Securitization rating performance and agency incentives

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Abstract

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 credit rating agencies (CRAs). This paper provides an empirical study, which assesses the historical performance of credit ratings for securitizations. The main findings are as follows. Firstly, CRAs do not sufficiently address the systematic risk of the underlying collateral pools as well as the tranche structure. Secondly, impairment risk is underestimated during origination years and years with high securitization volumes when CRA fee revenue is high. Thirdly, securitization ratings are unable to predict impairment risk.

Key words: 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, Structured Finance Transaction

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 (also known as structured finance transactions). Three distinct hypotheses are analyzed, which provide empirical evidence on the role of ratings for securitizations during the Global Financial Crisis (GFC). [2] 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. [3]

The Global Financial Crisis (GFC) 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 (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). 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). Despite their name, 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

[2] Namely, the Impairment Risk, Agency Incentive and Prediction hypotheses, compare Section 2.
[3] Rating fee revenue peaked in 2007. According to Table I, 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.

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.

Two main streams exist in literature on the measurement of financial risks of securitizations and – with regard to the risk exposure – similar credit derivatives. The first stream focuses on the pricing, where the central issue is to explain observed (market) prices such as credit spreads of credit default swap indices. The most 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 & 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. Examples are as follows: 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), Carey & Hrycay (2001), Crouhy et al. (2001), Koopman et al. (2005), 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 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 & 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. Loeffler (2004) finds that the default prediction power of ratings is low. 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's ratings of banks and Becker & Milbourn (2008) analyze the link between information efficiency of ratings and competition after the market entry of CRA Fitch.

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 linked to ratings quality. 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. 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.

Unfortunately, the literature has not yet empirically analyzed CRA ratings of securitizations and their accuracy in explaining impairment risk. This may have been due to the complexity of securitizations and the limited availability of data through traditional data sources. Impairment risk is the risk of a securitization to violate contractual payment obligations. Impairment events are a good proxy for the likelihood that an investor in a securitization may experience a loss. [4] To date, investors and prudential regulators assume the existence of such a link by acknowledging CRAs and assigning risk premia and risk weights to CRA rating categories. This paper addresses the accuracy of CRA securitizations. 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.

[4] Note that securitizations are generally structured as specific purpose companies which borrow from investors.

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 three central hypotheses. Section 4 discusses the major ramifications of the empirical results for securitizations risk models and provides first suggestions in relation to a new stability framework for financial markets, institutions and instruments.

2 Hypotheses

The paper aims to answer empirically whether CRA structured finance ratings (from now on referenced as 'ratings') are information efficient and may have been causal for the Global Financial Crisis. More specifically, information efficiency will be linked to i) the average impairment risk over time, ii) the impairment risk at and after origination and iii) the impairment risk given the economic cycle.

Rating agencies have been accused of the failure to measure impairment risk, i.e., the risk that investors may experience losses. Rating agencies address various elements of the asset (H1a) and liability side (H1b) of securitizations. Our *Impairment Risk Hypotheses* are 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: Ratings contain all information about the characteristics of securitizations relevant for impairment risk, such as subordination level and tranche thickness.

H1a addresses characteristics of the asset portfolio. 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.

H1b addresses the tranching structure of securitizations and the current 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. 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.

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. H2 addresses two potential ways in which rating agencies may 'circumvent' this rating-performance mechanism. Our *Agency Incentive Hypotheses* are:

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

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

The first incentive problem (H2a) relates to the assumption that investors do not price the risk with regard to origination and monitoring years. Rating performance measures are generally calculated as an average per rating class. 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.[5] 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.

[insert Figure 1 here]

The reason for this finding is that origination fees exceed the monitoring fees in absolute terms.[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) 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 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

[5] 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.
[6] 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.

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.

H3 addresses the information degree of credit ratings and their ability to forecast impairment risk. 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. Consequently, credit ratings which are overoptimistic and do not account for all relevant risk factors are poor predictors for impairment risk. Thus our *Prediction Hypothesis* is:

H3: Ratings predict impairment risk.

Please note that the Impairment Risk Hypotheses H1a and H1b relate to idiosyncratic risk. The Agency Incentive Hypotheses H2a and H2b relate to incentive mechanisms induced by the fee structure for securitization ratings. The Prediction Hypothesis H3 relates to the interaction between idiosyncratic and systematic risk characteristics of securitizations.

Following the models in Gordy (2000), Gordy (2003), McNeil & Wendin (2007), and Gupton et al. (1997), the attachment probability (i.e., the propensity of being exposed to a loss in the underlying asset pool) for a tranche i of transaction (or asset pool) j in period t $(i = 1, ..., I_j; j = 1, ..., J, t = 1, ..., T)$ is approximated by

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

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

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

Please note that $\eta_{ijt} \equiv \frac{-\sqrt{1-\rho}\Phi^{-1}(AL_{ijt})+\Phi^{-1}(\pi_{it})}{\sqrt{\rho}}$; $i = 1, ..., I_j; j = 1, ..., J, t = 1, ..., T$.

Reasonable assumptions in this body of literature are the modeling of credit risk of an individual borrower by a Gaussian factor model for the individual asset return based on Merton (1974) as well as a large number of assets in the pool.

All three hypotheses test whether CRAs capture impairment 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.

The impairment of tranche i ($i = 1, ..., I_j$) of pool j ($j = 1, ..., J$) in time t ($t = 1, ..., T$) is linked with observable information by the probit regression. [7]

$$P\left(D_{ijt} = 1\right) = \Phi\left(\beta' x_{ijt}\right) \tag{2}$$

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.

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 (1). If ratings fully explain the impairment probability, then no other variable besides the ratings should be significant in the probit regression. In other words, if ratings reflect the tranche impairment probability accurately, they should include the information as specified in Equation (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 about the business cycle. Consider an error in assigning one or more of the pool parameters resulting in $\widetilde{\eta}_{ijt} \neq \eta_{ijt}$ which will lead to a bias in the estimated impairment probability. Then the impairment probability can be written as

$$P(D_{ijt} = 1) = \Phi\left(\widetilde{\eta}_{ijt} + \Delta_{ijt}\right) \tag{3}$$

with $\Delta_{ijt} \equiv \eta_{ijt} - \widetilde{\eta}_{ijt}$ denoting the measurement error in pool variables which may refer to characteristics of the pool, the tranche or time. Model (3) will provide the basis for the empirical tests in the following section.

[7] 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 qualitatively similar to the ones presented.

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 & 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 bank's loan credit ratings (compare e.g., Grunert et al. 2005). [8]

3 Empirical analysis

3.1 Structured finance data

The 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 of tranches.

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):

> "[...] 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."

Alternative measures for rating performance may exist. Firstly, ratings may be compared to the performance of the asset portfolios. The approach may be reasonable for asset portfolios

[8] 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 & Milbourn (2008).

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. Firstly, we focus on the securitization market rather than mortgage-backed securities only and find distinct differences between various asset portfolios. Secondly, 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. Analyzing rating downgrades limits the interpretation of results as the link between downgrades and losses to investors is less transparent.

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 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 (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 (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 (4).

The resulting data comprises 325,443 annual tranche observations. The number of impaired tranche observations is 13,072.[9] The data set is one of the most comprehensive data sets on securitization collected to date.

Table I shows various proxies for origination[10] and outstanding volume of the data: number of tranches, number of deals and volume. 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.[11]

[insert Table I here]

From the resulting raw data, 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) reflects the risk of a tranche and is measured at the beginning of an observation year;[12]
- Rating at the beginning of the respective year (Aaa, Aa, A, Baa, Ba, B, Caa) 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 security);[13]
- 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: indicates the inflation-adjusted logarithm of the size of the underlying asset portfolio;

[9] The original data set included 15,083 impairment events before the application of filtering rules.
[10] Origination volume relates to the year starting from the time that a rating was first assigned.
[11] Compare Footnote 3.
[12] 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.
[13] 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.

- Subordination indicates the relative size (in relation to the deal size) of the tranches that are subordinated to the respective tranche;
- Thickness indicates the relative size (in relation to the deal size) of the respective tranche;
- Origination year: year in which a tranche was first rated which coincides with the year in which transaction was closed;
- Time since origination (TSO) indicates the time in years since a tranche was first rated;
- Securitization volume at origination (SVO) indicates logarithm of the volume of rated tranches for a given year. [14]

Table II and Table III describe the number of observations over time. The overall number of rated securitizations has increased at an increasing rate over time. [15]

[insert Table II here]

[insert Table III here]

Table II 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 CRA rating methodology.

Table III 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

[14] Alternative indicators of origination volumes such as the number of originated tranches or transactions were tested for robustness and resulted in similar results.

[15] All tables weight individual transactions equally and similar observations may be made for the value of securitizations.

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 published by CRAs. These tables aggregate the impairment events over dimensions such as rating class 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 IV and Table V 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 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. [16]

[insert Table IV here]

[insert Table V here]

Table IV shows the impairment rates for rating categories at origination (Panel A) and

[16] While this number underlines the severity of the GFC and the importance of this study it raises the concern of imbalances in the data set. We address this issue for 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.

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 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 Caa to Aaa-A). Ironically, investors were most surprised by the increase of impairment rates of highly rated securitizations. [17]

Table V 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. 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 more 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.

3.2 H1 – Impairment Risk Hypotheses

Table VI presents two probit models linking the impairment events with CRA ratings. Model 1 takes the dummy-coded ratings (reference category: Aaa-A) into account. Model 1 shows that CRA ratings explain the credit risk. 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). [18] The parameter estimates increase from rating Aaa-A to rating Caa and are significant. This demonstrates that the ratings imply higher impairment risk from Aaa to Caa and that ratings explain impairment risk.

Model 2 includes the ratings as well as the dummy-coded rating years (reference category:

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[17] 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 rates for the rating classes Ba (16.49%) and B (4.68%) in 2007 in Panel B of Table IV. These inconsistencies are in line with reports by the data-providing CRA (compare Moody's Investors Service 2008).

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

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.[19] In other words, Model 2 shows that CRA ratings do not explain the increased level of impairment risk especially during economic downturns. We include rating year dummies in all subsequent models to control for this and further analyze the prediction quality of ratings in hypothesis H3.

[insert Table VI here]

Table VII confirms that the inclusion of asset portfolio (Model 3 and 5, Model 6 and 7) and securitization (Model 4 and 5, Model 6 and 7) characteristics after controlling for credit ratings add to the explanation of impairment risk. 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 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.

[insert Table VII here]

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.[20]

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

[20] Despite the common use of ratings as metric risk measures, CRAs often claim to assess the relative risk, which essentially implies that a rating of a higher alphabetic order involves a lower level of financial risk. In an extension, all models were estimated controlling for the annual average impairment rate to ascertain that the findings relate to the absolute (calibration) as well as relative (discrimination) level of risk. The results are comparable to the ones reported in Tables VI and

3.3 H2 – Agency Incentive Hypotheses

Commercial CRAs may have a monetary incentive to bias the measures of impairment risk. The analyzed incentive hypotheses relate to the origination process during which a CRA may underestimate the risk in general (as fee revenue is high at origination) or during economic booms (as origination volumes and therefore fee revenue is high during economic booms [21]).

Model 8 in Table VIII shows that different origination years (also known as vintages) differ in risk. Models 9 and 10 [22] show that ratings are unable to explain the risk of the different vintages.

Even more interestingly, Models 11 and 12 show that the vintage risk differs between the years prior to the GFC and during the GFC. During the GFC, the risk which is not reflected in ratings, increases for more recent origination and is highest for securitizations, which were originated immediately before the GFC. Vice versa, during years before the GFC, the risk which is not reflected in ratings decreases for more recent originations.

[insert Table VIII here]

In order to test the hypotheses H2a and H2b, we replace the origination year dummies 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. [23]

Table IX 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. Thus we reject the

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VII.

[21] In addition, Bolton et al. (2009) argue that investors are naive and reputational risk is low.

[22] Model 10 controls for the rating year. Please note that the panel data set looks at origination and monitoring years, i.e., years between origination and maturity of securitizations.

[23] 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).

hypothesis H2a that rating-implied impairment risk and time since origination are positively correlated.

[insert Table IX here]

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.

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 H3 – Prediction Hypothesis

Ratings are generally applied as proxies for future impairment risk. The information content of corporate bond issue ratings has been analyzed (compare, e.g., Blume et al. 1998). However, no evidence for CRA ratings on securitizations has been presented. Our previous results show that credit ratings do not include all relevant risk factors and are overoptimistic when fee revenue is high. Therefore we now check how this affects the ability for predicting future impairment risk.

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

$$P\left(D_{ijt}=1\right)=\Phi\left(\beta' x_{ijt}\right) \tag{4}$$

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:

$$\hat{\eta}_{ijt+1}=\hat{\beta}' x_{ijt+1} \tag{5}$$

and the impairment probability prediction for the subsequent year

$$\hat{p}_{ijt+1} = \Phi(\hat{\beta}' x_{ijt+1}) \tag{6}$$

using the estimated coefficients $\hat{\beta}$ from Equation (4). Finally, the forecasting power is assessed by running a probit regression (Model 22).

$$P\left(D_{ijt+1} = 1\right) = \Phi\left(\gamma_0 + \gamma_1 \hat{\eta}_{ijt+1}\right) \tag{7}$$

We test for $\gamma_0 = 0$ and $\gamma_1 = 1$, i.e., whether ratings provide perfect forecasts. As a robustness check a linear regression is estimated (Model 23):

$$D_{ijt+1} = \delta_0 + \delta_1 \cdot \hat{p}_{ijt+1} + \varepsilon_{ijt+1} \tag{8}$$

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

Again, we test for $\delta_0 = 0$ and $\delta_1 = 1$. All steps are repeated for each year from 1999 to 2008 where in the probit regression (4) all data up to year t are used. Table X shows the parameter estimates from each regression Model 22 (Equation 7). Table XI contains the estimation results from each regression Model 23 (Equation 8).

[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 ratings quality has neither consistently declined nor improved.[24] 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

[24] A comparison of R^2 should be carefully interpreted as each year has a different number of observations. Please also note that our definition of rating quality differs from the definition of rating standard by Blume et al. (1998), compare Footnote 8.

years. In summary, the analysis shows that the rating quality has neither consistently declined 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.

In summary, we reject the hypothesis H3 that ratings predict impairment risk. The ramifications are that CRAs are poor predictors for impairment risk and that investors relying on predictions of future levels of impairment risk may have to build private models.[25] Alternatively, CRAs may 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.

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.

The most substantial findings are that 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;
- Measure a too low impairment risk level at origination when fee revenue is high;
- Measure a too low impairment risk level if a securitization was originated in a high securitization activity year;
- Are unable to predict impairment risk.

CRA ratings (like 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[26] with a limited number of financial analysts[27]. This paper has also shown that ratings are informative with regard to the average idiosyncratic impairment risk over the business cycle.

[25] The results confirm the findings by Loeffler (2004) for corporate ratings.
[26] 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.
[27] For instance, in 2007, Moody's Investors Service employed approximately 1,000 analysts.

There may be various ways to address the findings of this paper, which may include the knowledge transfer to the financial system (i.e., to CRAs and CRA rating users), independence between CRA fee revenue and origination process, cap for CRA fee revenues or introduction of minimum standards on resources spent on ratings. A public discussion is needed to transfer the findings into regulatory policy.

To date, mainly CRAs make histories of their financial risk measures as well as the respective realizations 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 information is kept private. However, recent negative earnings announcements of financial institutions suggest that other models applied in industry may share similar properties. Therefore, a formal validation of such models is important.

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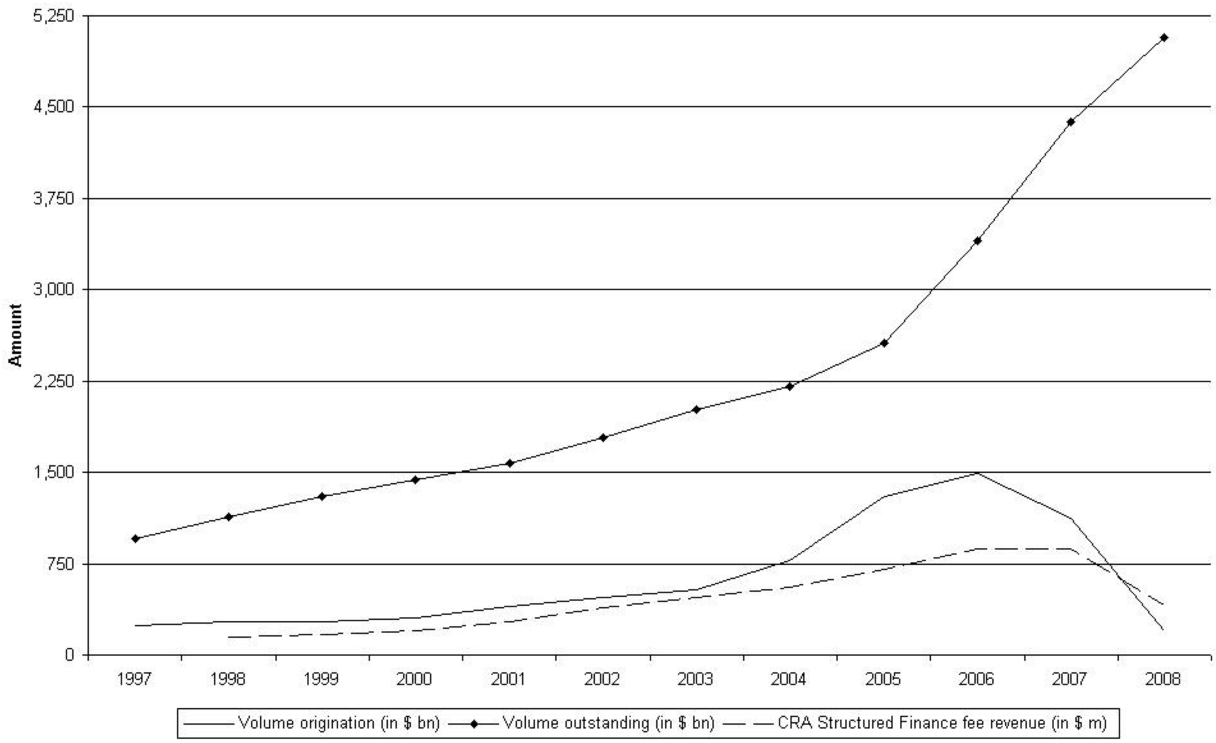
Figures

Fig. 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 starting from the time 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 which is in line with the recognition of the majority of fee revenue at or shortly after origination by the CRA.



Tables

Table I

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 II
Total number of observations, relative frequencies of ratings at origination and 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 III
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 IV

Impairment rates for all observations, per rating at origination and 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 V
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 especially 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 particularly 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 VI
The link between impairment risk, CRA ratings and time

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 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).
Model 1 shows that CRA ratings explain the credit risk over time. Model 2 shows that CRA ratings are unable to explain changes in the increased level of impairment risk over time.

Variable	Model 1	Model 2
Intercept	-2.1517***	-3.2346***
	0.0062	0.0741
Baa	0.8351***	1.0397***
	0.0107	0.0133
Ba	1.1900***	1.4301***
	0.0133	0.0163
B	1.3276***	1.5209***
	0.0167	0.0202
Caa	2.0038***	2.2803***
	0.0287	0.0344
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
Pseudo R-square	0.0520	0.1220
R-square rescaled	0.1818	0.4265
AUROC	0.7688	0.9231

Table VII
The link between impairment risk, CRA ratings, asset portfolio and securitization characteristics, with rating year dummies

This table shows parameter estimates for the probit model Model 3 to Model 7. 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 inclusion of asset portfolio (Model 3 and 5) and securitization (Model 4 and 5) 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 3	Model 4	Model 5	Model 6 (prior GFC)	Model 7 (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 VIII
The link between impairment risk, CRA ratings and incentive characteristics

This table shows parameter estimates for the probit model Model 8 to Model 12. 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 risk of securitization differs for each origination year (OY) and CRAs are unable to measure this element. In addition, Model 11 and Model 12 show that the risk of recent origination years is high for the GFC and low for years prior to the GFC.

Variable	Model 8	Model 9	Model 10	Model 11 (prior GFC)	Model 12 (GFC)
Intercept	-2.6520***	-3.2727***	-3.3453***	-3.2831***	-4.7431***
	0.0193	0.0264	0.0770	0.0789	0.1628
Baa		1.0302***	1.1717***	1.0443***	1.1979***
		0.0134	0.0146	0.0423	0.0157
Ba		1.4544***	1.5794***	1.5101***	1.5950***
		0.0164	0.0178	0.0433	0.0201
B		1.7405***	1.7628***	1.6905***	1.7774***
		0.0208	0.0224	0.0464	0.0270
Caa		2.5912***	2.7181***	2.4704***	2.9414***
		0.0344	0.0394	0.0616	0.0604
OY 1998	0.3606***	0.1266***	0.1171**	0.1030**	0.5618***
	0.0350	0.0446	0.0477	0.0486	0.2010
OY 1999	0.4210***	0.1307***	0.1160***	0.1294***	0.1775***
	0.0335	0.0423	0.0469	0.0473	0.2043
OY 2000	0.4817***	0.1095**	0.0866	0.0745	0.3565***
	0.0339	0.0426	0.0474	0.0486	0.1893
OY 2001	0.3010***	-0.0353	-0.0878***	-0.1836***	0.7052***
	0.0341	0.0428	0.0488	0.0526	0.1750
OY 2002	0.2784***	0.0618	0.0282***	-0.2806***	1.1220***
	0.0324	0.0400	0.0490	0.0596	0.1679
OY 2003	0.1400***	0.0613	-0.0233***	-0.8856***	1.1371***
	0.0329	0.0404	0.0521	0.1153	0.1660
OY 2004	0.2993***	0.2212***	0.1029***	-0.8876***	1.1386***
	0.0281	0.0346	0.0497	0.1611	0.1640
OY 2005	0.8911***	1.0017***	0.8465***	-1.0269***	1.8801***
	0.0219	0.0279	0.0445	0.2151	0.1623
OY 2006	1.6489***	1.7959***	1.5317***		2.5416***
	0.0207	0.0267	0.0435		0.1620
OY 2007	2.0051***	2.2405***	1.5700***		2.5816***
	0.0226	0.0286	0.0447		0.1623
Year Dummies	No	No	Yes	Yes	Yes
Pseudo R-square	0.0744	0.1246	0.1440	0.0205	0.2094
R-square rescaled	0.2602	0.4356	0.5035	0.3377	0.4439
AUROC	0.8533	0.9266	0.9479	0.9285	0.8995

Table IX

The link between impairment risk, CRA ratings and incentive characteristics (cont.)

This table shows parameter estimates for the probit model Model 13 to Model 21. 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 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 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21
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 X
The link between realized and predicted impairment risk (probit regression)

This table shows the results of out-of-sample prediction probit regression Model 22. 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
The link between realized and predicted impairment risk (linear regression)

This table shows the results of out-of-sample prediction linear regression Model 23. 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)	