.1136	0.1106	1.0000
t6	0.4216	0.0677	0.0654	1.0000	0.7059	0.1147	0.1106	1.0000
t7	0.3239	0.0683	0.0657	0.9970	0.5423	0.1158	0.1112	0.9950
t8	0.0344	0.0661	0.0674	0.0750	0.0581	0.1120	0.1145	0.0750
t9	0.3079	0.0668	0.0658	1.0000	0.5154	0.1130	0.1113	1.0000
t10	0.1644	0.0663	0.0665	0.6830	0.2763	0.1129	0.1127	0.6750
B	0.9865	0.0683	0.0692	1.0000	2.0290	0.1546	0.1559	1.0000
C	1.4352	0.0662	0.0674	1.0000	2.8027	0.1501	0.1518	1.0000
D	1.7182	0.0667	0.0668	1.0000	3.2659	0.1513	0.1507	1.0000
E	2.2403	0.0683	0.0669	1.0000	4.1058	0.1537	0.1508	1.0000
Instrument	0.0000	0.0141	0.0142	0.0530	0.0001	0.0239	0.0240	0.0510

Table 17. Robustness Test 4b: Dependence Assumption

This table shows results from 1,000 Monte-Carlo simulations when the dependence assumptions of the model are violated. True default generating process is from a Student-T copula, empirical model assumes either Probit (normality) or Logit model. The left panel shows results from the Probit specification, the right panel shows the results from the Logit specification. Column[1] contains the averages of the 1,000 parameter estimates. Column 2 shows their empirical standard deviation over the 1,000 samples. Column 3 contains the averages of the 1,000 estimates for the standard deviations. Column 4 gives the fraction of rejection of the Null hypothesis that the respective parameter equals zero. t2 to t10 denote the coefficients for the time dummies, B to E are the coefficients for the rating grades B to E. Year 1 and rating grade A is the reference category represented by the intercept. 'Instrument' is an additional randomly drawn regressor or distortion.

	K=10,000 assets							
	Probit				Logit			
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
Intercept	-1.8443	0.0701	0.0720	1.0000	-3.2244	0.1249	0.1300	1.0000
t2	-0.2284	0.0756	0.0752	0.8590	-0.3988	0.1327	0.1316	0.8540
t3	-0.2003	0.0740	0.0750	0.7710	-0.3500	0.1305	0.1313	0.7580
t4	-0.0719	0.0754	0.0745	0.1630	-0.1256	0.1325	0.1303	0.1610
t5	-0.0096	0.0753	0.0743	0.0580	-0.0162	0.1321	0.1298	0.0540
t6	-0.1902	0.0767	0.0750	0.7130	-0.3324	0.1352	0.1312	0.7090
t7	0.0122	0.0758	0.0742	0.0590	0.0212	0.1337	0.1297	0.0640
t8	-0.0497	0.0749	0.0744	0.1010	-0.0869	0.1318	0.1301	0.1030
t9	-0.1806	0.0781	0.0750	0.6610	-0.3150	0.1373	0.1312	0.6600
t10	-0.1010	0.0774	0.0746	0.2810	-0.1760	0.1361	0.1305	0.2840
B	0.9107	0.0605	0.0620	1.0000	1.6036	0.1084	0.1114	1.0000
C	1.3440	0.0617	0.0617	1.0000	2.3587	0.1102	0.1113	1.0000
D	1.6260	0.0623	0.0621	1.0000	2.8493	0.1116	0.1126	1.0000
E	2.1537	0.0630	0.0641	1.0000	3.7682	0.1139	0.1177	1.0000
Instrument	-1.3314	0.0259	0.0262	1.0000	-2.3261	0.0478	0.0501	1.0000

Figure 1. Origination Volume, Outstanding Volume and CRA Structured Finance Fee Revenue

This chart shows the origination volume, outstanding volume and structured finance fee revenue of the CRA Moody's Investors Service. Origination volume relates to the year that a rating was first assigned. Origination volume has increased prior to the GFC and decreased during the GFC. Outstanding numbers relate to issues which are rated at the beginning of the year and hence are originated in prior years. Outstanding volume has increased during the whole observation period. Origination volume and structured finance fee revenues have increased prior to the GFC and decreased during the GFC. Therefore, structured finance fee revenue coincides more with the origination volume than the outstanding volume. This is in line with the recognition of the majority of fee revenue at or shortly after origination by the CRA for accounting purposes.