Systematic Risk and Credit Ratings of Mortgage Securitizations

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1

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2

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Abstract

Investors were surprised during the Global Financial Crisis that mortgage securitizations implied larger default rates than corporate bonds given the same credit rating. This paper provides theoretical and empirical evidence that mortgage securitizations imply a larger degree of systematic risk than bonds. In addition, the paper shows that credit ratings do not reflect the systematic risk appropriately.

JEL classification: G20; G28; C51

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1 Introduction

1.1 Motivation and Contributions

The high levels of impairment rates and systematic downgrades of seemingly high quality (e.g., AAA-rated) mortgage-backed Securities in 2007 and 2008 took financial markets and investors by surprise during the Global Financial Crisis (GFC). Models applied by credit rating agencies (CRA) along with misaligned incentives based on 'paid-by-originator' business models have been blamed as major sources of the crisis (compare Hellwig 2008, Hull 2009, Crouhy et al. 2008).

In particular, market participants who applied interpretation standards to securitization ratings which are similar to corporate bond issue and issuer ratings [3] were surprised to see an unprecedented increase in impairment rates. Figure 1 compares the impairment rates for Baa-rated bonds with Baa-rated mortgage-backed securities (MBS) which are collateralized by prime mortgages and Baa-rated home equity loan (HEL) securities which are mostly collateralized by sub-prime mortgages. Both MBS and HEL are securitizations of real-estate collateralized loan portfolios. Default rates for Baa-rated bonds fluctuate from 1997 to 2008 between zero and 1.0%, while impairment rates for Baa-rated MBS fluctuate between zero and 29.2% and impairment rates for Baa-rated HEL fluctuate between 0.2% and 46.0%. [4]

[insert Figure 1 here]

This paper shows that the risk characteristics between securitizations and corporate bonds

[3] These have evolved over many years (see e.g., Ederington & Goh 1993).

[4] Please note that these numbers relate to ratings that are issued by credit rating agency Moody's and that default rates for corporate bond ratings are available from 1920 onwards. The default rate for Baa-rated bonds were between zero and 1.98% in the years 1920 to 1996 which are not shown in the figure. Impairment rates for securitizations prior to 1997 are not meaningful due to a low number of observations. The impairment rates for securitizations and default rates for bonds differ in a similar fashion for other rating classes.

differ significantly – particularly with respect to the exposure to systematic risk. The research question is of highest importance as bank regulators are currently discussion minimum standards for credit ratings.[5] In summary, Securitizations are portfolio-related instruments which contain a higher degree of systematic risk. This may result in higher default rates in economic downturns than for bonds, even if the unconditional default probability is the same.

We first develop a simple model for securitization impairment risk based on a standard Merton-type approach, which allows for exposure of the tranches to a systematic 'super-factor' which represents the economy. The approach accounts for correlated tranches and captures joint default behavior of securitizations. We calibrate the model to a time-series of rated tranches and show how the tranches are empirically correlated and exposed to systematic risk.

The model also allows for a comparison between the systematic risk exposure of straight corporate bonds on the one hand and securitizations (also known as structured investment tranches) on the other hand. The model gives insights into their behavior with respect to systematic risk. We show theoretically and empirically that the systematic risk is larger for securitizations than for bonds.

In addition, we show that credit ratings do not reflect the systematic risk appropriately. As a result, financial instruments such as securitizations and bonds may experience much higher default rates in an economic downturn than implied by their rating. This effect is more pronounced for securitizations than corporate bonds.

[5] Spurred by the European Regulation on Credit Rating Agencies, ratings require since 2010 the 'SF' designation to be differentiated from bond and other ratings.

1.2 Related Literature

This paper relates to three streams in literature. The first stream develops approaches to measure financial risks of securitizations and related credit derivatives. Longstaff & Rajan (2008) and Hull & White (2004) apply a risk-neutral pricing framework to develop pricing techniques for market prices. A central point of these risk models is the specification of the dependence structure for the portfolio assets. Benmelech & Dlugosz (2009) show empirically that rating inflation was an issue in the GFC and they argue that one of the causes of the crisis was overconfidence in statistical models. The authors use rating migration statistics and analyze up- and downgrades around the crisis. Ashcraft et al. (2009) find that CRA ratings for mortgage-backed securities provide useful information for investors, show significant time variation and become less conservative prior to the GFC. Griffin & Tang (2009) compare CRA model methodologies with CRA ratings for collateralized debt obligations and find that the models are more accurate than the ratings. Coval et al. (2009) argue that model risk and the exposure to systemic risk of securitization may explain the increase of impairment rates during the GFC. Heitfield (2009) provides a simulation study, which shows the impact of estimation errors in pool correlations on the risk measures and ratings of tranches.

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 defaults (or losses) based on individual risk parameters (such as the default probability) which are aggregated to a portfolio risk distribution. Important approaches which address the default probability are due to 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). In addition, Dietsch & Petey (2004) and McNeil & Wendin (2007) model the correlations between default events and Lee et al. (2011) between the underlying asset value process variables. Carey (1998), Acharya et al. (2007), Pan & Singleton (2008), Qi & Yang (2009), Grunert & Weber (2009) and Bruche & González-Aguado (2010) develop economically motivated empirical models for recoveries using explanatory co-variables. Altman et al. (2005) model correlations between default events and loss rates given default.

The third stream analyzes the information content of ratings for corporate bond issuers and issues. 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. Poon et al. (2009) analyze solicited and unsolicited bank credit ratings and show that solicitation is a significant explanatory variable between both groups. Jorion et al. (2005) show that after Regulation Fair Disclosure, the market impact of both downgrades and upgrades is significant and of greater magnitude compared to that observed in the pre-Regulation Fair Disclosure period. The relative roles of different CRAs have also been studied. For example, Miu & 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. Guettler & Wahrenburg (2007) find that bond ratings by Moody's and Standard & Poor's are highly correlated and Livingston et al. (2010) find that the impact of Moody's ratings on market reactions is stronger compared to Standard & Poor's.

In our paper we apply a model for the default probability and portfolio loss to mortgage asset pools and securitizations thereof. We provide a mathematical model representation which allows us to compare bonds and securitized tranches with respect to their exposure to systematic risk and estimate these models empirically.

The rest of the paper is organized as follows. Section 2 provides the data generation and description. The final data set includes 164,002 annual observations of mortgage-backed securities (MBS); 86,386 annual observations of home equity loan (HEL) securities which are in large collateralized by sub-prime mortgage loans; and 462,470 annual observations of corporate bonds. Section 3 shows the empirical analysis and focuses on the interaction between ratings and the economy. Section 4 concludes and provides practical implications in the context of general economic downturns and the GFC in particular.

2 The Data

The paper analyzes a comprehensive panel data set of Moody's-rated US mortgage securitization (MBS and HEL) and corporate bond rating data during the years 1997 to 2008. Similar conclusions may be drawn for other rating agencies.

Guettler & Wahrenburg (2007) find that bond ratings by Moody's and Standard & Poor's are highly correlated. Interviews with employees of the three CRAs support the conjecture that the information content is similar for ratings of the three major CRAs. In addition, Livingston et al. (2010) find that the impact of Moody's ratings on market reactions is slightly stronger compared to Standard & Poor's and supports the use of Moody's ratings.

However, for securitization ratings, no empirical evidence that ratings for different CRAs share the same features has been presented before. Therefore, we hand-collected the initial ratings of 1,000 randomly selected tranches and assigned numbers from 1 (rating Aaa for Moody's and rating AAA for Standard & Poor's and Fitch respectively) to 21 (rating C). Of the 1,000 tranches rated by Moody's, 680 are rated by Standard & Poor's and 356 are rated by Fitch. We find extremely high Spearman correlations [6] coefficients in excess of 90%: between Moody's and Standard & Poor's: 0.9339, between Moody's and Fitch: 0.9584 and between Standard & Poor's and Fitch: 0.9855. Moody's and Standard & Poor's differ in 88

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

of 680 cases. Moody's and Fitch differ in 49 of 356 cases and Standard & Poor's and Fitch differ in 11 of 163 cases. This implies that the empirical likelihood of a rating deviation is between 6.7% and 13.8%. Please note that most of ratings' difference relates to a single notch such as a rating 'A1' by Moody's and 'A' by Standard & Poor's. These findings suggest that results based on Moody's can be generalized to other major rating agencies.

Loss events are traditionally called impairment events for securitizations and default events for corporate bonds. 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."

Moody's records a default event for a corporate loan if: i) interest or principal payments are missed or delayed; ii) Chapter 11 or Chapter 7 bankruptcy is filed; or iii) a distressed exchange, such as a reduction in a financial obligation, occurs.

Despite the different terms, ratings aim to measure the financial risk in both instruments and investors assume that the realization of impairment and default events coincides with losses and that ratings for both financial instruments can be interpreted in a similar fashion.

Table 1 shows the number of observations and default rate per rating category for mortgage-backed securities (MBS, Panel A) and home equity loan securitizations (HEL, Panel B). The number of observed tranches increases over time, which reflects the growth of these financial instruments over recent years. The impairment rate increases during the GFC (2007 and 2008) and more generally from rating grades Aaa-A (Aaa, Aa and A) to Baa to Ba to B to

Caa. Generally speaking, impairment rates for given rating categories are higher for HELs than for MBSs. HELs include to a large degree sub-prime mortgage loans and the impairment risk increased to a larger degree than the one for MBSs. It can also be seen that HELs and MBSs did not experience an economic downturn in 2002 like corporate bonds did (compare Table 2).

[insert Table 1 here]

Table 2 shows the number of observations and default rate per rating category (Panel A) and per industry (Panel B) for corporate bonds. The number of rated bonds increases over time which reflects the growth of these financial instruments over recent years. The default rate increases after in 2002 and during the GFC (2008) and more generally from rating grades Aaa-A (Aaa, Aa and A) to Baa to Ba to B to Caa.

[insert Table 2 here]

3 Empirical Analysis

3.1 Fixed Effect Models

Securitizations are investments in special purpose companies, which invest the funds received in a portfolio of assets. The repayment of these investments is linked to the cash flows of the underlying asset portfolio. The asset portfolio or pool of a deal generally consists of financial assets (e.g., loans) that are subject to financial risk (e.g., credit risk). Therefore, investments in securitizations 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.

For modeling the risk of the asset pool we follow Vasicek (1987, 1991) and apply a latent variable factor model. Consistent with Merton (1974), a borrower in the pool defaults on his loan when the value of his assets (the latent variable) falls below the nominal amount of debt at maturity (the threshold). Asset returns are assumed to be normally distributed and driven by a common systematic risk factor and an independent idiosyncratic risk factor. Further, it is assumed that the asset portfolio is infinitely granular (see Gordy 2000, 2003), which implies that idiosyncratic risk is fully diversified away.[7]

The default rate of pool i in time period t $(i = 1, ..., I; t = 1, ..., T)$ is then modeled as

$$P_{it} = \Phi\left(\frac{c_{it} - \sqrt{\rho_{it}}X_{it}}{\sqrt{1-\rho_{it}}}\right) \tag{1}$$

where X_{it} is a time-specific systematic risk factor which affects all assets in the pool jointly, $\sqrt{\rho_{it}}$ is the exposure of the asset return to this factor, $\Phi(.)$ is the cumulative distribution function (CDF) of the standard normal distribution. c_{it} is the default threshold, i.e., $c_{it} = \Phi^{-1}(\pi_{it})$ where π_{it} is the probability of default (PD) and $\Phi^{-1}(.)$ is the inverse of the standard normal CDF. The default rate has the following CDF (see e.g., Bluhm et al. 2003):

$$F(p_{it}) = P(P_{it} < p_{it}) = \Phi\left(\frac{\sqrt{1-\rho_{it}}\Phi^{-1}(p_{it}) - c_{it}}{\sqrt{\rho_{it}}}\right) \tag{2}$$

P_{it} in Equation (1) can be interpreted as the loss rate (rather than the default rate) of the portfolio if loss rates given default are deterministic and equal to unity. Note that the CDF is

[7] This model and some more advanced variants are standard in literature and practice. The Gaussian factor model can also be interpreted in terms of a Gaussian copula for the borrowers' asset returns or their default times (see Li 2000). These models have also found their recognition in the supervisory rules for determining regulatory capital of banks (i.e., Basel II and Basel III).

obtained as a result of the distribution of the systematic risk factor. In other words, Equation (2) gives the 'unconditional' distribution with respect to the systematic factor.

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

$$D_{ijt} = 1 \Leftrightarrow P_{it} > AL_{ijt} \tag{3}$$

where D_{ijt} is an indicator variable with

$$D_{ijt} = \begin{cases} 1 & \text{tranche } j \text{ of deal } i \text{ is impaired in } t \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

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

$$P(D_{ijt} = 1) = P(P_{it} > AL_{ijt}) \tag{5}$$

Combining Equation (5) and Equation (2) and replacing c_{it} by $\Phi^{-1}(\pi_{it})$ results in

$$P(D_{ijt}=1) = 1-\Phi\left(\frac{\sqrt{1-\rho_{it}}\Phi^{-1}(AL_{ijt})-\Phi^{-1}(\pi_{it})}{\sqrt{\rho_{it}}}\right) \tag{6}$$
$$= \Phi\left(\frac{\Phi^{-1}(\pi_{it})-\sqrt{1-\rho_{it}}\Phi^{-1}(AL_{ijt})}{\sqrt{\rho_{it}}}\right)$$
$$= \Phi\left(\eta_{ijt}\right)$$

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

Equation (6) implies that the tranche impairment probability is a function of the

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

These factors should be incorporated in a credit rating which measures the tranche impairment risk.

The parameters of the asset pool generally vary over the business cycle. In particular, default probabilities are lower in economic upturns than in economic downturns. Loeffler (2004) shows that CRA corporate bond ratings reflect the credit risk 'through-the-cycle' and focus on 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 aims to avoid rating volatility over time. This explicitly does not address rating changes induced by changes in the general economy.

Omitting business-cycle information from ratings for securitizations may lead to a mismatch of the time-constant rating and cyclical impairment risk. In other words, the Probit link of Equation (6) between ratings and the impairment probability is distorted by time-varying risk characteristics which are not included in the ratings. Consider an error in assigning one or more of the pool parameters resulting in $\widetilde{\eta}_{ijt} \neq \eta_{ijt}$ which leads to a bias in the estimated impairment probability. Then the impairment probability can be written as

$$\begin{aligned} P(D_{ijt} = 1) &= \Phi\left(\widetilde{\eta}_{ijt} + \Delta_t\right) \\ &= \Phi\left(\beta' x_{ijt} + \Delta_t\right) \end{aligned} \tag{7}$$

with $\Delta_t \equiv \eta_{ijt} - \widetilde{\eta}_{ijt}$ denoting the measurement error in pool variables which may refer to the business cycle. Model (7) provides the basis for the empirical tests. The first term $\widetilde{\eta}_{ijt} \equiv \beta' x_{ijt}$ is the measured part of the risk.

Table 3 shows the estimates of the Probit models for MBS, HEL and corporate bonds.[8] The time intercepts account for omitted economic information in Equation (7).

[insert Table 3 here]

The coefficients are increasing with decreasing rating quality. This is in line with our expectation as well as the descriptive analysis. For all risk segments, the lower the credit quality, the higher the estimated default risk of a tranche or bond. In many years the estimates for the year dummies are significantly different from zero and positive during economic downturns such as the recent financial crisis for all segments and 2002 for corporate bonds only. This shows that time-specific (economic) influences are not able to be wholly explained by the rating.

[8] Similar results are obtained where i) no regressors are included and ii) only ratings are included as regressors.

3.2 Random Effect Models

3.2.1 Model Framework

The above time-specific intercepts may be interpreted as business cycle effects which may not be predictable for rating agencies and which do not diversify within the economy. These effects impact on all pools within a segment or in an economy jointly, which means that the pool default rates are correlated between the pools. To account for dependence across pools we extend our framework following Gordy & Howells (2006). We decompose the pool specific factors into

$$X_{it} = \sqrt{\delta_i} \cdot X_t^* + \sqrt{1 - \delta_i} \cdot U_{it} \tag{8}$$

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 (6) can be stated as a function of the systematic factor by

$$P(D_{ijt} = 1 | X_t^*) = \Phi\left(\frac{\Phi^{-1}(\pi_{it}) - \sqrt{1 - \rho_{it}}\Phi^{-1}(AL_{ijt}) - \sqrt{\rho_{it}}\sqrt{\delta}X_t^*}{\sqrt{\rho_{it}}\sqrt{1 - \delta}}\right) \tag{9}$$

$$= \Phi\left(\eta_{ijt}/\sqrt{1 - \delta} + b \cdot X_t^*\right) \tag{10}$$

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 time-specific random effects X_t^*. This type of model is similar to the 'frailty'-model for the time to default as in Duffie et al.

(2009). The regression model can be stated given co-variables as

$$P\left(D_{ijt} = 1|X_t^*\right) = \Phi\left(\beta' x_{ijt} + b \cdot X_t^*\right) \tag{11}$$

The higher the degree to which tranches are exposed to the common super-factor, the higher the standard deviation b is and the higher the deviations of the realized tranche impairment probability from the expected probability are.[9] This observation holds if the rating agency specifies the pool default probability and the asset correlation within the pool correctly.

The dispersion parameter b of the random effect model can be interpreted in terms of 'asset correlation' as in Basel II and Basel III when the model is reparameterized as

$$P\left(D_{ijt} = 1|X_t^*\right) = \Phi\left(\frac{\widetilde{\beta}' x_{ijt} + \sqrt{\delta} \cdot X_t^*}{\sqrt{1-\delta}}\right) \tag{12}$$

where $\delta = \frac{b^2}{1+b^2}$ and $\widetilde{\beta} = \beta \cdot \sqrt{1-\delta}$. Thus δ can be interpreted as the correlation between two asset returns which trigger a tranche impairment when crossing the thresholds $\widetilde{\beta}' x_{ijt}$.

3.2.2 Comparing Systematic Risks of Bonds and Tranches

The random effects model allows a proper comparison of systematic risk exposures of individual assets (e.g., straight bonds) versus tranches with comparable features. Consider a bond with unconditional default probability π.[10] Under the random effect model the conditional probability of default (CPD) of the *bond* given the systematic random factor X_t^* is

$$P\left(D_t^B = 1|X_t^*\right) = \Phi\left(\frac{\Phi^{-1}(\pi) - \sqrt{\rho\delta} X_t^*}{\sqrt{1-\rho\delta}}\right) \tag{13}$$

[9] Please note that this statement is conditional on the CRA rating.
[10] We skip the subscripts in this section for simplicity where reasonable.

Please refer to the Appendix for a proof. The unconditional default probability for a *tranche* is given by Equation (6). Setting this tranche default probability equal to the bond default probability π, leads to the 'implied' attachment level

$$AL(\pi) = \Phi\left(\Phi^{-1}(\pi)\frac{1-\sqrt{\rho}}{\sqrt{1-\rho}}\right) \tag{14}$$

for a tranche which has the same unconditional PD as the bond. Inserting $AL(\pi)$ into Equation (9) leads to the conditional default probability (CPD) of this tranche

$$P(D_t^{Tr} = 1|X_t^*) = \Phi\left(\frac{\Phi^{-1}(\pi) - \sqrt{\delta}X_t^*}{\sqrt{1-\delta}}\right) \tag{15}$$

The proof for these relationships is presented in the Appendix. Equation (13) and Equation (15) specify the conditional probability of a default of the bond, and the tranche respectively, in dependence on the macroeconomic environment.

Figure 2 compares how the probabilities react to changes in the systematic factor for various parameter settings. The upper four graphs assume an unconditional default probability π of 1%, the lower four graphs an unconditional default probability π of 5%. The default probabilities are shifted upwards or downwards conditional on the realization of the economy. For instance, for $\rho = 0.1$ and $\delta = 0.1$ (first graph), a macroeconomic realization of -2.5 or less (which has a probability of occurrence of approximately 0.6% as the factor is standard normally distributed) increases the bond PD to 1.8% and the tranche PD to 5.3%.

[insert Figure 2 here]

A higher ρ increases the impact on the bond but not on the tranche as it is already incorporated in the calculation of the implied attachment level. However, higher δ increases both the bond and the tranche impact. For instance, for $\rho = 0.1$ and $\delta = 0.5$, the bond PD increases to 3.4% (when the macroeconomic factor is -2.5) whereas the tranche PD goes up to 21.4%. Extreme economic downturns can shift the tranche PD up to almost 100%.

For both the bond and the tranche the sensitivities of the CPDs with respect to the economy can be derived. The first derivatives of Equation (13) and Equation (15) are given as

$$\kappa^B(X_t^*) = \frac{\partial P\left(D_t^B = 1|X_t^*\right)}{\partial X_t^*} = \phi\left(\frac{\Phi^{-1}(\pi) - \sqrt{\rho\delta}X_t^*}{\sqrt{1-\rho\delta}}\right) \cdot \frac{-\sqrt{\rho\delta}}{\sqrt{1-\rho\delta}} \tag{16}$$

and

$$\kappa^{Tr}(X_t^*) = \frac{\partial P\left(D_t^{Tr} = 1|X_t^*\right)}{\partial X_t^*} = \phi\left(\frac{\Phi^{-1}(\pi) - \sqrt{\delta}X_t^*}{\sqrt{1-\delta}}\right) \cdot \frac{-\sqrt{\delta}}{\sqrt{1-\delta}} \tag{17}$$

where $\phi(z)$ denotes the density function of the standard normal distribution evaluated at z.

Figure 3 draws the respective sensitivities for the above parameter constellations. The higher ρ the higher c.p. the sensitivity of the bond in absolute terms and the higher δ the higher the sensitivity of both the bond and the tranche for most factor values. Moreover, the sensitivity of the tranche is much higher in absolute terms than that of the bond for negative values of the macroeconomic factor (economic downturn).

[insert Figure 3 here]

These findings may explain why during the GFC, the impairment rates for mortgage securitizations have increased by much more than bonds despite similar rating levels which refer to an 'average' economic environment.

3.2.3 Model Estimation and Results

The parameters of the random effect model are estimated by the Maximum Likelihood method as outlined in Hamerle & Rösch (2006) and McNeil & Wendin (2007) for common credit portfolios. We estimate the model both using several tranches per deal (shown here) and using one tranche per deal only as a control.[11] The results are comparable.

Table 4 shows the estimation result for MBS, HEL and bonds:

[insert Table 4 here]

The coefficients for the unobservable macroeconomic effect are statistically significantly different from zero given credit ratings in all models. The coefficients for the credit ratings change differ for MBS and HEL, which reflects different impairment rate levels for given rating classes. The exposure to the economic factor are higher for HEL than for MBS.

The previous model assumes that exposures to the economy are homogeneous across the rating grades. In order to allow for heterogenous exposures, the models are estimated for each rating grade separately. The results are shown in Table 5.

[insert Table 5 here]

The exposure of the macroeconomic factor varies greatly between the rating grades. The exposures are generally higher for HEL than for MBS. Note also that the estimated standard errors are high for the macroeconomic exposures reflecting the high degree of estimation uncertainty induced by the relative short time series.

Next, we compare the results for bond data as we argued earlier in our theoretical approach that the exposure to systematic risk is higher for securitizations than for bonds. A proper measure for comparison is the coefficient of the random systematic factor, which is estimated in the same way for bond data.

Table 4 and Table 5 also show the estimation results for bonds using the same rating grades as for securitizations. The intercepts increase with decreasing rating quality (i.e., the im-

[11] This approach applies a bootstrap method to use the data most efficient and is described in Section 3.3.2.

plied default probability rises) as expected. Moreover the estimates for the coefficient of the systematic factor are considerably lower for bonds than for comparable grades of the securitizations.

Table 6 estimates the models for four different industries. The industries are Financial, Manufacturing, Services and Others. Others is comprised of mainly commerce and public utility bonds. All random effects are significant. Financial bonds have the largest systematic risk which is mainly driven by the recent financial crisis.

[insert Table 6 here]

For a better comparison, we transform the estimate for b into the implied 'asset correlation' by $\frac{b^2}{1+b^2}$. Asset correlation are common in the banking literature and applied in Basel II and Basel III for calculating regulatory capital charges (compare Gordy 2003). Table 7 compares the implied correlations for securitizations and bonds. For bonds they are of a magnitude which is roughly in line with former studies (compare Gordy 2000, Lee et al. 2011) and similar to those used in minimum capital regulations.[12] However, for securitizations they are much higher and particularly for investment grade tranches they are well over 50%, both for MBS and HEL. Thus, the empirical exercise supports the assertion that the systematic risk exposure of securitizations is much higher than for bonds.

[insert Table 7 here]

[12] For example Lee et al. (2011) use equity return data and derive empirically annual asset correlations for different size and probability categories. The results are consistent with Table 6 as a lower rating implies a higher default probability and lower implied asset correlation.

3.3 *Robustness Checks*

3.3.1 *Tranche Dependencies*

The empirical Probit regression model assumes independence of the tranches. However, the impairment events may exhibit dependence between the tranches of the same deal. [13]

Therefore, a three-step bootstrap technique is applied. In the first step, the models from Table 4 are estimated for randomly drawn tranches. The random selection is stratified per deal. In the second step, Step 1 is repeated 200 times. In Step 3, the average parameter estimates and their standard deviations are calculated. Table 8 shows these estimates for Table 4. The values are close to the estimates we obtain in Table 4 for MBS and HEL despite the larger standard errors. We have applied the same techniques to other outputs and found consistent results in all instances.

[insert Table 8 here]

3.3.2 *Estimation Accuracy*

In the previous sections, we used estimated values for the tranche PD and the correlations conditional on the rating grades which are the most likely point estimates according to the Maximum Likelihood (ML) principle. However, by doing so, we neglect the properties of the estimation procedure. Gordy & Heitfield (2000) show that using short time-series the estimates are very volatile as can be seen from the high standard errors provided in Tables 4 and 5. Random errors affect the historical estimates and therefore the resulting Value-at-Risk figures (see Jorion 1996) and particularly for securitizations (see Heitfield 2009).

For an assessment of the estimation accuracy and the estimation error we conduct several

[13] The authors would like to thank our seminar participants for raising this concern.

Monte-Carlo simulations and proceed as follows:

(1) We provide values for the parameters of an artificial portfolio of tranches, particularly, the number of tranches, the attachment points of the tranches, the within-pool asset correlation, and the exposure b to the global risk factor;

(2) We randomly generate pool and tranche defaults according to Equation (1) and Equation (3) for a time series of length T;

(3) Given the realized time series we estimate the parameters β and b;

(4) We repeat Step (2) and Step (3) 1,000 times and aggregate the results.

We assume for simplicity that the segments are homogenous (i.e., each tranche is segmented according to its rating). The number of tranches is set to 10,000 and the time series length is set to 10 years as in our empirical study. We also run simulations with 100 years as a control for the asymptotic properties of the estimator.[14]

[insert Table 9 here]

Table 9 shows the simulation results. The left part shows the result for $T = 10$ years, the right part shows the result for $T = 100$ years. Panel A assumes a default probability of 0.0003, Panel B a default probability of 0.001, and Panel C a default probability of 0.01 for various settings of the parameter b. The first row contains the true parameter. The second row contains the average of the $1,000$ simulated estimates, the third row shows the average standard deviation of the $1,000$ respective estimates, the fourth row presents the empirical standard deviation of the $1,000$ parameter estimates in the simulation.

The table shows that the estimates for the constant c are on average close to their true counterparts. However, the standard errors of the estimates are high, particulary for larger values of b. The estimates of the dispersion parameter are slightly biased downwards in small

[14] The simulation time for the parameter estimation in 1,000 runs is approximately 5 days for $T = 100$ on a standard desktop computer.

samples. This is in line with the results from Gordy & Heitfield (2000). In some instances the underestimation may average 20%. We see the asymptotic unbiasedness for a sample size of $T = 100$. Moreover, the standard error for the small sample size $T = 10$ is high and may exceed 50% of the parameter estimate ($PD = 0.0003$, $b = 0.42$ and $b = 1$). Low default and high systematic risk segments imply a large impact of the estimator error. This is consistent with our earlier empirical results where we found similarly high standard errors. [15]

4 Summary

This paper provides theoretical and empirical evidence that mortgage securitizations imply a larger degree of systematic risk than bonds given the credit rating. In addition, the paper shows that credit ratings do not reflect the systematic risk appropriately.

The study includes various robustness checks. We analyze the impact of tranche/issuer dependencies within a bootstrap approach and confirm the robustness of the chosen parameter estimation methodology within a Monte Carlo simulation.

The implications of these findings are as follows. Firstly, given this knowledge, high default rates for securitizations would not have come as unexpected as they hit many investors in the financial crisis. Secondly, we show that using historical estimates the amount of estimation error is large. These findings imply that model properties such as securitization-induced systematic risk and parameter uncertainty may complement the information provided by credit ratings. National bank regulators require the stress-testing of financial risk models with regard to risk factors. Going forward, banks and model vendors may be asked to assess

[15] In an unreported study, the authors predict impairment rate distributions out-of-time given the systematic risk exposure rating-implied default rates and take parameter uncertainty into account. The study finds that the high empirical default rates of the rated tranches in the financial crisis are within the expectations. This finding implies that parameter uncertainty may complement the information provided by credit ratings next to systematic risk. Detailed results are available upon request.

the systematic risk and estimation error in relation to the assessed financial risk exposures and the impact of model and parameter errors. Thirdly, the assessment of systematic risk requires the data underlying the model development which is often unavailable to the users of risk models. A valuable undertaking may be an open-source modeling environment. This will enable model users to better interpret the associated systematic risk and vendors may benefit from a validation by the crowd.

Appendix

Proof of conditional bond PD

Proof of Equation (13): A borrower k in sector or pool i defaults on his bond when his asset return R_{kt} crosses a threshold c at time t

$$D_{kt} = 1 \Leftrightarrow R_{kt} < c \tag{18}$$

where D_{kt} is an indicator variable with

$$D_{kt} = \begin{cases} 1 & \text{borrower } k \text{ defaults in } t \\ 0 & \text{otherwise} \end{cases} \tag{19}$$

The normalized asset return is modeled as

$$R_{kt} = \sqrt{\rho} X_{it} + \sqrt{1-\rho} S_{kt} \tag{20}$$

where X_{it} and S_{kt} are standard normally distributed variables independent from each other and through time. X_{it} is the sector or pool specific risk factor which is decomposed as

$$X_{it} = \sqrt{\delta} \cdot X_t^* + \sqrt{1-\delta} \cdot U_{it} \tag{21}$$

The unconditional default probability (PD) of the bond is $P(R_{kt} < c) = \Phi(c) = \pi$. The default probability of the bond conditional on the super factor is

$$
\begin{aligned}
P\left(D_{kt}^{B}=1|X_t^*\right) &= P\left(\sqrt{\rho}X_{it}+\sqrt{1-\rho}S_{kt}<c|X_t^*\right) \\
&= P\left(\sqrt{\rho}(\sqrt{\delta}X_t^*+\sqrt{1-\delta}\cdot U_{it})+\sqrt{1-\rho}S_{kt}<\Phi^{-1}(\pi)|X_t^*\right) \\
&= P\left(\sqrt{\rho}\sqrt{1-\delta}U_{it}+\sqrt{1-\rho}S_{kt}<\Phi^{-1}(\pi)-\sqrt{\rho}\sqrt{\delta}X_t^*\right)
\end{aligned}
\tag{22}
$$

The left hand side in the probability operator in Equation (22) has expectation zero and variance $\rho(1-\delta)+1-\rho=1-\rho\delta$ and thus the probability becomes

$$
P\left(D_{kt}^{B}=1|X_t^*\right)=\Phi\left(\frac{\Phi^{-1}(\pi)-\sqrt{\rho\delta}X_t^*}{\sqrt{1-\rho\delta}}\right) \tag{23}
$$

Proof of conditional tranche PD

Proof of Equation (9): Setting the unconditional tranche PD equal to the bond PD π yields

$$
\pi=\Phi\left(\frac{\Phi^{-1}(\pi)-\sqrt{1-\rho}\Phi^{-1}(AL_{ijt})}{\sqrt{\rho}}\right) \tag{24}
$$

After solving for AL and rearranging we obtain

$$
AL(\pi)=\Phi\left(\Phi^{-1}(\pi)\frac{1-\sqrt{\rho}}{\sqrt{1-\rho}}\right) \tag{25}
$$

Inserting Equation (25) into the conditional tranche PD of Equation (9) yields

$$
\begin{aligned}
P(D_t^{Tr}=1|X_t^*) &= \Phi\left(\frac{\Phi^{-1}(\pi)-\sqrt{1-\rho}\Phi^{-1}(AL(\pi))-\sqrt{\rho}\sqrt{\delta}X_t^*}{\sqrt{\rho}\sqrt{1-\delta}}\right) \\
&= \Phi\left(\frac{\Phi^{-1}(\pi)-\sqrt{1-\rho}\Phi^{-1}\left(\Phi\left(\Phi^{-1}(\pi)\frac{1-\sqrt{\rho}}{\sqrt{1-\rho}}\right)\right)-\sqrt{\rho}\sqrt{\delta}X_t^*}{\sqrt{\rho}\sqrt{1-\delta}}\right) \\
&= \Phi\left(\frac{\Phi^{-1}(\pi)-\sqrt{1-\rho}\Phi^{-1}(\pi)\frac{1-\sqrt{\rho}}{\sqrt{1-\rho}}-\sqrt{\rho}\sqrt{\delta}X_t^*}{\sqrt{\rho}\sqrt{1-\delta}}\right) \\
&= \Phi\left(\frac{\Phi^{-1}(\pi)-\Phi^{-1}(\pi)(1-\sqrt{\rho})-\sqrt{\rho}\sqrt{\delta}X_t^*}{\sqrt{\rho}\sqrt{1-\delta}}\right) \\
&= \Phi\left(\frac{\Phi^{-1}(\pi)-\sqrt{\delta}X_t^*}{\sqrt{1-\delta}}\right)
\end{aligned} \tag{26}
$$

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Tables

Table 1
Total number of observations and impairment rates, MBS and HEL, 1997-2008

This table shows the number of observations (NO) and impairment rate (IR) per rating category for mortgage-backed securities (MBS, Panel A) and home equity loan securitizations (HEL, Panel B) from 1997 to 2008. The number of observed tranches increases over time which reflects the growth of these financial instruments during recent years. The impairment rate increases during the GFC (2007 and 2008) and more generally from rating grades Aaa-A (Aaa, Aa and A) to Baa to Ba to B to Caa. Generally speaking, impairment rates for given rating categories are higher for HELs than for MBSs. HELs include to a large degree 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 as corporate bonds did (compare Table 2).

Panel A: MBS

Year	All Grades		Aaa-A		Baa		Ba		B		Caa-C	
	NO	IR	NO	IR	NO	IR	NO	IR	NO	IR	NO	IR
1997	7,377	0.0009	6,820	0.0000	304	0.0033	167	0.0180	86	0.0349		
1998	7,715	0.0003	7,051	0.0000	369	0.0000	180	0.0056	114	0.0088	1	0.0000
1999	7,458	0.0008	6,629	0.0000	454	0.0000	213	0.0047	151	0.0133	11	0.2727
2000	7,361	0.0007	6,356	0.0000	535	0.0037	249	0.0080	204	0.0049	17	0.0000
2001	7,632	0.0012	6,474	0.0000	602	0.0017	281	0.0036	250	0.0240	25	0.0400
2002	9,131	0.0022	7,574	0.0000	826	0.0048	384	0.0260	321	0.0187	26	0.0000
2003	10,557	0.0021	8,434	0.0001	1,103	0.0036	540	0.0074	440	0.0136	40	0.1750
2004	10,290	0.0020	7,928	0.0004	1,156	0.0009	643	0.0000	513	0.0195	50	0.1400
2005	12,857	0.0017	9,987	0.0000	1,374	0.0007	813	0.0049	608	0.0115	75	0.1333
2006	20,229	0.0011	16,363	0.0000	2,025	0.0005	1,036	0.0010	710	0.0099	95	0.1474
2007	28,859	0.0033	23,677	0.0001	2,937	0.0170	1,331	0.0188	822	0.0146	92	0.0544
2008	34,536	0.0839	28,051	0.0315	3,324	0.2924	1,743	0.3138	1,197	0.2924	221	0.6516
All	164,002	0.0191	135,344	0.0027	15,009	0.0274	7,580	0.0343	5,416	0.0388	653	0.1468

Panel B: HEL

Year	All Grades		Aaa-A		Baa		Ba		B		Caa-C	
	NO	IR	NO	IR	NO	IR	NO	IR	NO	IR	NO	IR
1997	1,630	0.0141	1,528	0.0000	53	0.0189	30	0.3667	19	0.5790		
1998	2,401	0.0079	2,243	0.0013	111	0.0631	31	0.2258	16	0.1250		
1999	2,982	0.0097	2,735	0.0011	154	0.0844	62	0.1129	29	0.2069	2	0.0000
2000	3,297	0.0049	2,989	0.0000	216	0.0139	49	0.0612	30	0.1333	13	0.4615
2001	3,579	0.0034	3,224	0.0003	247	0.0122	71	0.0423	29	0.1724	8	0.0000
2002	3,903	0.0036	3,422	0.0000	348	0.0115	93	0.0215	27	0.1111	13	0.3846
2003	4,462	0.0058	3,787	0.0000	543	0.0184	95	0.0947	25	0.2000	12	0.1667
2004	5,493	0.0020	4,416	0.0002	932	0.0043	104	0.0289	27	0.0741	14	0.0714
2005	7,999	0.0021	6,109	0.0000	1,633	0.0018	204	0.0147	40	0.2250	13	0.1539
2006	12,549	0.0016	9,183	0.0000	2,716	0.0022	596	0.0084	43	0.1628	11	0.1818
2007	18,339	0.0553	13,059	0.0074	4,017	0.1061	1,142	0.3853	95	0.3263	26	0.7692
2008	19,752	0.2900	13,503	0.1326	3,303	0.4593	1,455	0.7464	1,095	0.8758	396	0.9495
All	86,386	0.0802	66,198	0.0119	14,273	0.0663	3,932	0.1757	1,475	0.2660	508	0.3139

Table 2
Total number of observations and default rates, corporate bonds, 1997-2008

This table shows the total numbers of observations (NO) and the default rate (DR) for corporate bonds from 1997 to 2008 per rating category (Panel A) and per industry (Panel B). The number of rated bonds increases over time, which reflects the growth of these financial instruments during recent years. The default rate increases after in 2002 and during the GFC (2008) and more generally from rating grades Aaa-A (Aaa, Aa and A) to Baa to Ba to B to Caa.

Panel A: Bonds per rating class

Year	All Grades		Aaa-A		Baa		Ba		B		Caa-C	
	NO	DR	NO	DR	NO	DR	NO	DR	NO	DR	NO	DR
1997	15,118	0.0017	11,681	0.0000	1,871	0.0000	557	0.0000	995	0.0101	108	0.1481
1998	20,936	0.0020	16,194	0.0000	2,452	0.0004	1,150	0.0026	1,152	0.0156	138	0.1449
1999	26,542	0.0037	20,627	0.0000	3,182	0.0003	1,239	0.0024	1,395	0.0351	291	0.1546
2000	30,587	0.0035	24,267	0.0000	3,345	0.0009	1,217	0.0000	1,412	0.0312	347	0.1729
2001	31,270	0.0069	25,201	0.0000	3,142	0.0003	1,238	0.0032	1,270	0.0528	419	0.3413
2002	31,701	0.0072	25,505	0.0001	3,242	0.0096	1,554	0.0039	899	0.0501	501	0.2854
2003	33,949	0.0037	27,688	0.0000	3,294	0.0000	977	0.0072	1,475	0.0075	515	0.2078
2004	39,955	0.0008	33,556	0.0000	3,527	0.0000	914	0.0000	1,510	0.0020	448	0.0670
2005	52,288	0.0004	44,686	0.0000	4,866	0.0002	985	0.0000	1,287	0.0047	464	0.0323
2006	59,570	0.0006	51,725	0.0000	3,891	0.0000	2,298	0.0000	1,187	0.0059	469	0.0618
2007	60,942	0.0002	54,265	0.0000	3,580	0.0000	1,702	0.0000	1,145	0.0009	250	0.0400
2008	59,612	0.0023	52,644	0.0004	4,000	0.0083	1,616	0.0149	997	0.0211	355	0.1211
All	462,470	0.0028	388,039	0.0000	40,392	0.0017	15,447	0.0028	14,724	0.0197	4,305	0.1481

Panel B: Bonds per industry

Year	All Grades		Financial		Manufacturing		Services		Others	
	NO	DR	NO	DR	NO	DR	NO	DR	NO	DR
1997	15,118	0.0017	9,729	0.0002	1,555	0.0032	1,863	0.0027	1,971	0.0071
1998	20,936	0.0020	13,999	0.0003	1,876	0.0027	2,551	0.0055	2,510	0.0076
1999	26,542	0.0037	18,128	0.0002	2,304	0.0122	3,136	0.0108	2,974	0.0111
2000	30,587	0.0035	21,520	0.0002	2,457	0.0151	3,403	0.0112	3,207	0.0087
2001	31,270	0.0069	22,103	0.0021	2,394	0.0288	3,303	0.0206	3,470	0.0089
2002	31,701	0.0072	22,105	0.0009	2,456	0.0171	3,290	0.0356	3,850	0.0125
2003	33,949	0.0037	23,927	0.0005	2,668	0.0082	3,371	0.0190	3,983	0.0068
2004	39,955	0.0008	28,704	0.0000	2,994	0.0040	3,711	0.0032	4,546	0.0020
2005	52,288	0.0004	40,236	0.0000	3,013	0.0027	4,155	0.0012	4,884	0.0014
2006	59,570	0.0006	46,875	0.0000	2,775	0.0043	4,506	0.0044	5,414	0.0004
2007	60,942	0.0002	47,964	0.0000	2,246	0.0031	4,459	0.0004	6,273	0.0003
2008	59,612	0.0023	45,617	0.0012	2,043	0.0162	4,550	0.0035	7,402	0.0051
All	462,470	0.0028	340,907	0.0005	28,781	0.0098	42,298	0.0098	50,484	0.0060

Table 3
Parameter estimates for fixed effect models

This table shows the estimates of the Probit models for MBS, HEL and corporate bonds. Standard errors are below each estimate. The significance is indicated as follows: ***: significant at 1%, **: significant at 5%, *: significant at 10%. AUROC is the area under the Receiver Operating Characteristic.
The coefficients are increasing with decreasing rating quality in the model without year dummies. The year dummies are significantly different from zero in many years and positive during economic downturns such as the recent financial crisis for all segments and 2002 for corporate bonds only. This shows that time-specific (economic) influences are not able to be wholly explained by the rating. Similar results are obtained where i) no regressors are included and ii) only ratings are included as regressors.

Variable	MBS	HEL	Bonds
Intercept	-3.6538***	-2.7534***	-3.6783***
std error	0.1375	0.1129	0.0867
Baa	1.2838***	1.0632***	0.3465***
std error	0.0255	0.0212	0.0449
Ba	1.3739***	1.8959***	0.5216***
std error	0.0312	0.0286	0.0555
B	1.4027***	2.3008***	1.3377***
std error	0.0358	0.0434	0.0344
Caa	2.4145***	2.7990***	2.4338***
std error	0.0655	0.0849	0.0347
1998	-0.4676*	-0.1047	0.1318
std error	0.2649	0.1538	0.1053
1999	-0.2525	-0.1331	0.3097***
std error	0.2051	0.1436	0.0950
2000	-0.3305	-0.6120***	0.2858***
std error	0.2049	0.1679	0.0944
2001	-0.1983	-0.7088***	0.5644***
std error	0.1829	0.1712	0.0902
2002	0.0156	-0.7857***	0.6155***
std error	0.1607	0.1675	0.0898
2003	-0.0911	-0.5173***	0.2109**
std error	0.1591	0.1445	0.0942
2004	-0.1392	-0.9799***	-0.3639***
std error	0.159	0.1645	0.1126
2005	-0.2454	-1.0631***	-0.4954***
std error	0.1593	0.1513	0.1192
2006	-0.3495**	-1.2291***	-0.3255***
std error	0.1582	0.142	0.1096
2007	0.1607	0.4294***	-0.6270***
std error	0.1424	0.1141	0.1444
2008	1.7910***	1.6145***	0.9652***
std error	0.1372	0.1131	0.0869
Obs	164,002	86,386	462,470
Pseudo R-square	0.0748	0.2379	0.0157
R-square rescaled	0.4349	0.5559	0.4845
AUROC	0.944	0.939	0.9477

Table 4
Parameter estimates of random effects models

This table shows parameter estimates from the random effects Probit model. Standard errors are below each estimate. The significance is indicated as follows: ***: significant at 1%, **: significant at 5%, *: significant at 10%. AIC is the Akaike Information Criterion.
The coefficients for the unobservable random effect are statistically significantly different from zero in all models. After including credit ratings, the coefficients become higher. This underlines that ratings do not properly account for macroeconomic effects. The coefficients for the credit ratings change both for MBS and HEL and the estimates for the exposure to the economic factor which are higher for HEL. The coefficient of the systematic factor are considerably lower for bonds than for securitizations.

	MBS	HEL	Bonds
Intercept	-3.6646***	-3.0967***	-4.0458***
std error	0.1713	0.2207	0.0826
Baa	1.2830***	1.0628***	0.9835***
std error	0.0255	0.0213	0.0687
Ba	1.3732***	1.8955***	1.1527***
std error	0.0312	0.0284	0.0756
B	1.4019***	2.3011***	1.9046***
std error	0.0357	0.0432	0.0629
Caa	2.4143***	2.7984***	2.9874***
std error	0.0646	0.0849	0.0626
b	0.5782***	0.7564***	0.4757***
std error	0.1197	0.1555	0.0686
Obs	164,002	86,386	462,470
AIC	18,281	24,864	8,007

Table 5

Parameter estimates of random effects models, per rating category

This table shows parameter estimates from the random effects Probit model per rating category. 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 coefficients for the unobservable macroeconomic effect are statistically significantly different from zero in all models. The coefficients for the credit ratings change both for MBS and HEL and the estimates for the exposure to the economic factor which are higher for HEL. The exposure of the macroeconomic factor varies greatly between the rating grades. The exposures are generally higher for HEL. The coefficient of the systematic factor are considerably lower for bonds than for comparable grades of the securitizations.

Panel A: MBS					
	Aaa-A	Baa	Ba	B	Caa-C
Intercept	-4.4068***	-2.7711***	-2.3793***	-2.0515***	-1.2087***
std error	0.5923	0.2617	0.2242	0.1585	0.2610
b	1.2058**	0.8301***	0.7241***	0.5104***	0.7322***
std error	0.5033	0.1954	0.1663	0.1108	0.2127
Obs	135,344	15,009	7,580	5,416	653
AIC	8,015	4,780	2,763	2,120	599
Panel B: HEL					
	Aaa-A	Baa	Ba	B	Caa-C
Intercept	-3.6863***	-1.9722***	-1.2555***	-0.6768***	-0.5364***
std error	0.4339	0.2305	0.2626	0.2155	0.3870
b	1.2031***	0.7753***	0.8833***	0.6953***	1.0807***
std error	0.3764	0.1621	0.1865	0.1527	0.3006
Obs	66,198	14,273	3,932	1,475	508
AIC	11,891	7,872	3,585	1,242	296
Panel C: Bonds					
	Aaa-A	Baa	Ba	B	Caa-C
Intercept	-4.9817***	-3.5021***	-3.1475***	-2.2339***	-1.1344***
std error	0.7466	0.2411	0.2421	0.1305	0.1248
b	0.9038	0.6569***	0.6117**	0.4349***	0.4207***
std error	0.5555	0.2000	0.2283	0.0994	0.0903
Obs	388,039	40,392	15,447	14,724	4,305
AIC	402	890	586	2,602	3,408

Table 6

Parameter estimates of random effects models, corporate bonds per industry

This table shows parameter estimates from the random effects Probit model for bonds per. 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 coefficients for the unobservable macroeconomic effect are statistically significantly different from zero in all models. Financial bonds have the largest systematic risk.

	Financial	Manufacturing	Services	Others
Intercept	-4.6107***	-7.7799***	-4.0136***	-3.8030***
std error	0.2241	0.1042	0.2390	0.1950
Baa	1.7130***	4.2647***	0.6890***	0.4960**
std error	0.1017	0.1221	0.2126	0.1639
Ba	1.1605***	4.8129***	1.2527***	0.6396***
std error	0.1273	0.1223	0.2152	0.1655
B	1.6803***	5.6508***	1.8814***	1.4848***
std error	0.1244	0.0609	0.2008	0.1467
Caa	3.9587***	6.6222***	2.8818***	2.5643***
std error	0.1460	0.0611	0.2005	0.1449
b	0.6450***	0.4015***	0.4587***	0.4656***
std error	0.1682	0.0895	0.1038	0.1095
Obs	340,907	28,781	42,298	50,484
AIC	1,233	1,928	2,617	2,014

Table 7

Comparison of estimated implied asset correlations

This table shows the estimates for the implied asset correlations which given is by $\frac{b^2}{1+b^2}$ where b is the coefficient of the systematic factor from Equation (11). Panel A reports the implied asset correlations for Table 4. Panel B reports the implied asset correlations for Table 4. Panel C reports the implied asset correlations for Table 6. For bonds they are of a magnitude which is roughly in line with former studies (compare Gordy 2000, Lee et al. 2011) and similar to those used under Basel II and Basel III. However, for securitizations they are much higher and particularly for investment grade tranches they are well over 50%, both for MBS and HEL. Thus, the empirical exercise supports the assertion that the systematic risk exposure of securitizations is higher than for bonds.

Panel A: MBS, HEL and bonds

	All	Aaa-A	Baa	Ba	B	Caa-C
MBS	0.2506	0.5925	0.4079	0.3440	0.2067	0.3490
HEL	0.3639	0.5914	0.3754	0.4383	0.3259	0.5387
Bonds	0.1764	0.4496	0.3014	0.2723	0.1591	0.1504

Panel B: bond per industry

	Financial	Manufacturing	Services	Others
Bonds	0.2938	0.1388	0.1738	0.1782

Table 8

Parameter estimates of random effects models, MBS and HEL; bootstrap methodology

This table shows averages of the parameter estimates from the random effects Probit model using a bootstrap methodology in Column 2 and Column 4. The empirical standard deviations are given in Column 3 and Column 5. The results are consistent to the ones presented in Table 4.

	MBS		HEL	
	Average	Std. dev.	Average	Std. dev.
Intercept	-3.7302	0.2159	-3.0752	0.0649
Baa	1.2318	0.0853	1.0597	0.0629
Ba	1.5144	0.0850	1.7494	0.0774
B	1.4987	0.1202	2.1394	0.0884
Caa	2.0270	0.1508	2.5762	0.1191
b	0.6416	0.0518	0.7428	0.0628

Table 9

Monte-Carlo simulation results

This table shows the results of a Monte-Carlo simulation to assess the accuracy of parameter estimates. The left part of the table shows the result for $T = 10$ years, the right part shows the result for $T = 100$ years. The upper part assumes a default probability of 0.0003 (Panel A), the middle part a default probability of 0.001 (Panel B), the lower part a default probability of 0.01 (Panel C), each for various settings of the parameter b. The first row contains the true parameter. The second row contains the average of the $1,000$ simulated estimates, the third row shows the average standard deviation of the $1,000$ respective estimates, the fourth row contains the empirical standard deviation of the $1,000$ parameter estimates in the simulation.
The Table shows that while the estimates for the constant c are on average close to their true counterparts, their standard errors can be very high, particulary for larger values of b. The estimates of the dispersion parameter however, are biased in the small samples. This is in line with results due to Gordy & Heitfield (2000). In some instances the underestimation may average 20%. We see the asymptotic unbiasedness for a sample size of $T = 100$. However, the standard error for the small sample size $T = 10$ is high and may exceed 50% of the parameter ($PD = 0.0003$, $b = 0.42$ and $b = 1$).

	T=10						T=100					
	Panel A: Tranche PD = 0.0003											
	c	b	c	b	c	b	c	b	c	b	c	b
Parameter	-3.6172	0.3333	-3.7221	0.4201	-4.8530	1.0000	-3.6172	0.3333	-3.7221	0.4201	-4.8530	1.0000
Average of estimates	-3.6171	0.2673	-3.7246	0.3487	-4.7253	0.8329	-3.6169	0.3285	-3.7242	0.4187	-4.8756	1.0072
Average of Std. deviation estimates	0.1383	0.1403	0.1800	0.1746	0.9057	0.7558	0.0438	0.0381	0.0569	0.0494	0.2954	0.2243
Std. deviation of estimates	0.1593	0.1872	0.1981	0.2123	0.8452	0.7260	0.0454	0.0486	0.0572	0.0499	0.3135	0.2418
	Panel B: Tranche PD = 0.001											
	c	b	c	b	c	b	c	b	c	b	c	b
Parameter	-3.2574	0.3333	-3.3518	0.4201	-4.3702	1.0000	-3.2574	0.3333	-3.3518	0.4201	-4.3702	1.0000
Average of estimates	-3.2601	0.2909	-3.3491	0.3810	-4.3464	0.8924	-3.2581	0.3239	-3.3495	0.4132	-4.3975	1.0066
Average of Std. deviation estimates	0.1113	0.0930	0.1412	0.1200	0.6031	0.5241	0.0366	0.0298	0.0463	0.0383	0.1887	0.1601
Std. deviation of estimates	0.1192	0.1429	0.1478	0.1478	0.5991	0.5476	0.0365	0.0731	0.0442	0.0573	0.1952	0.1654
	Panel C: Tranche PD = 0.01											
	c	b	c	b	c	b	c	b	c	b	c	b
Parameter	-2.4522	0.3333	-2.5233	0.4201	-3.2900	1.0000	-2.4522	0.3333	-2.5233	0.4201	-3.2900	1.0000
Average of estimates	-2.4567	0.3056	-2.5221	0.3957	-3.3120	0.9525	-2.4512	0.3313	-2.5235	0.4180	-3.2860	0.9923
Average of Std. deviation estimates	0.0980	0.0711	0.1268	0.0926	0.3429	0.2962	0.0335	0.0243	0.0423	0.0308	0.1084	0.0923
Std. deviation of estimates	0.1101	0.0757	0.1355	0.1015	0.3847	0.3284	0.0335	0.0238	0.0418	0.0311	0.1043	0.0936

Figures

Fig. 1. Impairment Rates for MBS securitizations, HEL securitizations and Baa-rated bonds

This figure compares the impairment rates for Baa-rated bonds with Baa-rated mortgage-backed securities (MBS) which are collateralised by prime mortgages and Baa-rated home equity loan (HEL) securities which are mostly collateralized by subprime mortgages. Both MBS and HEL are securitizations of real-estate linked loan portfolios. Default rates for Baa-rated bonds fluctuate from 1997 to 2008 between zero and 1.0%, while impairment rates for Baa-rated MBS fluctuate between zero and 29.2% and impairment rates for Baa-rated HEL fluctuate between 0.2% and 46.0%. Values for impairment rates of MBS securitizations and HEL securitizations are shown in Table 1 and for default rates of Baa-rated bonds are shown in Table 2.

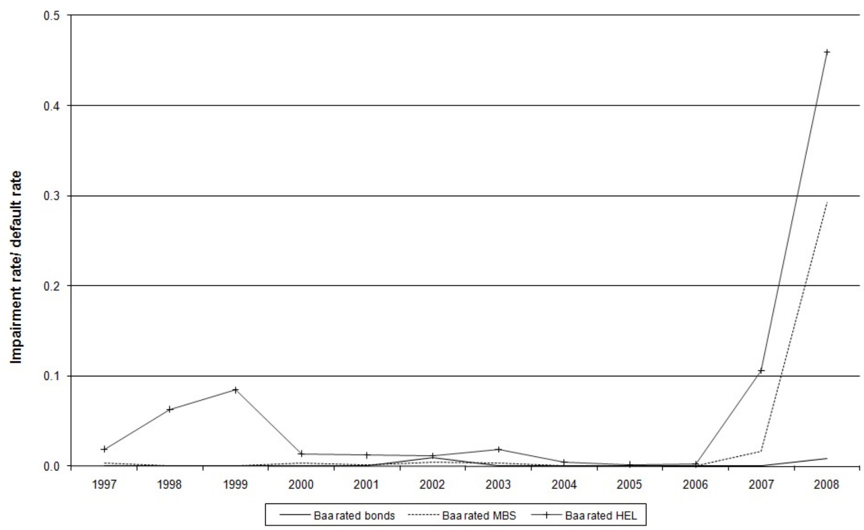

Fig. 2. Macroeconomic Impact on Default Probabilities of Bonds vs. Tranches

This figure compares how the probabilities react to changes in the systematic factor for various parameter settings. The upper four graphs assume an unconditional default probability π of 1%, the lower four graphs an unconditional default probability π of 5%. Conditional on the realization of the economy, the default probabilities are shifted upwards or downwards. For instance, for $\rho = 0.1$ and $\delta = 0.1$ (first graph), a macroeconomic realization of -2.5 or less (which has a probability of occurrence of approximately 0.6% as the factor is standard normally distributed) increases the bond PD to 1.8% and the tranche PD to 5.3%.

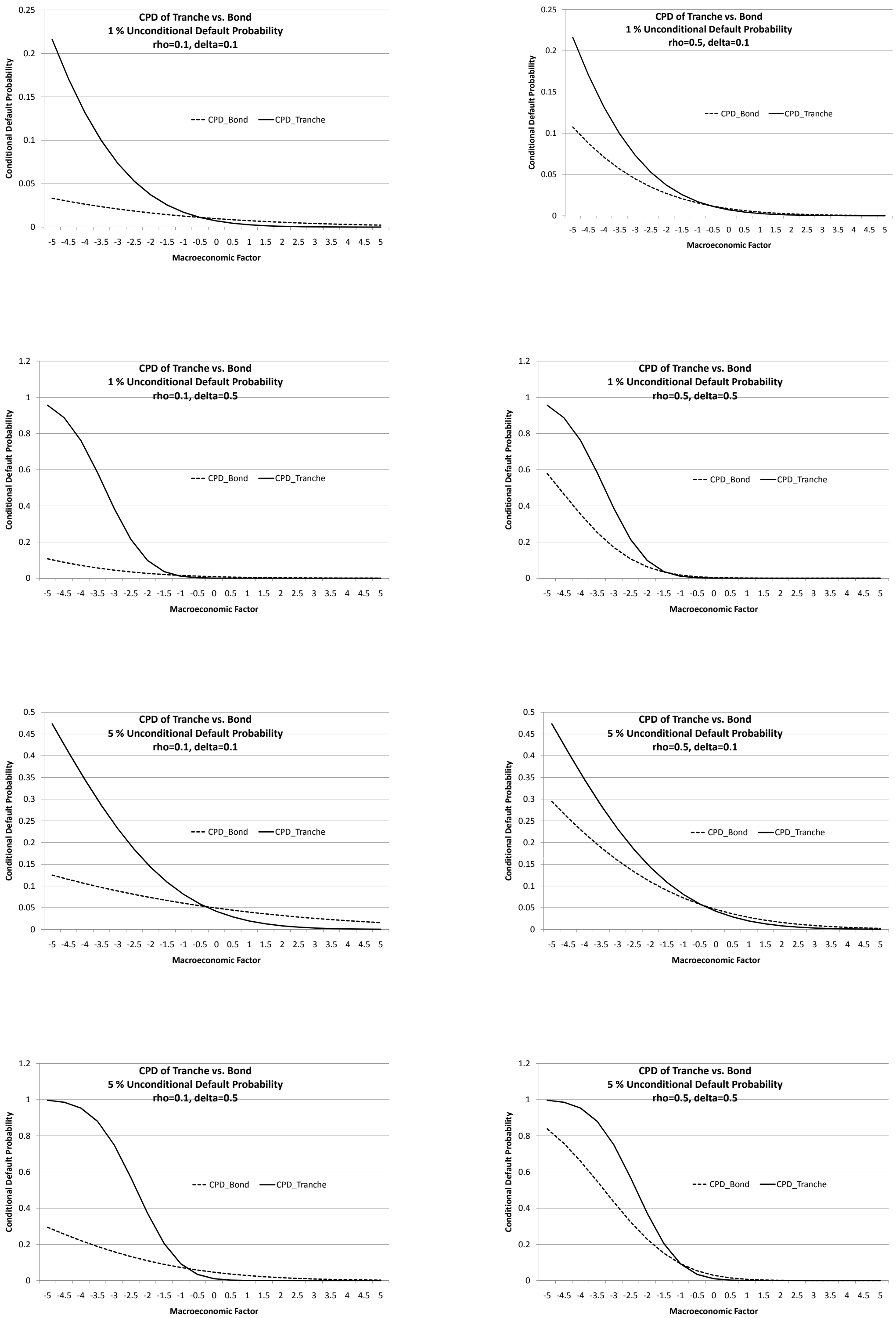

Fig. 3. Macroeconomic Sensitivity of Default Probabilities of Bonds vs. Tranches

This figure compares the macroeconomic sensitivities for various parameter settings. The upper four graphs assume an unconditional default probability π of 1%, the lower four graphs an unconditional default probability π of 5%. A higher ρ increases the impact on the bond but not on the tranche because it is already incorporated in the calculation of the implied attachment level, whereas higher δ increases both the bond and the tranche impact.