Rating performance and agency incentives of structured finance transactions

Daniel Rösch [a] Harald Scheule [b] [1]

[a] *Institute of Banking & Finance, Leibniz University of Hannover, Königsworther Platz 1, 30167 Hannover, Germany, Phone: +49-511-762-4668, Fax: +49-511-762-4670. mailto: Daniel.Roesch@finance.uni-hannover.de*

[b] *Department of Finance, Faculty of Economics and Commerce, University of Melbourne, Victoria 3010, Australia, Phone: +61-3-8344-9078, Fax: +61-3-8344-6914, mailto: hscheule@unimelb.edu.au*

[1] The authors would like to thank the participants of financial seminars at the Deutsche Bundesbank, Global Association of Risk Professionals, Leibniz University Hannover, Melbourne Centre for Financial Studies and The University of Melbourne as well as the discussants of various conferences for valuable comments. The paper was presented and discussed at the C.R.E.D.I.T. 2009 conference, the Asian Finance 2009 conference and International Risk Management Conference 2009. The support of the Melbourne Centre for Financial Studies and the Hong Kong Institute for Monetary Research is gratefully acknowledged.

Rating performance and agency incentives of structured finance transactions

Abstract

The mismatch between credit ratings of structured finance transactions and their true risks has been a source of the Global Financial Crisis which manifested in criticism of models and techniques applied by credit rating agencies (CRA). This paper provides an empirical study which assesses the historical performance of credit ratings for structured finance transactions and finds that CRAs do not include all factors explaining securitization impairment risk. In addition, CRA ratings for selected asset categories underestimate risk in origination years when the fee revenue is high.

Key words: Asset-backed Security, Collateralized Debt Obligation, Economic Downturn, Fee Revenue, Forecasting, Global Financial Crisis, Home Equity Loans, Impairment Rate, Mortgage-backed Security, Structured Finance Rating

JEL classification: G20, G28, C51

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 (structured finance transactions). This is of highest importance as past shortcomings may have been instrumental to past, current and future loss rates of financial institutions in relation to securitizations. Structured finance ratings and associated fee revenue have experienced an unprecedented growth in past years and dominate today in terms of numbers as well as CRA fee revenue. [2]

The Global Financial Crisis (GFC) led to an unprecedented and unexpected increase of impairment and loss rates for securitizations. The disappointment of investors manifested in the criticism of models applied by credit rating agencies (CRAs). 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). Similar critique has been put forward 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 have occurred subsequent to the crisis.

Securitizations involve the sale of assets into 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 (HEL) and mortgage-backed securities (MBS). Despite their name, securitizations are generally over-the-counter contracts and involve funded as well as unfunded risk transfers. Therefore, no secondary market prices are available. Counterparties publish accounting values for funded, and to a lesser degree for unfunded transactions. [3] Information is generally available to measure the risk of securitizations and includes credit ratings, impairment histories

[2] For example, in the financial year 2007, CRA Moody's Investor Services has generated a fee revenue of $873.3 million for structured finance ratings, $411.5 million for corporate issuer and issue ratings, $274.3 million for financial institution issuer and issue ratings and $220.8 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.

[3] The latter are accounted for off-balance sheet and thus only included in the notes of annual reports.

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 (i.e., the funded or unfunded exposures of investors and guarantors) is complicated by the low liquidity of the underlying assets, the unavailability of secondary markets and the recent origination of such transactions.

Two main streams exist in literature on the measurement of financial risks of securitizations. The first stream focuses on the pricing of structured finance transactions where the central issue is to explain observed (market) prices such as credit spreads of credit default swap (CDS) indices. The most prominent examples are the CDX North America and iTraxx Europe indices, which reference firm portfolios. These indices were originated in 2003 and 2004. Credit spreads for the index as well as tranches are available daily. Longstaff & Rajan (2008) and Hull & 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.

The second 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 & Turnbull (1995), Longstaff & Schwartz (1995), Madan & Unal (1995), Leland & Toft (1996), Jarrow et al. (1997), Duffie & Singleton (1999), Shumway (2001), McNeil & Wendin (2007) and Duffie et al. (2007) address the default likelihood. Dietsch & Petey (2004) and McNeil & Wendin (2007) model the correlations between default events. Carey (1998), Acharya et al. (2007), Pan & Singleton (2008), Qi & Yang (2009) and Grunert & Weber (2009) 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 as explanations of financial risk. Ratings measure the financial 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 beyond question. Previous research focuses on the degree to which corporate credit rating changes introduce new information. For example, Radelet & 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 & Goh (1993), Dichev & Piotroski (2001) and Purda (2007) find that corporate credit rating downgrades provide news to the market. 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 & Ozdemir (2002) examine the effect of divergent Moody's and S&P ratings of banks.

With regard to the GFC, Rajan et al. (2008) show that 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 & Dlugosz (2008) analyze collateralized loan obligations (CLOs) rated by Standard and Poor's and find a mismatch between credit ratings and the quality of the underlying loan portfolios. Crouhy et al. (2008) point out that CRAs' fee revenues depend on the number of ratings and may be supported by higher ratings. Similarly, Franke & Krahnen (2008) argue that incentive effects 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.

Unfortunately, the literature has not yet analyzed CRA ratings of securitizations and their accuracy. This paper addresses this shortcoming. Based on the rating and impairment data of one CRA, cross-sectional and time-series characteristics of ratings, implied impairment rate estimates and realized impairment rates of asset portfolio securitizations are compared and analyzed.

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

2 Model Framework and Hypothesis Development

2.1 Model for the asset pool

Structured finance transactions are investments in special purpose companies investing the funds in a portfolio of assets. These investments cover, within legal maturities, losses to the asset portfolio in excess of a retention (also known as attachment or subordination level) and up to a limit (also known as detachment level). The paper refers to the entire transaction as 'deal' and the individual investment segment as 'tranche'. In other words, one transaction may consist of one or more tranches of various seniority levels. The asset portfolio of a deal generally consists of financial assets (e.g., loans) that are subject to financial risk (e.g., credit risk).

The major CRA models to evaluate structured finance transactions share a similar structure. 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).

Following Gordy (2000), Gordy (2003), McNeil & Wendin (2007), and Gupton et al. (1997) (CreditMetrics), credit risk of an individual borrower is modeled by a Gaussian factor model for the individual asset return based on Merton (1974). The assumption is made that borrowers are pooled into portfolios such that firms in the pool share a common systematic risk factor (see Gordy & Howells 2006). Let R_{kt} denote the asset return of borrower k in time period t belonging to asset pool i ($k = 1, ..., K; t = 1, ..., T; i = 1, ..., I$) which is generated by the following process

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

where X_{it} and ε_{kt} are standard normally distributed pool specific and idiosyncratic risk factors and ρ is a parameter denoting the correlation between asset returns which measures the strength of association between borrowers within the pool. The factors are assumed to be serially independent and independent from each other

A default event occurs if the asset return R_{kt} falls below a threshold c_{it}. The threshold may be interpreted as the credit quality. It is assumed that all assets in a portfolio are of equal credit quality c_{it} at time t for a given risk segment.[4] A borrower default event then occurs if

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

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 $\pi_{it} = \Phi(c_{it})$ where $\Phi(.)$ is the standard normal cumulative distribution function. K_{it} assets are pooled to an asset portfolio i and the pool default rate is the average over the default indicators defined as

$$P_{it} = \frac{1}{K_{it}} \sum_{k}^{K_{it}} D_{kt} \tag{4}$$

For a large number of assets in the pool the pool default rate converges against the 'Vasicek'-distribution (see Vasicek 1987, 1991, Gordy 2000, 2003) with density

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

where $\Phi^{-1}(.)$ is the inverse of the standard normal cumulative distribution function. The default rate has the cumulative distribution function (see eg. Bluhm et al. 2003)

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

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

[4] Risk segments may be defined by transaction types such as asset-backed securities (ABS), collateralized debt obligations (CDO), home equity loan-backed securities (HEL) or mortgage-backed securities (MBS).

unity.

2.2 *Model for the tranche default*

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

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

where D_{ijt} is an indicator variable with

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

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

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

Inserting Equation (9) into Equation (6) and replacing c_{it} by $\Phi^{-1}(\pi_t)$ results in

$$\begin{aligned} P(D_{ijt} = 1) &= 1 - \Phi\left(\frac{\sqrt{1-\rho}\Phi^{-1}(AL_{ijt}) - \Phi^{-1}(\pi_{it})}{\sqrt{\rho}}\right) \\ &= \Phi\left(\frac{-\sqrt{1-\rho}\Phi^{-1}(AL_{ijt}) + \Phi^{-1}(\pi_{it})}{\sqrt{\rho}}\right) \\ &= \Phi\left(\eta_{ijt}\right) \end{aligned} \tag{10}$$

where $\eta_{ijt} \equiv \frac{-\sqrt{1-\rho}\Phi^{-1}(AL_{ijt})+\Phi^{-1}(\pi_{it})}{\sqrt{\rho}}$.

Note that this probability is unconditional with respect to the pool specific factors, i.e. it does not assume that their realizations are known ex ante. Equation (10) implies that the tranche impairment probability is a function of the

- Average portfolio asset quality;

- Asset correlation;
- Attachment level of a tranche relative to the total deal principal.

A credit rating measuring the impairment risk of a securitized tranche should thus account for these factors to explain tranche impairment probabilities. On the other hand, 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 about the business cycle. Consider an error in assigning one or more of the pool parameters resulting in $\tilde{\eta}_{ijt} \neq \eta_{ijt}$ which will lead to a bias in the estimated impairment probability. Then the impairment probability can be written as

$$P(D_{ijt} = 1) = \Phi\left(\tilde{\eta}_{ijt} + \Delta_{\eta}\right) \tag{11}$$

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

2.3 Hypotheses development

The following hypotheses aim to answer whether CRA structured finance ratings (from now on referenced as 'ratings') are inaccurate and may have been causal for the Global Financial Crisis. Based on the stylized model and the previous research, the hypotheses are as follows:

- H1a: Ratings represent the average asset quality of the asset portfolio;
- H1b: Ratings represent structured finance transaction characteristics such as resecuritization status, subordination level and transaction cash flow structure;
- H2: Ratings include macroeconomic information;
- H3a: Rating standards have not declined over time;
- H3b: Ratings predict impairment risk;
- H4: Ratings indicate low risk in origination years and high risk in monitoring years.

The hypotheses H1a and H1b relate to idiosyncratic, H2 to systematic and H3a and H3b to the interaction between idiosyncratic and systematic risk characteristics of securitizations. H4 relates to incentive mechanisms induced by the fee structure for securitization ratings.

H1a addresses characteristics of the asset portfolio. Rajan et al. (2008) find that securitization risk models omit ‘soft’ information. This implies that the CRA ratings, relying on such models, mis-evaluate the average credit quality of the asset portfolio. Crouhy et al. (2008) suggest that CRAs did not monitor raw data, CRAs were tardy in recognizing the implications of the declining state of the sub-prime market for the ratings of monoline insurers, CRAs were paid by clients for ratings and that CRA competition is limited by regulation. Important drivers of asset portfolio risk may be ratings as well as other asset portfolio characteristics.

H1b addresses the tranching structure of securitizations and the current discussion on the appropriate specification of the dependence structure of various assets in a portfolio (compare Hull 2009, Hellwig 2008). The probability distribution as well as the percentiles of losses associated with the pool are particularly sensitive to the correlations in the underlying asset pool. Thus, the level of subordination may be a key driver if correlations are mis-specified and should explain tranche impairments after controlling for credit ratings.

H2 identifies the degree to which business cycles are included in CRA risk models. Previous research has analyzed whether CRA ratings for corporate issuer and bond issue ratings address the state of the economy (point-in-time rating) or not (through-the-cycle rating). An analysis of both rating paradigms is given in Loeffler (2004). While through-the-cycle ratings are often more stable through time, (see Nickell et al. 2000), they may react too slowly in economic up- or downturns. Franke & Krahnen (2008) argue that sensitivities to macroeconomic factors may be higher for securitized tranches than for corporate bonds.

H3a relates to a hypothesis suggested by various authors (e.g., Crouhy et al. 2008) that lending standards have declined in recent years. Blume et al. (1998) present a similar hypothesis for corporate bond issuers. Rajan et al. (2008) analyze individual securitized sub-prime mortgage loans and assess the performance of the FICO score[5] and loan-to-value ratio for the prediction of mortgage default events. They find that the default model performs poorly in times of higher securitization. Downing et al. (2008) present evidence for declining subordination levels for commercial MBSs.

H3b addresses the information degree of credit ratings. Hellwig (2008) argues that the omission of systematic factors related to real-estate prices such as interest rates and the availability of housing finance may have led to an overoptimism of valuations and ratings. Such expectations may be adjusted in an economic downturn.

[5] Developed by Fair, Isaac and Company.

H4 addresses a potential conflict of interest of rating agencies. Crouhy et al. (2008) argue that CRA fees are paid by issuers. This may imply that the credit quality measured by CRAs 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. Generally speaking, 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).[6] 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) low risk ratings in origination years to increase fee revenue and ii) high risk ratings in monitoring years to maintain stable default and rating migration performance measures. These measures are generally calculated as an average per rating class or per observation year.

3 Empirical analysis

3.1 Structured finance data

The paper analyzes a panel data set of structured finance transactions rated by CRA Moody's Investors Service. The data covers characteristics of transactions, characteristics of tranches, ratings of tranches over time as well as occurrences of impairment events. The time horizon is 1987-2008.

The central event in the present study is the impairment event. An impairment event is defined as (compare Moody's Investors Service 2008):

> "[...] 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-

[6] In financial year 2007, CRA Moody's Investors Service has 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.

impaired securities, include securities that are not principal impaired and have experienced only interest shortfalls."

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

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

The resulting data comprises 325,443 annual tranche observations. The number of impaired tranche observations is 13,072 while the original data set included 15,083 impairment events before the application of filtering rules.

The following categorical variables were generated:

- Impairment (1: impairment, 0: no impairment) indicates that a tranche is impaired in the observation year;
- Rating at the origination of the transaction (Aaa, Aa, A, Baa, Ba, B, Caa-C) reflects the expected loss of a tranche and is measured at the beginning of an observation year;[7]

[7] In the empirical analysis, the rating categories Aaa to A are aggregated to category Aaa-A due to the limited number of past impairment events in these categories.

- Rating at the beginning of the respective year (Aaa, Aa, A, Baa, Ba, B, Caa-C) reflects the expected loss 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 security);
- Original Rating Year (ORY; 1: transaction is originated, 0: transaction is not originated) indicates whether the transaction is originated and rated for the first time by the CRA in the observation year;
- Principal Payment Year (PPY; 1: principal is repayable, 0: principal is not repayable) indicates whether principal is repayable in the observation year;
- 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 allowed for the identification of resecuritizations for CDO and MBS transactions;
- Relative subordination level (Junior, Mezzanine and Senior) indicates the subordination level relative to the average impairment rate of an asset class (see below).

The relative subordination level (RSUB) is divided into the levels 'Junior', 'Mezzanine' and 'Senior':

$$RSUB_{it} = \begin{cases} \text{Junior} & SUB_{it} \in [0, IR_j[\\ \text{Mezzanine} & SUB_{it} \in [IR_j, k \cdot IR_j[\\ \text{Senior} & SUB_{it} \in [k \cdot IR_j, 1] \end{cases} \tag{12}$$

with the multiplier k and the average impairment rate IR_j of asset class j with $j \in \{ABS, CDO, HEL, MBS\}$. The empirical analysis applies a multiplier of $k = 2$. [8]

Table I and Table II describe the number of observations over time. The overall number of rated securitizations has increased at an increasing rate over time. Similar observations may be made for the value of securitizations. [9]

[insert Table I here]

[8] Other multipliers ($k > 2$) were used to analyze the robustness of results. The results were similar to the case presented.

[9] All tables weight individual transactions equally. The average transaction size has declined during the observation period: 1997: $87.5 million, 1998: $88.1 million, 1999: $93.7 million, 2000: $96.5 million, 2001: $96.8 million, 2002: $94.7 million, 2003: $93.9 million, 2004: $96.9 million, 2005: $90.6 million, 2006: $82.5 million, 2007: $76.0 million, and 2008: $76.3 million.

[insert Table II here]

Table I 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 asset portfolio quality, ii) a higher average risk level induced by the securitization structure (e.g., subordination, thickness or features such as embedded options, which are not addressed in this paper) or iii) a change of the rating process.

Table II shows the relative frequency of deal and transaction characteristics. Deal characteristics (Panel A) include the asset portfolio type and the resecuritization status. Generally speaking, asset portfolio securitizations are relatively heterogeneous despite the contribution by the International Swap and Derivatives Dealer Association by providing transaction templates. Retail asset portfolios generally comprise a large number of exposure amounts (e.g., 100,000) with small exposures (e.g., \$100,000) and are mainly exposed to systematic risk. Corporate/wholesale asset portfolios comprise a smaller number (e.g., 100) of exposures with large exposure amounts (e.g., \$10 million) and may be exposed to idiosyncratic as well as systematic risk. ABSs generally comprise retail asset portfolios (e.g., auto, credit card and student loans) as well as corporate/wholesale asset portfolios (e.g., equipment loans and leases). CDOs generally comprise corporate/wholesale asset portfolios (e.g., unsecured or secured corporate loan exposures). HELs include retail sub-prime mortgage portfolios while MBSs generally relate to prime mortgage portfolios of commercial (CMBS) and residential (RMBS) real estate loans. This is of high relevance as the impairment rate for HELs (next to CDOs) has increased over-proportionately. Resecuritizations have decreased over time.

Transaction characteristics (Table II, Panel B) include the subordination level, the origination year and the principal payment year The relative frequency of mezzanine tranches has increased and the one of senior tranches has decreased. Origination years increased over time and sharply dropped in 2008 due to the Global Financial Crisis. The relative frequency of principal payment years is very cyclical as investors change their maturity preferences over time.

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 as investors rely on impairment rate tables. These tables aggregate the impairment events over dimensions such as rating or observation year. 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 III and Table IV show the impairment rates over time for all tranches as well as per rating category, asset portfolio type, resecuritization status, subordination level, principal payment years and origination years.

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 airlines) and the Global Financial Crisis. With regard to the GFC, the 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. The sharp increase of impairment events in 2008 is true for most risk segments and the following analysis focuses on relative differences.

[insert Table III here]

[insert Table IV here]

Table III shows that 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 Aaa-A to Caa) and fluctuate over time. Please note that inconsistencies (e.g., a higher impairment rate for a lower risk rating in a selected year) may reflect the stochastic nature of impairment events. The latter is particularly relevant if the number of observations is low for a given category. [10]

Table IV shows the impairment rates for deal (Panel A) and transaction characteristics (Panel B). The impairment rates are fundamentally different between the various asset portfolio categories. The economic downturn in 2002 relates mainly to CDOs while the GFC has dramatically increased the impairment rates for CDOs, HELs and MBSs. HELs include sub-prime mortgage loans and the impairment risk has 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. Impairment rates of resecuritizations have increased to a larger degree in 2008.

Transaction characteristics (Table IV, Panel B) show that impairment rates have increased

[10] Such inconsistencies are in line with reports by the data-providing CRA (compare Moody's Investors Service 2008).

in 2008, especially for mezzanine and senior tranches.[11] The impairment rate has increased in 2008 particularly for original rating years and principal payment years.

3.2 H1a: Ratings represent the average asset quality of the asset portfolio

A major concern with regard to the GFC is that current credit portfolio risk models, including the models used by CRAs, do not capture credit portfolio risk accurately. If credit ratings correctly assess the impairment risk of a tranche, then the tranche impairment probability should solely be explained by the ratings. In other words, if ratings reflect the tranche impairment probability accurately, they should include the information as specified in Equation (10). Alternatively, any additional significant information indicates that ratings omit information.

The impairment of tranche j $(j = 1, ..., J_i)$ of pool i $(i = 1, ..., I)$ in time t $(t = 1, ..., T)$ is linked with observable information by the probit regression.[12]

$$P\left(D_{ijt} = 1\right) = \Phi\left(\beta' x_{ijt}\right) \tag{13}$$

where x_{ijt} is a vector of observable and thus known variables. β is the respective vector of sensitivities and includes an intercept. The models may be used for forecasting as the CRA ratings are measured at the beginning of the observation year. 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 probit regression.

Table V presents in Column 1 and Column 2 two probit models linking the impairment. Model 1 (Column 1) takes the dummy-coded ratings provided by CRAs into account. Rating Aaa-A is the reference category. 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 (AUROC) are calculated (see Agresti 1984). The parameter estimates increase from rating Aaa-A to rating Caa. This demonstrates the predictive power of ratings. Model 2 (Column 2) includes the ratings as well as the dummy-coded type of the underlying asset portfolios. The impairment likelihood of HEL is larger than CDO, which is larger than MBS, which is larger than

[11] Transactions may consist of single and multiple tranches.

[12] The models are estimated using only one tranche per pool to analyze the dependence between multiple tranches in relation to a single asset portfolio. The results are similar.

ABS (the reference category).[13]

[insert Table V here]

In summary, CRAs do not take all available asset portfolio information into account. Important ramifications are that i) CRAs may have to include asset portfolio characteristics into the rating models and ii) investors should apply asset portfolio specific impairment rates to ratings when interpreting CRA ratings.

3.3 H1b: Ratings represent structured finance transaction characteristics such as resecuritization status, subordination level and transaction cash flow structure

In order to test the hypothesis whether CRAs mis-specify structured finance transaction characteristics, three additional variables are included:

- Resecuritization: the variable indicates whether the transaction consists of a resecuritized asset portfolio. Hull (2009) suggests that resecuritizations contributed to the increased number of impaired structured finance transactions. Resecuritizations were originated to create a market for mezzanine tranches. Mezzanine tranches are generally less popular amongst investors. Thus a resecuritization often involves the tranching of a portfolio of mezzanine investment tranches. To date, no empirical evidence is available as to whether ratings for resecuritizations have the same information content as ratings for primary securitizations;
- Subordination: the metric variable represents the subordination level of the observed tranche and relates to an ongoing discussion of whether CRAs apply reasonable levels of asset correlations. Asset correlations measure the dependence between the asset performances of the portfolio underlying the transaction and are an important input parameter in the risk models of CRAs as well as many financial institutions;
- Principal payment year (PPY): securitizations may be more likely to be impaired in the principal payment year than in an interest payment year. Structured finance transactions are fundamentally different in this regard to other credit risk exposures such as corporate bonds and retail loans:
  - Retail loan repayments are generally structured as annuities and aligned with the income of a borrower. Early years relate mainly to interest payments while later years

[13] Logit models are estimated as a robustness check (i.e., nonlinear models with a logistic link function). The results are similar.

relate mainly to principal repayments. Retail borrowers who are unable to meet payment obligations may avoid impairment by refinancing or renegotiating their debt. [14]

- Corporate loans or bonds involve periodic interest payments and repayment of principal at maturity. However, bonds are issued by large corporations and financed by a portfolio of equity, hybrid capital and debt of various maturities. Corporate borrowers who are unable to meet payment obligations may avoid default by refinancing or renegotiating their debt. Please note that restructuring may or may not be a default criteria in risk models.
- Structured finance transactions are fundamentally different from retail and corporate loans as the life of the special purpose vehicles and thus the liabilities are generally termed. This implies that the liquidation value of the assets has to be sufficient to meet all contractual interest and principal payments in the final period. Impairment occurs per definition if this is not the case.

Table V confirms that impairment risk i) decreases insignificantly, if a transaction is a resecuritization (Model 3, Column 3), ii) decreaeses significantly if the subordination increases (Model 4, see column 4) and iii) increases significantly in principal payment years (Model 5, see column 5) after controlling for rating and asset portfolio characteristics. [15]

The significance of the subordination may imply that the CRA risk models do not properly include the subordination level or alternatively, the distribution of portfolio losses is mis-specified. In the instance of CRA risk models, this may imply that the Gaussian copula model may not reflect the empirical data or that a dependence parameter such as the asset correlation or the correlation between default events and loss given default may be mis-specified. Asset correlations are naturally asset specific. [16] Table VI shows the parameter estimates for Model 6, which includes the subordination level relative to the average impairment rate of a given asset class as defined in Equation (12).

[insert Table VI here]

The positive (negative) coefficient for 'Mezzanine' and 'Senior' exposures indicates that the risk is higher (lower) than reflected in CRA ratings. This implies that ratings underestimate (overestimate) the likelihood of losses in excess of the subordination level. An underestimation (overestimation) may be caused by the underestimation (overestimation) of positive

[14] Please note that restructuring may or may not be a default criteria in risk models.
[15] Model 6 (Column 6) confirms the robustness of the results by including all three variables. Interestingly, resecuritization is now significant and negative.
[16] Despite the common practice to estimate implied volatilities and correlation per tranche.

correlations between underlying stochastic asset value processes or a mis-specification of functional forms such as the copula model. The empirical results for the senior tranches may suggest with regard to the asset correlations, that the standard correlation assumptions applied by CRAs should be higher for ABS and lower for CDO, HEL and MBS securitizations.

Hence, CRAs do not take all available information on structured finance transaction characteristics into account. Similar to hypothesis H1a, important ramifications are that i) CRAs may have to include structured finance transaction characteristics into their rating models and ii) investors should apply transaction structure-specific impairment rates to CRA ratings.

3.4 H2: Ratings include macroeconomic information

CRAs are known to rate 'through-the-cycle' for corporate bonds (see e.g., Loeffler 2004) and include mainly idiosyncratic characteristics. Cyclical effects or macroeconomic information are not included as the assessment of credit quality should reflect a borrower's ability to pay based on firm fundamentals and aim to avoid rating changes over time. This explicitly includes rating changes induced by changes of the general economy. Omitting business-cycle information from ratings for securitizations may lead to the observed mismatch of the time-constant rating and cyclical impairment risk. In other words, the probit relation of Equation (13) between ratings and the impairment probability is distorted by time varying risk characteristics which are not included in the ratings.

In a next step, the model framework is extended to dependence across pools following Gordy & Howells (2006). This is modeled by decomposing the pool specific factor into

$$X_{it} = \sqrt{\delta_i} \cdot X_t^* + \sqrt{1 - \delta_i} \cdot U_{it} \tag{14}$$

where X_t^* is a univariate standard normally distributed 'super'-factor measuring the state of the economy, U_{it} is a pool specific factor, and δ_i measures the strength of dependence across pools. All factors are standard normally distributed, independent from each other and serially independent. For simplicity $\delta_i = \delta$ for all pools. Then the tranche impairment probability from Equation (10) can be stated as function of the systematic factor by

$$P(D_{ijt}=1|X_t^*) = 1-\Phi\left(\frac{\sqrt{1-\rho}\Phi^{-1}(AL_{ijt})-\Phi^{-1}(\pi_{it})-\sqrt{\rho}\sqrt{\delta}X_t^*}{\sqrt{\rho}\sqrt{1-\delta}}\right) \tag{15}$$

$$= \Phi\left(\eta_{ijt}/\sqrt{1-\delta}+b\cdot X_t^*\right) \tag{16}$$

where $b=\sqrt{\delta}/\sqrt{1-\delta}$ is the exposure to the 'super'-factor. This model specification extends the common probit model to a probit model with random effects X_t^* . Given some co-variates the regression model can be stated as

$$P\left(D_{ijt}=1|X_t^*\right) = \Phi\left(\beta' x_{ijt}+b\cdot X_t^*\right) \tag{17}$$

The parameters are estimated by the Maximum-Likelihood method.

In a first step, the stand-alone sensitivity to systematic risk (i.e., without co-variates) is estimated. The parameter estimates (Model 7) are shown in Table VII (Panel A). The first version is based on the whole data set and serves as a base case (Column 1). The estimate for the intercept is -2.4397, the estimate for the exposure to the latent factor is 0.5127 and highly significant. This shows that tranche impairment risk is driven by the overall economy. Columns 2 to 6 estimate Model 7 for data sets, which are restricted to the same rating grade. Higher rated tranches (Aaa to Ba) are more sensitive to the economy than lower rated tranches (B and Caa). Vice versa, this implies that if economic information is omitted from the ratings, a change in macroeconomic conditions will lead to a higher discrepancy of rating and true risk for the higher rated tranches. All macroeconomic exposures are significant at the 1 per cent level.

[insert Table VII here]

Table VII (Panel B) presents the estimation results of Model 7 per deal type. All macroeconomic exposures are highly significant and there is a clear difference between asset pool types. ABSs (Column 1) and MBS (Column 3) have a lower sensitivity, CDOs (Column 2) and HELs (see column 4) have a higher exposure. Hence, HELs are more sensitive to economic downturns than other securitization categories.

Table VII (Panel C) investigates whether differences exist between resecuritized deals and primary securitizations. Such structures are known as 'tranches of tranches' or 'squared' products. The intuition is that resecuritization eliminates idiosyncratic risk and therefore tranches of tranches should be exposed to a larger degree to systematic risk (see Hull 2009). The results confirm that the exposure of resecuritized tranches is 0.9058 (Column 2) and more higher than for unsecuritized tranches where it is 0.5104 (Column 1). This result is reflected in Table III (Panel A) where it can be seen that in 'normal' economic times impairment rates of the resecuritised instruments which are highly exposed to systematic risk are small while they may sharply increase during an economic downturn in 2008.

After analyzing the macroeconomic exposure of tranches in general, the degree to which business cycle information is included in CRA ratings is tested (Model 8). The exposure b of the latent factor should no longer be significant after controlling for ratings if all time-varying information (e.g., business cycle information) affecting the impairment probabilities is captured by the rating. Table VIII shows the estimates for the base case model (Model 7 without ratings, Column 1) and the model controlling for the ratings (Model 8 with ratings, Column 2). The analysis shows that ratings increase the sensitivity to the business cycle. The hypothesis that CRA ratings include time-varying systematic information on the economy is rejected. In other words, CRA ratings do not explain systematic risk components.

[insert Table VIII here]

The ramifications are that the exposure to the business cycle increases i) with a CRA rating indicating lower financial risk, ii) for sub-prime mortgage loans and iii) for resecuritizations. Thus, CRA ratings should reflect the degree of systematic risk or alternatively, investors should assign time-varying impairment rates controlling for asset portfolio type and resecuritization status next to CRA ratings.

3.5 H3a: Rating standards have not declined over time

The next hypothesis addresses the critique that rating standards of CRAs may have declined over time. The deterioration of rating quality by CRAs may have been a possible reason for the GFC. This should be reflected in a declining quality of rating standards or deteriorating quality of risk forecasts from credit ratings, particularly in the years prior to the Global Financial Crisis. In other words, the implied impairment probability and thus observed impairment rate of a given rating grade may have increased over time as the impairment risk of transactions has increased. This hypothesis is tested using a fixed effects model (Model 9) of the form

$$P\left(D_{ijt}=1\right)=\Phi\left(\alpha+\beta\cdot t\right) \tag{18}$$

where $t = (year - 1996)$ counts the number of years from the beginning of the observation period and is thus a year effect. If the sensitivity of the variable is positive, then the impairment probability of a rating grade increases over time. This may imply that in year $t+1$ the same rating grade exhibits higher impairment risk than in year t.[17] Table IX shows the results for Model 9. For all rating grades a significant positive time trend of impairment probabilities is found. For a rating grade the default probability increased through time. Therefore, the hypothesis that the rating standards have not declined over time can be rejected.

[insert Table IX here]

3.6 H3b: Ratings predict impairment risk

Ratings are generally applied as proxies for future impairment risk. The information content of corporate bond issue ratings has been analyzed by Blume et al. (1998). However, no evidence for CRA ratings on securitizations has been presented.

The forecasting power of credit ratings is tested by an approach related to Rajan et al. (2008). The approach proceeds in three steps. Firstly, a probit regression is estimated for each year

$$P\left(D_{ijt}=1\right)=\Phi\left(\beta' x_{ijt}\right) \tag{19}$$

where x_{jit} are dummy variables for the ratings, which are observed at the beginning of the observation period. Next, the linear predictor for the subsequent year is calculated:

$$\hat{\eta}_{ijt+1}=\hat{\beta}' x_{ijt+1} \tag{20}$$

and the impairment probability prediction for the subsequent year

[17] Nonlinear transformations of the time-variable are included as a robustness check. The results were comparable.

$$\hat{p}_{ijt+1} = \Phi(\hat{\beta}' x_{ijt+1}) \tag{21}$$

using the estimated coefficients $\hat{\beta}$ from (19). Finally, the forecasting power is assessed by running a probit regression (Model 10).

$$P\left(D_{ijt+1} = 1\right) = \Phi\left(\gamma_0 + \gamma_1 \hat{\eta}_{ijt+1}\right) \tag{22}$$

If the rating provides perfect forecasts, then $\gamma_0 = 0$ and $\gamma_1 = 1$, which will be tested. As a robustness check a linear regression is estimated(Model 11):

$$D_{ijt+1} = \delta_0 + \delta_1 \cdot \hat{p}_{ijt+1} + \varepsilon_{ijt+1} \tag{23}$$

so that $E(D_{ijt+1}) = P(D_{ijt+1}) = \delta_0 + \delta_1 \cdot \hat{p}_{ijt+1}$ where $\delta_0 = 0$ and $\delta_1 = 1$.

All steps are repeated for each year from 1999 to 2008 where in the probit regression (19) all data up to year t is used. Table X shows the parameter estimates from each regression Model 10 (Equation 22). Table XI contains the estimation results from each regression Model 11 (Equation 23).

[insert Table X here]

[insert Table XI here]

It can be seen that in most years, both coefficients of either regression are statistically significant and thus different from their ideal values (Columns 1 and 2). Moreover, the respective R^2s neither increase nor decrease throughout. This implies that the rating quality has neither consistently declined nor improved.[18] While for most years, the evidence of underprediction or overprediction is mixed, particularly the downturn years 2002, 2007 and 2008 exhibit a significant underestimation of risk by the ratings. If ratings predict impairment risk accurately, they should have anticipated the downturns and should have downgraded the transactions accordingly. However, the observation that the estimates of γ_0 and δ_0 are greater than zero indicates that impairment risk has been under-predicted by the ratings in these years. In summary, the analysis shows that the rating quality has neither consistently declined

[18] A comparison of the R^2s should be carefully interpreted as each year has a different number of observations.

nor improved through time. In other words, there has been a mix of years of overprediction and years of underprediction of impairment risk. This indicates that CRA ratings have a limited ability to predict impairment risk.

The ramifications are that CRAs do not predict impairment risk and that investors relying on predictions of future levels of impairment risk may have to build private models. Alternatively, CRAs may easily adjust their ratings by a projection of the future state of the economy. This may be accomplished by including time-lagged variables of the level and change of the total impairment rate.

3.7 H4: Ratings indicate low risk in origination years and high risk in monitoring years

Rating agencies face a potential conflict of interest. CRAs may have an incentive to assign i) low risk ratings in origination years to increase fee revenue and ii) high risk ratings in monitoring years to maintain stationary default and rating migration performance measures over origination and monitoring years.

In order to test the hypothesis, Model 6 is extended by an origination year effect. Table XII shows the parameter estimates for the whole data set as well as the various asset classes.

[insert Table XII here]

The parameter of the dummy variable ORY is positive and significant for the categories CDO, MBS and HEL, which suggests that the impairment risk in the origination year is higher than suggested by the CRAs. These risk segments have experienced the largest impairment rate increases (and thus disappointments of investors) during the GFC. This result suggests that ratings are overoptimistic (i.e., reflect a level of risk, which is too low) in the origination year. It should also be mentioned that the parameter estimate for ABS is negative but insignificant for ABS securitizations.

In summary, the empirical analysis finds evidence that financial risk for the asset classes CDOs, MBS and HEL is higher than indicated by ratings in the original rating year. This mis-specification of financial risk coincides with high fee revenues. Fee revenues for original rating years exceed fee revenues for monitoring years and the fees for original rating and monitoring years are paid in the original rating year. [19]

[19] Compare Footnote 2.

4 Discussion and Outlook

To date, no empirical evidence on the accuracy of ratings and risk models for securitizations exists. The article's main objective is to analyze the impact of idiosyncratic and systematic risk characteristics on impairment risk of securitizations.

The most substantial finding is that rating agencies do not include all factors explaining securitization impairment risk. In particular, the state of the economy is not addressed as CRAs average over the business cycle. Hence, CRA ratings are unable to predict impairment risk. In addition, a recent deterioration of CRA rating standards was found. Additional results are that CRA ratings for securitizations do not fully account for the average credit quality in asset portfolios and do not fully account for structural elements of structured finance transactions. Such elements include the subordination level, the resecuritization status and principal payment years.

In response to the presented hypotheses, CRA ratings for securitizations

- Do not fully account for the average credit quality in asset portfolios;
- Do not fully account for the structure of asset securitizations;
- Reflect the average impairment risk over the business cycle: risks are assessed through-the-cycle rather than point-in-time;
- Are based on rating standards, which have systematically declined over time;
- Do not predict impairment risk;
- Under-predict financial risk in origination years and over-predict risk in monitoring years for CDOs, MBS and HELs.

The findings may not be interpreted as a critique of the valuable work CRAs provide. Please note that the major CRAs cover a large number of rated debt issuers and issues per year [20] with a limited number of financial analysts [21] . These ratings may provide useful information on the average idiosyncratic impairment risk over the business cycle.

To date, only CRAs make their financial risk measures as well as the respective realizations (e.g., impairment histories) available to the general public. Little is known of the quality of models of other vendors as well as financial institution internal models as the respective

[20] For instance, in 2007, Moody's Investors Service rated 100 sovereign nations; 12,000 corporate issuers; 29,000 public finance issuers; and 96,000 structured finance obligations.
[21] For instance, in 2007, Moody's Investors Service employed more than 1,000 analysts.

information is kept private. However, recent negative earnings announcements of financial institutions suggest that other models applied in industry may share similar properties.

References

Acharya, V. V., Bharath, S. T. & Srinivasan, A. (2007), 'Does industry-wide distress affect defaulted firms? - Evidence from creditor recoveries', *Journal of Financial Economics* **85**, 787–821.

Agresti, A. (1984), *Analysis of Ordinal Categorical Data*, Wiley, New York.

Altman, E., Brady, B., Resti, A. & Sironi, A. (2005), 'The link between default and recovery rates: Theory, empirical evidence and implications', *Journal of Business* **78**, 2203–2227.

Benmelech, E. & Dlugosz, J. (2008), 'The alchemy of CDO credit ratings', *Working Paper, Harvard University* .

Bluhm, C., Overbeck, L. & Wagner, A. (2003), *An Introduction to Credit Risk Modeling*, Chapman/CRC, London.

Blume, M., Lim, F. & MacKinlay, A. (1998), 'The declining credit quality of U.S. corporate debt: Myth or reality?', *Journal of Finance* **53**, 1389–1413.

Carey, M. (1998), 'Credit risk in private debt portfolios', *Journal of Finance* **53**, 1363–1387.

Crouhy, M., Jarrow, R. & Turnbull, S. (2008), 'The Subprime Credit Crisis of 07', *Working Paper, University of Houston, Natixis and Cornell University* .

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

Dietsch, M. & Petey, J. (2004), 'Should SME exposures be treated as retail or corporate exposures? a comparative analysis of default probabilities and asset correlations in French and German SMEs', *Journal of Banking and Finance* **28**, 773–788.

Downing, C., Stanton, R. & Wallace, N. (2008), 'Volatility, mortgage default and CMBS subordination', *Working Paper, University of California at Berkeley* .

Duffie, D., Saita, L. & Wang, K. (2007), 'Multi-period corporate default prediction with stochastic covariates', *Journal of Financial Economics* **83**, 635–665.

Duffie, D. & Singleton, K. (1999), 'Modeling term structures of defaultable bonds', *Review of Financial Studies* **12**, 687–720.

Ederington, L. H. & Goh, J. C. (1993), 'Is a bond rating downgrade bad news, good news, or no news for stockholders?', *Journal of Finance* **48**, 2001–2008.

Fitch Ratings (2006), 'Exposure draft: Introducing the Fitch VECTOR Default Model Version 3.0'.

Franke, G. & Krahnen, J. (2008), 'The future of securitization', *Working Paper, Frankfurt Center for Financial Studies* .

Gordy, M. (2000), 'A comparative anatomy of credit risk models', *Journal of Banking and Finance* **24**, 119–149.

Gordy, M. (2003), 'A risk-factor model foundation for ratings-based bank capital rules', *Journal of Financial Intermediation* **12**, 199–232.

Gordy, M. & Howells, B. (2006), Procyclicality in basel ii: Can we treat the disease without killing the patient?, Technical report.

Grunert, J. & Weber, M. (2009), 'Recovery rates of commercial lending: Empirical evidence for German companies', *Journal of Banking and Finance* **33**, 505–513.

Gupton, G., Finger, C. & Bhatia, M. (1997), 'CreditMetrics technical document'.

Hellwig, M. (2008), 'Systemic risk in the financial sector: An analysis of the Subprime-Mortgage Financial Crisis', Max Planck Institute for Research on Collective Goods, Working Paper.

Hull, J. (2009), 'The credit crunch of 2007: What Went Wrong? Why? What Lessons Can Be Learned?', *Journal of Credit Risk* **5**, 3–18.

Hull, J. & White, A. (2004), 'Valuation of a CDO and nth to default CDS without monte carlo simulation', *Journal of Derivatives* **12**, 8–23.

Jarrow, R., Lando, D. & Turnbull, S. (1997), 'A Markov model for the term structure of credit risk spreads', *Review of Financial Studies* **10**, 481–523.

Jarrow, R. & Turnbull, S. (1995), 'Pricing derivatives on financial securities subject to credit risk', *Journal of Finance* **50**, 53–85.

Jorion, P., Liu, Z. & Shi, C. (2005), 'Informational effects of regulation fd: Evidence from rating agencies', *Journal of Financial Economics* **76**, 309–330.

Leland, H. (1994), 'Corporate debt value, bond covenants and optimal capital structure', *Journal of Finance* **49**, 1213–1252.

Leland, H. & Toft, K. (1996), 'Optimal capital structure, endogeneous bankruptcy, and the term structure of credit spreads', *Journal of Finance* **51**, 987–1019.

Leot, P., Arber, D. & Schou-Zibell, L. (2008), 'Securitisation in east asia, asian development bank working paper series on regional economic integration', *Asian Development Bank Working Paper Series on Regional Economic Integration* .

Loeffler, G. (2004), 'An anatomy of rating through the cycle', *Journal of Banking and Finance* **28**, 695–720.

Longstaff, F. & Rajan, A. (2008), 'An empirical analysis of the pricing of collateralized debt obligations', *Journal of Finance* **63**, 529–563.

Longstaff, F. & Schwartz, E. (1995), 'A simple approach to valuing risky fixed and floating rate debt', *Journal of Finance* **50**, 789–819.

Madan, D. & Unal, H. (1995), 'Pricing the risk of recovery in default with apr violation', *Journal of Banking and Finance* **27**, 1001–1218.

Mayer, C., Pence, K. & Sherlund, S. (2008), 'The rise in mortgage defaults: Facts and myths', *forthcoming in Journal of Economic Perspectives* .

McNeil, A. & Wendin, J. (2007), 'Bayesian inference for generalized linear mixed models of portfolio credit risk', *Journal of Empirical Finance* **14**, 131–149.

Merton, R. C. (1974), 'On the pricing of corporate debt: The risk structure of interest rates', *Journal of Finance* **29**, 449–470.

Miu, P. & Ozdemir, B. (2002), 'Rating banks, risk and uncertainty in an opaque industry', *American Economic Review* **92**, 874–888.

Moody's Investors Service (2006), 'CDOROM v2.3 user guide'.

Moody's Investors Service (2008), 'Default & loss rates of structured finance securities: 1993-2007'.

Nickell, P., Perraudin, W. & Varotto, S. (2000), 'Stability of rating transitions', *Journal of Banking and Finance* **24**, 203–227.

Pan, J. & Singleton, K. (2008), 'Default and recovery implicit in the term structure of sovereign cds spreads', *Journal of Finance* **68**, 2345–2384.

Purda, L. (2007), 'Stock market reactions to anticipated versus surprise rating changes', *Journal of Financial Research* **30**, 301–320.

Qi, M. & Yang, X. (2009), 'Loss given default of high loan-to-value residential mortgages', *Journal of Banking and Finance* **33**, 788–799.

Radelet, S. & Sachs, J. (1998), 'The East Asian Financial Crisis: Diagnosis, remedies, prospects', *Brookings Papers* **28**, 1–90.

Rajan, U., Seru, A. & Vig, V. (2008), 'The failure of models that predict failure: distance, incentives and defaults', *Working paper, University of Michigan, University of Chicago and London Business School* .

Shumway, T. (2001), 'Forecasting bankruptcy more accurately: a simple hazard-rate model', *Journal of Business* **74**, 101–124.

Standard & Poor's (2005), 'CDO Evaluator Version 3.0: Technical document.'.

Vasicek, O. (1987), Probability of loss on loan portfolio, Working paper, KMV Corporation.

Vasicek, O. (1991), Limiting loan loss probability distribution, Working paper, KMV Corporation.

Tables

Table I

Total number of observations, relative frequencies of ratings at origination and at the beginning of the year, 1997-2008

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 structured finance transactions 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-C
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-C
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 II
Total number of observations, relative frequencies of deal and transaction characteristics, 1997-2008

This table shows the total number of observations and the relative frequencies of deal and transaction characteristics. Deal characteristics are the deal category and the resecuritization status. Transaction characteristics are the subordination level, the original rating year status and the principal rating year status.

The deal 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 (1: resecuritization, 0: no resecuritization) indicates whether a transaction is a resecuritization of previous transactions. The Original Rating Year (ORY; 1: transaction is originated, 0: transaction is not originated) indicates whether the transaction is originated and rated for the first time by the CRA in the observation year. The Principal Payment Year (PPY; 1: principal is repayable, 0: principal is not repayable) indicates whether principal is repayable in the observation year. The relative subordination level (Junior, Mezzanine and Senior) indicates the subordination level relative to the average impairment rate of an asset class (compare Equation 12).

The number of rated tranches has increased at an increasing rate. The relative frequency of CDO and HEL has increased. The resecuritization level has generally decreased. The relative frequency of mezzanine tranches has increased and of and senior tranches has decreased.

Panel A: Deal characteristics

Year	All	ABS	CDO	CMBS	HEL	RMBS	Resec.=0	1
1997	10,957	17.03%	0.77%	2.92%	14.88%	64.41%	93.01%	6.99%
1998	12,839	20.05%	1.16%	4.15%	18.70%	55.94%	94.34%	5.66%
1999	13,855	22.29%	2.36%	6.05%	21.52%	47.78%	95.51%	4.49%
2000	14,941	23.97%	4.69%	8.28%	22.07%	40.99%	96.31%	3.69%
2001	16,309	24.29%	6.97%	9.60%	21.94%	37.19%	96.87%	3.13%
2002	18,814	21.95%	8.77%	11.43%	20.75%	37.11%	97.47%	2.53%
2003	21,416	19.91%	9.96%	12.49%	20.83%	36.81%	97.87%	2.13%
2004	22,728	18.73%	11.83%	13.24%	24.17%	32.03%	97.95%	2.05%
2005	28,302	14.17%	12.14%	13.20%	28.26%	32.23%	98.32%	1.68%
2006	41,247	9.53%	11.00%	11.35%	30.42%	37.69%	98.85%	1.15%
2007	57,661	6.75%	11.40%	10.38%	31.80%	39.67%	98.97%	1.03%
2008	66,374	6.11%	12.10%	10.70%	29.76%	41.33%	98.85%	1.15%
Total	325,443	17.06%	7.76%	9.48%	23.76%	41.93%	97.03%	2.97%

Panel B: Transaction characteristic

Year	All	Junior	Mezzanine	Senior	ORY=0	1	PPY=0	1
1997	10,957	23.20%	3.46%	73.34%	81.54%	18.46%	92.50%	7.50%
1998	12,839	22.29%	3.87%	73.84%	77.90%	22.10%	88.44%	11.56%
1999	13,855	22.22%	4.35%	73.44%	81.18%	18.82%	88.63%	11.37%
2000	14,941	21.62%	4.97%	73.41%	81.47%	18.53%	91.27%	8.73%
2001	16,309	21.17%	5.76%	73.06%	84.00%	16.00%	87.58%	12.42%
2002	18,814	21.24%	6.89%	71.87%	76.35%	23.65%	83.46%	16.54%
2003	21,416	22.11%	8.05%	69.84%	74.26%	25.74%	74.58%	25.42%
2004	22,728	24.82%	9.24%	65.95%	71.10%	28.90%	82.32%	17.68%
2005	28,302	25.72%	11.15%	63.13%	67.18%	32.82%	87.10%	12.90%
2006	41,247	25.25%	12.57%	62.18%	60.98%	39.02%	91.48%	8.52%
2007	57,661	26.78%	13.64%	59.58%	66.18%	33.82%	92.67%	7.33%
2008	66,374	25.43%	14.35%	60.21%	81.11%	18.89%	80.95%	19.05%
Total	325,443	23.49%	8.19%	68.32%	75.27%	24.73%	86.75%	13.25%

Table III

Impairment rates for all observations, per rating at origination and at the beginning of the year, 1997-2008

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 per rating category 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-C
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-C
1997	0.27%		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%		0.12%	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%	0.11%	1.75%	5.27%	5.76%	17.71%

Table IV
Impairment rates for all observations, per deal and transaction characteristics, 1997-2008

This table shows the impairment rates for all observations, per deal and transaction characteristics. Deal characteristics are the deal category and the resecuritization status. Transaction characteristics are the subordination level, the original rating year status and the principal rating year status. 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.
The deal 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 (1: resecuritization, 0: no resecuritization) indicates whether a transaction is a resecuritization of previous transactions. The Original Rating Year (ORY; 1: transaction is originated, 0: transaction is not originated) indicates whether the transaction is originated and rated for the first time by the CRA in the observation year. The Principal Payment Year (PPY; 1: principal is repayable, 0: principal is not repayable) indicates whether principal is repayable in the observation year. The relative subordination level (Junior, Mezzanine and Senior) indicates the subordination level relative to the average impairment rate of an asset class (compare Equation 12).
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 especially for CDOs, MBSs and HELs. The asset classes CMBS and RMBS are aggregated to the category MBS due to the limited number of impairment events. The impairment rate has particularly increased in 2008 especially for resecuritizations, all subordination levels, original rating years and principal payment years.

Panel A: Deal characteristics

Year	All	ABS	CDO	HEL	MBS	Resec.=0	1
1997	0.27%			1.41%	0.09%	0.29%	0.00%
1998	0.19%	0.16%		0.79%	0.03%	0.20%	0.14%
1999	0.35%	0.36%	0.61%	0.97%	0.08%	0.36%	0.00%
2000	0.31%	0.42%	1.43%	0.49%	0.07%	0.30%	0.54%
2001	0.58%	0.73%	3.96%	0.34%	0.12%	0.60%	0.20%
2002	1.08%	2.15%	4.91%	0.36%	0.22%	1.11%	0.00%
2003	0.85%	2.18%	1.97%	0.58%	0.21%	0.87%	0.22%
2004	0.94%	3.27%	1.56%	0.20%	0.20%	0.95%	0.21%
2005	0.27%	0.45%	0.58%	0.21%	0.17%	0.28%	0.00%
2006	0.20%	0.69%	0.26%	0.16%	0.11%	0.20%	0.00%
2007	2.49%	0.46%	4.67%	5.53%	0.33%	2.51%	0.17%
2008	16.02%	0.17%	24.93%	29.00%	8.39%	15.98%	19.40%
Total	1.96%	1.09%	2.22%	1.00%	0.15%	0.70%	1.74%

Panel B: Transaction characteristics

Year	All	Junior	Mezzanine	Senior	ORY=0	1	PPY=0	1
1997	0.27%	1.18%	0.00%	0.00%	0.34%	0.00%	0.00%	3.65%
1998	0.19%	0.73%	0.40%	0.02%	0.25%	0.00%	0.00%	1.68%
1999	0.35%	1.10%	0.33%	0.12%	0.39%	0.15%	0.02%	2.92%
2000	0.31%	1.21%	0.00%	0.06%	0.35%	0.11%	0.00%	3.53%
2001	0.58%	1.94%	0.85%	0.17%	0.69%	0.00%	0.01%	4.59%
2002	1.08%	4.30%	0.85%	0.16%	1.38%	0.13%	0.04%	6.33%
2003	0.85%	2.22%	0.41%	0.47%	1.13%	0.05%	0.08%	3.12%
2004	0.94%	1.56%	0.57%	0.75%	1.27%	0.12%	0.03%	5.18%
2005	0.27%	0.80%	0.13%	0.08%	0.41%	0.00%	0.00%	2.08%
2006	0.20%	0.49%	0.15%	0.09%	0.32%	0.01%	0.01%	2.28%
2007	2.49%	8.61%	0.81%	0.12%	0.77%	5.85%	0.03%	33.48%
2008	16.02%	46.66%	20.49%	2.02%	13.78%	25.65%	0.35%	82.62%
Total	1.96%	2.19%	0.41%	0.19%	0.66%	0.59%	0.02%	6.26%

Table V
Parameter estimates for Model 1 to Model 6

This table shows parameter estimates from the probit models Model 1 to Model 6. The model specification is $P(D_{ijt} = 1) = \Phi(\beta' x_{ijt})$. Standard errors are in parentheses. 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 deal categories are asset backed security (ABS), collateralized debt obligation (CDO), home equity loan security (HEL) and mortgage-backed security (MBS). The resecuritization status (1: resecuritization, 0: no resecuritization) indicates whether a transaction is a resecuritization of previous transactions. The Subordination indicates the fraction of tranches which are subordinate to the observed tranche. The Principal Payment Year (PPY; 1: principal is repayable, 0: principal is not repayable) indicates whether principal is repayable in the observation year.
The inclusion of deal type and structural elements after controlling for credit ratings explains impairment risk. The ramifications are that CRA ratings do not sufficiently account for the average credit quality in asset portfolios and for structural elements of securitizations.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-2.1517***	-2.7526***	-2.7525***	-2.2999***	-5.3792***	-4.8784***
	(0.0062)	(0.0217)	(0.0217)	(0.0219)	(0.0410)	(0.0406)
Baa	0.8351***	0.7665***	0.7663***	0.4011***	1.4614***	0.8678***
	(0.0107)	(0.0112)	(0.0112)	(0.0122)	(0.0195)	(0.0214)
Ba	1.1900***	1.1796***	1.1793***	0.8107***	1.8105***	1.2190***
	(0.0133)	(0.0140)	(0.0140)	(0.0148)	(0.0248)	(0.0267)
B	1.3276***	1.4386***	1.4384***	1.0722***	2.1331***	1.5404***
	(0.0167)	(0.0176)	(0.0176)	(0.0184)	(0.0332)	(0.0352)
Caa	2.0039***	2.0664***	2.0658***	1.7282***	2.6476***	2.1340***
	(0.0287)	(0.0298)	(0.0298)	(0.0306)	(0.0533)	(0.0557)
CDO		0.8693***	0.8712***	0.9516***	1.5297***	1.7869***
		(0.0239)	(0.0239)	(0.0240)	(0.0347)	(0.0352)
HEL		0.9766***	0.9765***	0.9736***	1.3014***	1.5029***
		(0.0223)	(0.0223)	(0.0221)	(0.0307)	(0.0308)
MBS		0.2611***	0.2627***	0.2542***	0.5990***	0.7674***
		(0.0227)	(0.0227)	(0.0227)	(0.0310)	(0.0312)
Resecuritisation			-0.0616			-0.3597***
			(0.0396)			(0.0681)
Subordination				-2.2553***		-3.1891***
				(0.0483)		(0.0620)
PPY					3.3434***	3.4086***
					(0.0267)	(0.0268)
Pseudo R-square	0.0520	0.0704	0.0704	0.0848	0.2030	0.2166
R-square rescaled	0.1818	0.2460	0.2460	0.2965	0.7098	0.7571
AUROC	0.7688	0.8362	0.8368	0.8754	0.9826	0.9858

Table VI
Parameter estimates for Model 6 with subordination dummy variables, per deal type

This table shows parameter estimates from the probit model Model 6 with subordination dummies for the complete data set and per asset portfolio category. The model specification is $P(D_{ijt} = 1) = \Phi(\beta' x_{ijt})$. Standard errors are in parentheses. The significance is indicated as follows: ***: significant at 1%, **: significant at 5%, *: significant at 10%. The parameter for resecuritisation can not be estimated for ABS and HEL as resecuritisations can not be identified for these categories. AUROC is the area under the receiver operating characteristic curve (see Agresti 1984).
The deal categories are asset backed security (ABS), collateralized debt obligation (CDO), home equity loan security (HEL) and mortgage-backed security (MBS). The resecuritization status (1: resecuritization, 0: no resecuritization) indicates whether a transaction is a resecuritization of previous transactions. The Subordination indicates the fraction of tranches which are subordinate to the observed tranche. The Principal Payment Year (PPY; 1: principal is repayable, 0: principal is not repayable) indicates whether principal is repayable in the observation year.
The positive (negative) coefficient for 'Mezzanine' and 'Senior' exposures indicates that the risk is higher (lower) than reflected in CRA ratings. This implies that ratings underestimate (overestimate) the likelihood of losses in excess of the subordination level. An underestimation (overestimation) may be caused by the underestimation (overestimation) of positive correlations between underlying stochastic asset value processes or a mis-specification of functional forms such as the copula model. The empirical results for the senior tranches may suggest with regard to the asset correlations, that the standard correlation assumptions applied by CRAs should be higher for ABS and lower for CDO, HEL and MBS securitizations.

	(1)	(2)	(3)	(4)	(5)
Variable	All	ABS	CDO	MBS	HEL
Intercept	-4.4862***	-5.4037***	-2.0539***	-3.7617***	-4.9686***
	(0.0425)	(0.1468)	(0.0434)	(0.0528)	(0.1087)
Baa	0.9361***	1.6439***	-0.1457***	1.1246***	1.3471***
	(0.0222)	(0.0910)	(0.0476)	(0.0392)	(0.0408)
Ba	1.2719***	2.8411***	-0.3175***	1.4710***	2.0348***
	(0.0274)	(0.1047)	(0.0567)	(0.0506)	(0.0581)
B	1.6501***	2.9505***	0.1005	1.4766***	2.5362***
	(0.0366)	(0.1220)	(0.0835)	(0.0574)	(0.0950)
Caa	2.2321***	3.4406***	0.6706***	2.2727***	2.3765***
	(0.0560)	(0.1261)	(0.0983)	(0.0929)	(0.1361)
CDO	1.2431***				
	(0.0362)				
HEL	0.9390***				
	(0.0317)				
MBS	0.4250***				
	(0.0323)				
Resecuritisation	-0.3586***		-0.0146	-1.3246***	
	(0.0654)		(0.0806)	(0.1659)	
Mezzanine	0.0487**	0.2257	-0.8224***	0.1246***	0.5985***
	(0.0236)	(0.2580)	(0.0497)	(0.0431)	(0.0406)
Senior	-1.3416***	0.3552***	-1.2657***	-1.7405***	-1.4763***
	(0.0207)	(0.0797)	(0.0477)	(0.0403)	(0.0411)
PPY	3.4119***	2.7729***	2.9209***	3.1355***	4.6154***
	(0.0271)	(0.1023)	(0.0428)	(0.0453)	(0.1045)
Obs.	325,443	43,603	31,452	164,002	86,386
Pseudo R-square	0.2166	0.0709	0.3078	0.1267	0.3611
R-square rescaled	0.7572	0.6528	0.7131	0.7366	0.8437
AUROC	0.9866	0.9758	0.9753	0.9871	0.9927

Table VII
Parameter estimates for Model 7 (random effect), per rating and deal type

This table shows parameter estimates from the random effects probit model model 7. The model specification is $P(D_{ijt} = 1|F_t) = \Phi(\alpha + b \cdot F_t)$. Standard errors are in parentheses. The significance is indicated as follows: ***: significant at 1%, **: significant at 5%, *: significant at 10%. AIC is the Akaike Information Criterion.
The deal 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 time specific random effects are significant. The ramification is that CRA ratings do not fully account for systematic risk, that systematic risk increases with rating quality, and that HEL, CDO and RMBS are more cyclical than other transaction categories.

Panel A: Rating at the beginning of the years

	(1)	(2)	(3)	(4)	(5)	(6)
Rating	All Grades	Aaa-A	Baa	Ba	B	Caa
Intercept	-2.4397***	-3.3066***	-2.1409***	-1.6311***	-1.4887***	-0.6545***
	(0.1484)	(0.2383)	(0.1979)	(0.1840)	(0.1659)	(0.1778)
b	0.5127***	0.7873***	0.6770***	0.6300***	0.5627***	0.5375***
	(0.1050)	(0.1884)	(0.1405)	(0.1301)	(0.1174)	(0.1241)
Obs.	325,443	259,647	39,472	15,960	8,349	2,015
AIC	84,153	30,858	17,594	10,780	5,810	2,059

Panel B: Deal type

	(1)	(2)	(3)	(4)
Deal Type	ABS	CDO	MBS	HEL
intercept	-2.5410***	-2.1236***	-2.8868***	-2.3594***
	(0.1234)	(0.1903)	(0.1466)	(0.1898)
b	0.4106***	0.6186***	0.4987***	0.6530***
	(0.0979)	(0.1476)	(0.1040)	(0.1339)
Obs.	43,603	31,452	164,002	86,386
AIC	4,665	13,979	23.290	34,063

Panel C: Resecuritisation

	(1)	(2)
resecuritisation	no (0)	yes (1)
intercept	-2.4331***	-3.1145***
	(0.1478)	(0.3244)
b	0.5104***	0.9058***
	(0.1045)	(0.2615)
Obs	318,560	6,883
AIC	83,230	898

Table VIII
Parameter estimates for Model 7 (random effect) and Model 8 (random effect controlling for rating)

This table shows parameter estimates from the random effects probit model Model 7 and Model 8. The model specification is $P(D_{ijt} = 1|F_t) = \Phi(\beta' x_{ijt} + b \cdot F_t)$. Standard errors are in parentheses. The significance is indicated as follows: ***: significant at 1%, **: significant at 5%, *: significant at 10%. AIC is the Akaike Information Criterion.
The time specific random effects are significant. The parameter estimate b is greater after CRA ratings are included. The ramification is that CRA ratings do not explain (and may increase) systematic risk.

	(1)	(2)
	Model 7	Model 8
intercept	-2.4397***	-3.0700***
	(0.1484)	(0.1676)
Baa		1.0396***
		(0.0133)
Ba		1.4300***
		(0.0162)
B		1.5208***
		(0.0203)
Caa		2.2800***
		(0.03396)
b	0.5127***	0.5781***
	(0.1050)	(0.1183)
Obs.	325,443	325,443
AIC	84,153	67,408

Table IX
Parameter estimates for Model 9 (controlling for time), per rating

This table shows parameter estimates from the probit model. The model specification is $P(D_{ijt} = 1) = \Phi(\alpha + \beta \cdot t)$. $t = (year - 1996)$ and counts the number of years from the beginning of the observation period and is thus a year effect. Standard errors are in parentheses. The significance is indicated as follows: ***: significant at 1%, **: significant at 5%, *: significant at 10%. AIC is the Akaike Information Criterion.
The passage of time from the beginning of the observation period is significant. The ramification is that CRA rating standards have declined over time.

	(1)	(2)	(3)	(4)	(5)	(6)
	All grades	Aaa-A	Baa	Ba	B	Caa
c	-4.7931***	-8.3537***	-5.1749***	-3.4782***	-3.3223***	-2.8037**
	(0.0398)	(0.1183)	(0.0815)	(0.0721)	(0.0863)	(0.1596)
beta	0.2965***	0.5677***	0.3696***	0.2493***	0.2498***	0.2581***
	(0.0032)	(0.0102)	(0.0074)	(0.0067)	(0.0081)	(0.0151)
Obs.	325,443	259,647	39,472	15,960	8,349	2,015
AIC	92,232	32,808	20,198	12,537	7,185	2,440

Table X
Parameter estimates for Model 10 (prediction model, probit regression)

This table shows the results of out-of-sample prediction probit regression Model 10. The model specification is $P\left(D_{ijt+1}=1\right) = \Phi\left(\gamma_0+\gamma_1\hat{\eta}_{ijt+1}\right)$. Standard errors are in parentheses. The significance is indicated as follows: ***: significant at 1%, **: significant at 5%, *: significant at 10%. The tested hypotheses are that $\gamma_0 = 0$ and $\gamma_1 = 1$.
The estimated parameters γ_0 and γ_1 are statistically different from $\gamma_0 = 0$ and $\gamma_1 = 1$. The ramification is that CRA ratings do not predict impairment risk.

	(1)	(2)	(3)	(4)	(5)
Prediction year	γ_0	γ_1	Pseudo R^2	R^2 Rescaled	AUROC
1999	-0.7917***	0.6206***	0.0079	0.741	0.851
	(0.1668)	(0.0587)			
2000	0.1750	1.1776	0.0158	0.3852	0.949
	(0.2309)	(0.1210)			
2001	-0.1547	0.8558***	0.0180	0.2607	0.905
	(0.1321)	(0.0540)			
2002	0.5501***	1.1008*	0.0375	0.3328	0.926
	(0.1160)	(0.0529)			
2003	-0.1045	0.9276	0.0271	0.2896	0.913
	(0.0995)	(0.0482)			
2004	-0.6379***	0.6700***	0.0193	0.1916	0.821
	(0.0820)	(0.0351)			
2005	-0.3331**	1.1792**	0.0131	0.3553	0.958
	(0.1376)	(0.0854)			
2006	0.2745*	1.5383***	0.0121	0.4276	0.941
	(0.1596)	(0.1008)			
2007	0.6017***	0.9468***	0.0442	0.2127	0.839
	(0.0493)	(0.0192)			
2008	1.4974***	0.9788**	0.1453	0.2482	0.750
	(0.0252)	(0.0098)			

Table XI

Parameter estimates for Model 11 (prediction model, linear regression)

This table shows the results of out-of-sample prediction linear regression Model 11. The model specification is $D_{ijt+1} = \delta_0 + \delta_1 \cdot \hat{p}_{ijt+1} + \varepsilon_{ijt+1}$. Standard errors are in parentheses. The significance is indicated as follows: ***: significant at 1%, **: significant at 5%, *: significant at 10%. The tested hypotheses are that $\delta_0 = 0$ and $\delta_1 = 1$.
The estimated parameters δ_0 and δ_1 are statistically different from $\delta_0 = 0$ and $\delta_1 = 1$. The ramification is that CRA ratings do not predict impairment risk.

	(1)	(2)	(3)
Prediction year	δ_0	δ_1	Adj. R^2
1999	0.0014***	0.6513***	0.0178
	(0.0005)	(0.0410)	
2000	-0.0018***	1.1613***	0.1009
	(0.0004)	(0.0284)	
2001	0.0029***	0.6721***	0.0265
	(0.0006)	(0.0319)	
2002	0.0024***	1.6082***	0.0678
	(0.0008)	(0.0435)	
2003	0.0007	0.9589***	0.0587
	(0.0006)	(0.0262)	
2004	0.0001	0.9407***	0.0683
	(0.0007)	(0.0230)	
2005	-0.0017***	0.4375**	0.0567
	(0.0003)	(0.0106)	
2006	-0.0024***	0.6031***	0.0768
	(0.0002)	(0.0103)	
2007	0.0155***	1.7140***	0.0322
	(0.0007)	(0.0391)	
2008	0.0925***	5.1955***	0.1573
	(0.0014)	(0.0467)	

Table XII
Parameter estimates for Model 12

This table shows parameter estimates from the probit model Model 12. The model specification is $P\left(D_{ijt}=1\right)=\Phi\left(\beta' x_{ijt}\right)$. Standard errors are in parentheses. The significance is indicated as follows: ***: significant at 1%, **: significant at 5%, *: significant at 10%. The parameter for resecuritisation can not be estimated for ABS and HEL as resecuritisations can not be identified for these categories. AUROC is the area under the receiver operating characteristic curve (see Agresti 1984).
For the categories CDO, MBS and HEL, the parameter for ORY is positive and significant, which suggests that the impairment risk in the origination year is higher than suggested by the CRA. The ramification is that financial risk for the asset classes CDO, MBS and HEL is higher than implied by ratings and structural elements in original rating years.

	(1)	(2)	(3)	(4)	(5)
Variable	All	ABS	CDO	MBS	HEL
Intercept	-4.7611***	-5.3854***	-2.4693***	-4.2004***	-5.4708***
	(0.0441)	(0.1482)	(0.0536)	(0.0603)	(0.1106)
Baa	0.9345***	1.6387***	-0.1309***	1.1180***	1.3754***
	(0.0226)	(0.0913)	(0.0482)	(0.0402)	(0.0421)
Ba	1.3020***	2.8402***	-0.3291***	1.5721***	2.0600***
	(0.0280)	(0.1047)	(0.0577)	(0.0517)	(0.0601)
B	1.7735***	2.9423***	0.1453	1.6224***	2.6968***
	(0.0375)	(0.1222)	(0.0890)	(0.0583)	(0.0988)
Caa	2.4627***	3.4301***	0.8430***	2.5608***	2.5345***
	(0.0602)	(0.1265)	(0.1129)	(0.0986)	(0.1431)
CDO	1.1180***				
	(0.0365)				
HEL	0.8083***				
	(0.0319)				
MBS	0.3172***				
	(0.0325)				
Resecuritisation	-0.4253***		-0.2474***	-1.1830***	
	(0.0700)		(0.0869)	(0.1673)	
Mezzanine	0.0383	0.2249	-0.8426***	0.1323***	0.5729***
	(0.0241)	(0.2579)	(0.0504)	(0.0441)	(0.0417)
Senior	-1.3448***	0.3516***	-1.3166***	-1.7760***	-1.4367***
	(0.0213)	(0.0797)	(0.0488)	(0.0421)	(0.0425)
PPY	3.6199***	2.7645***	3.1522***	3.3842***	4.8974***
	(0.0289)	(0.1029)	(0.0492)	(0.0499)	(0.1042)
ORY	0.8272***	-0.1115	0.8853***	0.8585***	0.8997***
	(0.0199)	(0.1447)	(0.0443)	(0.0367)	(0.0365)
Obs.	325,443	43,603	31,452	164,002	86,386
Pseudo R-square	0.2208	0.0709	0.3175	0.1297	0.3659
R-square rescaled	0.7719	0.6529	0.7357	0.7536	0.8548
AUROC	0.9874	0.9762	0.9773	0.9876	0.9939