Capital adequacy and systematic risk of asset securitizations

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Abstract

This paper develops a framework to measure the exposure to systematic risk of asset securitizations. The paper measures empirically whether current ratings-based rules for regulatory capital of securitization reflect this exposure. The analysis is based on US data for asset securitizations for the time period between 2000 and 2008. The paper finds that the shortfall of regulatory capital during the Global Financial Crisis is strongly related to ratings. The paper shows empirically that insufficient capital is allocated to tranches with the highest rating. The problem is exacerbated by the fact that these tranches account for the greatest part of the total issuance volumes. Furthermore, this paper is the first to calibrate risk weights which provide sufficient capital charges to cover the exposure during economic downturns. These policy-relevant findings suggest a re-calibration of RBA risk weights and may contribute to the current efforts to re-establish sustainable securitization markets.

Key words: Asset-backed Security, Basel II and III, Collateralized Debt Obligation, Economic Downturn, Mortgage-backed Securities, Home Equity Loan Securities, Rating-based Approach, Regulation, Regulatory Capital, Risk Weights, Securitization

JEL classification: G20, G28, C51

1 Introduction

1.1 Motivation

Asset securitizations are attractive to the financial industry as a source of funding, risk intermediation as well as balance sheet management. The merits of securitization despite the controversial public discussion are recognized by regulators. The Basel Committee on Banking Supervision (2011) is concerned about the decline of issuance volumes (e.g., in the US, from about US$ 2 trillion in 2007 to around US$ 400 billion in 2008). Therefore, regulators are working on re-establishing sustainable securitization markets. This paper contributes to these efforts and looks into the rules for the ratings-based calculation of regulatory capital in relation to the financial risks of asset securitizations.

Asset securitizations include asset backed securities (ABSs), collateralized debt obligations (CDOs), commercial and residential mortgage-backed securities (CMBSs and RMBSs) and home equity loan securitizations (HELs). These financial instruments have been a major source of financial losses to investors and institution failures during the Global Financial Crisis (GFC). In hindsight, the ratings-based regulatory capital requirements for securitizations have often been insufficient to cover losses during the GFC.

In principle, rating agencies primarily consider probabilities of default (PDs) or expected losses (i.e., PDs weighted by losses given default) as rating criteria. The structure of the credit rating models for securitizations used by the major rating agencies is quite similar. CDO evaluation models are VECTOR from Fitch rating agency (compare Fitch Ratings 2006), CDOROM from Moody's Investors Service (compare Moody's Investors Service 2006) and CDO Evaluator from Standard and Poor's (compare Standard & Poor's 2005). The default rates for the individual tranches are derived based on expected future cash flows generated by the underlying asset pool for different scenarios using simulations. Gaussian Copulas are used to model the co-movement between the default processes of the underlying individual assets. The calculation of default rates of the defined scenarios follows the Value-at-Risk (VaR) approach for a given confidence level. A further essential analysis is the simulation of cumulative portfolio loss rates based on probabilities of default, recovery rates and asset correlations. Rating agencies estimate expected losses or default probabilities of the different tranches as a result of these quantitative models. To which degree the final rating grades provided by rating agencies account for systematic risk characteristics is unclear.

The current numbers of rating changes from rating agencies for structured products may indicate that ratings are very limited in terms of economic informativeness. From 2008 to 2011, the bulk of rating changes were downgrades. In 2010 Standard & Poor's reports for European securitizations 617 upgrades and $2,663$ downgrades. The US figures amount to 662 upgrades and $18,461$ downgrades. For January to September 2011 European upgrades were 410 versus $2,177$ downgrades and for the US $1,427$ upgrades versus $12,971$ downgrades. The other main rating agencies Moody's Investors Service and Fitch Ratings report similar relations between upgrade- and downgrade-numbers (compare, e.g., Association of Financial Markets in Europe 2011). The downgrades may be explained by a revision of rating agency expectations, poorer collateral performances and possibly by changes in the rating methodologies, to address underestimated concentration- and correlation risks (compare European Central Bank 2011). [1]

The current regulatory framework of risk-based capital provision for structured financial instruments depends strongly on the quality of the rating from external rating agencies. At present two different ways for financial institutions to determine regulatory capital for securitized assets are provided: Ratings Based Approach (RBA) and Supervisory Formula Approach (SFA). A bank is obliged to apply the RBA for securitization exposures if a credit rating is available.

The RBA for securitizations is attractive for its simplicity. It consists of two look-up tables displaying risk weights for long-term and short-term rated securitization tranches. The risk weights for the tranches vary according to the external rating grade (or an inferred rating grade if available), the seniority of a specific tranche, the granularity of the underlying pool and whether assets include securitizations (i.e., transaction is a re-securitization). Risk characteristics such as the exposure to systematic risk may be included either in the ratings or in the mapping methodology.

Our first contribution is to demonstrate empirically that securitized tranches react highly sensitive to macroeconomic changes and to measure the exposure of tranches to systematic risk given credit ratings per securitization category, granularity and re-securitization exposures. We apply a comprehensive data set of asset securitizations including five different transaction types with more than $200,000$ annual tranche observations and specify the intensity of the effects from systematic risk on securitization exposures. Furthermore, we measure the shortfall of regulatory capital related to ratings which do not include macroeconomic

[1] Plank (2011) demonstrates that the diversification of structured securities in particular CDOs is not effective in decreasing the risk of tranches.

information sufficiently. We show that the capital shortfall from the underestimation of systematic risk predominantly concerns the tranches with higher ratings, which is consequential because the top-rated tranches count for the major part of issuance volumes. In addition, we empirically calibrate risk weights which fully include the systematic risk exposure.

The paper proceeds as follows. Section 1.2 gives a brief overview of the relevant literature. Section 2 provides an empirical analysis of systematic risk in external credit ratings. Firstly, in Section 2.1, we explain our two main hypotheses which are tested in the empirical analysis. Secondly, Section 2.2 introduces and describes the data set of asset securitizations used in the investigation. Thirdly, Section 2.3 presents the model framework. Subsection 2.3.1 explains the basic model and in Subsection 2.3.2 the applied estimation methodology is described. Section 3 presents the main conclusions from the analysis. Section 4 provides robustness tests. Finally, in Section 5 prudential regulatory policy implications are discussed.

1.2 Related Literature

This paper relates to three streams in literature. The first stream focuses on the theoretical framework of the regulatory approaches for securitizations. The RBA Approach is based on an analytical model for calculating capital charges for tranches of securitized large portfolios (so called 'pools') by Pykhtin & Dev (2002, 2003). The model is related to a single-factor model for individual asset returns by Merton (1974), which is also known as the 'Gaussian one factor copula model'. In order to develop a simple industry standard Peretyatkin & Perraudin (2004) have employed the Pyktin-Dev model to calibrate risk weights for tranches of structured financial instruments. Their simulation results are a major contribution to the final determination of the risk weights in the Basel documents. The risk weights range from 7% which is the floor for AAA tranches up to $1,250\%$ for tranches rated below Ba3. Please note that a risk weight of $1,250\%$ implies that the whole securitization tranche has to be funded by capital as the required capital to risk-weighted assets is 8% ($1,250\% * 8\% = 100\%$). The SFA approach which can be applied if no credit rating is available has been developed by Gordy & Jones (2003) and Gordy (2004). Regulatory capital requirements are calculated based on a supervisory formula which requires certain input parameters determined by the bank. The parameters used in the model are the capital requirements prior to securitization, the weighted average loss given default of the underlying pool, the actual number of assets in the pool, the thickness of the tranches and the attachment levels. Thus the model completely relies on internal credit risk information of the bank.

The second stream analyzes the effects from systematic risk on financial products. Iannotta & Pennacchi (2011) find that the ratings of external rating agencies do not reflect systematic risk adequately because they are focussing basically on default probabilities or expected losses respectively. The authors argue that the 'through-the-cycle' approach applied by the major rating agencies is not suitable to reflect the fact that two bonds with the same probability of default and loss given default (LGD) and thus sharing the same rating may react differently during an economic downturn. They suggest that credit spreads for corporate bonds would embed systematic risk to a far better extend than credit ratings based on physical risk measures. Accordingly, the authors conclude that banks choose bonds within the same rating grade that have the highest credit spreads and therefore the highest systematic risk. The authors underline that this conclusion can also explain why banks may have an interest to retain tranches of securitizations on their balance sheet which are highly rated but imply a high systematic risk.

Claußen et al. (2010) demonstrate using an analytical model that structured financial instruments are more sensitive to macroeconomic risk factors than comparable straight bonds. Furthermore the authors find that the effects are even more pronounced for multiple structure securitizations. Fender et al. (2008) show that the tranching process of a portfolio of bonds may lead to a higher probability of rating downgrades for tranched products compared to the underlying assets. Furthermore the authors find that tranching has a strong impact on the probability of large losses. Krahnen & Wilde (2009) compare risk characteristics of asset backed securities and those of corporate bonds referring to expected loss, LGD and macroeconomic risk sensitivity across all rating grades.

The third stream focusses on the quality of securitization credit ratings from external rating agencies. The conflict of interest between the issuers and the credit rating agencies has been regarded as one source of failure for spectacular downgrades of top-rated structured financial products. Originators generally chose and pay the rating agencies directly ('Paid-by-Originator-Approach') and therefor have an incentive to pick the credit rating agency offering the most optimistic rating ('rating-shopping').[2] A further key problem for the evaluation of structured products has been revealed by Bar-Isaac & Shapiro (2010). The authors find that credit ratings for securitizations are more likely to understate the credit risk in booms rather than in recessions.

Various authors suggest that external credit ratings assigned to securitization exposures by credit rating agencies may underestimate the underlying risk. Rajan et al. (2008) find that

[2] Compare Fons (2008), Skreta & Veldkamp (2009) and Bolton et al. (2012).

credit ratings may rely on models which mis-evaluate the average credit quality of an asset portfolio because 'soft' information is omitted. Rösch & Scheule (2012) find that capital levels for securitizations based on the RBA are insufficient to cover implied losses during economic downturns such as the GFC. The authors also highlight that asset class specific risk characteristics may differ for different asset portfolios.

Further important approaches which address the quality issue of external ratings are due to Heitfield (2008), Heitfield (2009), Benmelech & Dlugosz (2009), Coval et al. (2009), Stolper (2009), He et al. (2010), Pagano & Volpin (2010) and Griffin & Tang (2012).

2 Empirical Analysis

2.1 Derivation of Hypotheses

The RBA to determine regulatory capital requirements for securitizations relies on the accuracy of external ratings. Rating agencies do not consider the systematic risk for their ratings adequately. In our paper we will give a strong indication that indeed in external ratings the systematic risk is not acceptably included:

- Hypothesis 1: There are systematic fluctuations that are not captured by the ratings.

As a consequence from Hypothesis 1 there will be the discussion whether the rating agencies will change their rating approach or whether the capital regulation has to account for the higher systematic risk. As it is practically impossible to influence the methodology of the rating agencies we propose that capital regulation needs to account for the higher systematic risk. Therefore, we propose a re-calibration of the risk weights for securitizations in order to avoid unexpected losses to financial institutions during economic downturns.

We will also show in this paper that the capital charges especially for the most senior tranches may be insufficient to cover losses during economic downturns. The most senior tranches are of a particular interest: On the one hand they count for vast quantities. Accoring to Benmelech & Dlugosz (2010) nearly 50% of the securitized tranches rated by Moody's in 2008 were AAA-rated. Erel et al. (2011) show that the largest write-downs and respective losses came from highly-rated tranches. Furthermore, the higher rated tranches are regarded as most sensitive to macroeconomic shocks (compare, e.g., Coval et al. 2009). Rösch & Scheule (2012) demonstrate that capital requirements for securitizations and especially for highly-rated tranches were not sufficient to cover losses during the GFC.

- Hypothesis 2: The risk weights of the higher rated tranches in the RBA do not consider the systematic risk adequately whereas the risk weights of the lower rated tranches are sufficient.

Finally, we investigate in our paper whether capital charges would have been sufficient if the systematic risk would have been fully involved in the risk weights of the RBA.

2.2 Securitization Data

The data set we are utilizing in order to test our developed hypothesis has been provided by Moody's credit rating agency and comprises $223,886$ annual tranche observations. The data set is concordant with the data used by Rösch & Scheule (2012). We consider the data history for the period from 2000 to 2008. The data set contains five different categories of transaction observations according to the following classes: ABS (asset backed securities), CDO (collateralized debt obligations), CMBS (commercial mortgage-backed securities), HEL (home equity loans) and RMBS (residential mortgage-backed securities). The data set provides the ratings and characteristics of the tranches (among others: attachment levels and thicknesses of the tranches) as well as occurrences of impairment events. The detailed information about the tranches (e.g., seniority and granularity) enables us to determine the risk weights accurately and to calculate the capital requirements under the RBA.

In our data set retail asset portfolios comprise a large number of exposures with small amounts. They are basically exposed to systematic risk and can be generally considered to be granular. In particular ABSs, HELs and RMBSs generally relate to retail assets (e.g., auto, credit cards and retail loans). Corporate/wholesale asset portfolios can generally be considered to be non-granular because they comprise a small number of exposures with large amounts. They are exposed to idiosyncratic and systematic risk. In particular CDOs and CMBSs comprise corporate/wholesale loan portfolios (e.g., unsecured or secured corporate loan exposures) and a part of ABSs exposures relates to corporate/wholesale asset portfolios (e.g., equipment loans and leases) as well. Regarding seniority a tranche is considered as the most senior tranche if it is a position with a first claim on the assets or the cash flows in the portfolio.

In addition, we have hand-collected from the Bloomberg database securitization ratings at origination from Fitch, Moody's and Standard & Poor's to analyze whether the results can be generalized from Moody's to other major rating agencies. 54,628 securitization ratings at origination which were rated by Moody's and Standard & Poor's, 29,323 securitization ratings at origination which were rated by Moody's and Fitch and 18,325 securitization ratings at origination which were rated by Standard & Poor's and Fitch.[3] The Spearman correlation coefficient is 0.9762 for Moody's and Standard and Poor's, 0.9719 for Moody's and Fitch and 0.9924 for Standard and Poor's and Fitch.

[3] This information was used in the generation of the number of CRAs which rate financial instruments and was included as a control variable in prior models.

2.3 Model Framework

2.3.1 The Model

The analytical model behind the RBA and thus the basis for the derivation of the risk weights is the Model by Pykhtin & Dev (2002, 2003) which is an extension and generalization of the single-factor approach where a common factor is driving the default risk of a portfolio of loans. [4]

$$R_{k,t} = X_{i,t}\sqrt{\rho_{i,t}} + S_{k,t}\sqrt{1-\rho_{i,t}} \tag{1}$$

Where $R_{k,t}$ denotes the asset return of the borrower k at time t ($k = 1, ..., K$; $t = 1, ..., T$) and depends on a systematic $X_{i,t}$ and on an idiosyncratic risk component $S_{k,t}$. $X_{i,t}$ and $S_{k,t}$ are independent and standard normal. The parameter $\rho_{i,t}$ denotes the asset correlation and may vary across time and borrowers. The systematic risk factor of sector i ($i = 1, ..., I$) can be decomposed into two further factors:

$$X_{i,t} = X_t^*\sqrt{\beta_i} + U_{i,t}\sqrt{1-\beta_i} \tag{2}$$

X_t^* denotes the macroeconomic risk factor and $U_{i,t}$ denotes the sector specific risk factor. Both factors X_t^* and $U_{i,t}$ are standard normally distributed and serially independent. Bank portfolios can be different in their regional or industrial structure which may cause different effects from systematic risk. In practice, macroeconomic shifts do not necessarily activate changes across all banks to the same extent. In order to capture this feature, market segmentation has been introduced to the model. The parameter β_i denotes the factor loading of the macroeconomic risk factor ($\beta_i \epsilon [0, 1]$).

Pyktin and Dev investigate appropriate capital charges for securitized tranches based on the assumption that the tranches are held as a negligible fraction of a wider bank portfolio. Furthermore they suppose that the bank's portfolio is diversified and driven by a single risk factor. Thus, aggregate losses may be modeled as a function of the single risk factor. The

[4] See Merton (1974), Vasicek (1987) Gordy (2000) and Gordy & Howells (2006).

expected loss conditional on the single risk factor equals then the marginal Value-at-Risk for the tranche (compare Peretyatkin & Perraudin 2004, Perraudin 2006).

The conditional expected loss of the tranche is given by:

$$CEL^{Tr}(x_t^*) = \frac{LGD}{AL_2 - AL_1}\Big[H(AL_2) - H(AL_1)\Big] \tag{3}$$

with

$$H(AL) = \begin{cases} \Phi_2\left(\Phi^{-1}\left(\frac{AL}{LGD}\right), \frac{\Phi^{-1}(\pi_{i,t})+\sqrt{\rho_{i,t}\cdot\beta_i}\cdot x_t^*}{\sqrt{1-\rho_{i,t}\cdot\beta_i}}, \frac{\sqrt{1-\rho_{i,t}}}{\sqrt{1-\rho_{i,t}\cdot\beta_i}}\right), & \text{if } AL < LGD \\ \Phi\left(\frac{\Phi^{-1}(\pi_{i,t})+\sqrt{\rho_{i,t}\cdot\beta_i}\cdot x_t^*}{\sqrt{1-\rho_{i,t}\cdot\beta_i}}\right), & \text{otherwise} \end{cases} \tag{4}$$

Where AL_1 is the lower attachment level and AL_2 is the upper attachment level of the particular tranche. Φ represents the standard normal distribution function and Φ^{-1} the inverse of the standard normal distribution. $\Phi_2(\cdot,\cdot,\cdot)$ denotes the bivariate normal distribution function. Pykhtin & Dev (2002) show that this expression can be used to determine the tranche capital. We get the capital allocation model for securitized tranches if x_t^* in Formula 4 is replaced by the quantile of the confidence level $\Phi^{-1}(q)$. In Basel II, q is set to 99.9%.

$$H(AL) = \begin{cases} \Phi_2\left(\Phi^{-1}\left(\frac{AL}{LGD}\right), \frac{\Phi^{-1}(\pi_{i,t})+\sqrt{\rho_{i,t}\cdot\beta_i}\cdot\Phi^{-1}(q)}{\sqrt{1-\rho_{i,t}\cdot\beta_i}}, \frac{\sqrt{1-\rho_{i,t}}}{\sqrt{1-\rho_{i,t}\cdot\beta_i}}\right), & \text{if } AL < LGD \\ \Phi\left(\frac{\Phi^{-1}(\pi)+\sqrt{\rho_{i,t}\cdot\beta_i}\cdot\Phi^{-1}(q)}{\sqrt{1-\rho_{i,t}\cdot\beta_i}}\right), & \text{otherwise} \end{cases} \tag{5}$$

The formula can be interpreted as the marginal Value-at-Risk for a given confidence level. β_i denotes the strength of the dependence between pools and can be interpreted as measure of systematic risk.

Figure 1 below shows the effect of an increasing value of β_i on the Value-at-Risk (99.9th percentile) of the tranche (right graphic) and the tranche capital (left graphic) respectively. For our example we assume a LGD of 100%, a default probability of the pool of 1% and an asset return correlation of 20%. All these parameters are held constant in order to illustrate the impact of β_i for different tranches.

[Insert Figure 1 here]

The tranche capital requirements are calculated by Equation (3) and Equation (5) for different values of β_i and weighted by the thickness of the tranches (left graphic). In our example, the thickness of all tranches is equal and amounts to 3%. For $\beta_i = 1$ all tranches require 3% regulatory capital and are therefore fully covered by capital ($VaR = 100\%$).

2.3.2 Model Estimation

In our approach, we will estimate β_i for our portfolio of securitizations in order to calculate the capital requirements based on the formula given above and to compare the results with the capital requirements under the RBA. If the capital requirements based on our estimation for β_i are higher compared to RBA requirements then we conclude that the ratings do not sufficiently consider the macroeconomic risk for securitized tranches. We skip the subscript i for simplicity, although we estimate β separately for the individual asset classes and other asset categories, which are described later on in this paper.

Along the conditional expected loss of a tranche we can derive the expression for the default probability of the tranche j of sector i in time t again related to the realization of the macroeconomic risk factor (x_t^*). The formula is given by:

$$PD_{i,j,t}^{Tr}(x_t^*) = \Phi\left(\frac{\Phi^{-1}(\pi_{i,t}) - \sqrt{1-\rho_{i,t}} \cdot \Phi^{-1}(\frac{AL_{i,j,t}}{LGD}) - \sqrt{\rho_{i,t}}\sqrt{\beta} \cdot x_t^*}{\sqrt{\rho_{i,t}} \cdot \sqrt{1-\beta}}\right) \tag{6}$$

and includes all relevant input parameters to determine the tranche capital. Solving Equation (6) for the attachment level as a function of the conditional default probability of the tranche results in:

$$AL_{i,j,t} = LGD \cdot \Phi\left(\frac{\Phi^{-1}(\pi_{i,t}) - \sqrt{\rho_{i,t}} \cdot \sqrt{1-\beta} \cdot \Phi^{-1}(PD_{i,j,t}^{Tr}(x_t^*)) - \sqrt{\rho_{i,t}} \cdot \sqrt{\beta} \cdot x_t^*}{\sqrt{1-\rho_{i,t}}}\right) \tag{7}$$

If we account for an error and solve the equation for the error term we obtain the following expression:

$$\varepsilon_{i,j,t} = AL_{i,j,t} - LGD \cdot \Phi\left(\frac{\Phi^{-1}(\pi_{i,t}) - \sqrt{\rho_{i,t}} \cdot \sqrt{1-\beta} \cdot \Phi^{-1}(PD^{Tr}_{i,j,t}(x^*_t)) - \sqrt{\rho_{i,t}} \cdot \sqrt{\beta} \cdot x^*_t}{\sqrt{1-\rho_{i,t}}}\right) \quad (8)$$

We follow the approach by Rösch & Scheule (2012) to estimate the parameters $\pi_{i,t}$ and $\rho_{i,t}$ and use a non-linear regression model and estimate $\pi_{i,t}$ and $\rho_{i,t}$ for each pool and for each year. Furthermore, we assume LGD of the asset portfolio to be 100%. Note that according to Equation (3) and Equation (5) of this model, tranches with both attachment levels above the LGD of the pool would require a capital coverage of 0%. As we are particulary interested in top-rated tranches with typically high attachment levels, we need to assume a LGD of 100% in order to be able to determine the capital charges for all tranches based on the CEL-Formula and to compare them with RBA capital charges. However as we will show in Section 4 that our estimation results for β are robust with respect to the LGD assumption.

We use the actual default rates of the tranches per rating grade for each year and each asset class as a proxy for the term $PD^{Tr}_{i,j,t}(x^*_t)$. We estimate β using the Maximum Likelihood method and the results of the first estimation ($\pi_{i,t}$ and $\rho_{i,t}$) introducing three different classifications: Panel A is classified according to our five different asset classes (i) ABS, (ii) HEL, (iii) RMBS, (iv) CDO, (v) CMBS and one β is estimated for for each asset class. Panel B is classified according to granularity of tranches following one main classification criterion in the Basel documents: (i) Granular, (ii) Non-granular. In Panel C, β is estimated for re-securitization exposures.

The model is generally known as a non-linear mixed model, in which the error terms are modeled explicitly in terms of unobserved random effects x^*_t. The distribution of $\varepsilon_{i,j,t}$ conditional on a realization of the time-specific random effect x^*_t is given by: $p_t(\varepsilon_{i,j,t}|\beta, x^*_t)$ with the standard normal distribution of X^*_t: $\phi(x^*_t)$ leading to the joint probability density function: $p_t(\varepsilon_{i,j,t}|\beta, x^*_t) \cdot \phi(x^*_t)$ and results in the marginal likelihood:

$$m(\beta) = \prod_{t=1}^{T} \int p_t(\varepsilon_{i,j,t}|\beta, x^*_t) \cdot \phi(x^*_t) dx^*_t \quad (9)$$

The expression is maximized to obtain the estimate of β. We assume that $\varepsilon_{i,j,t}$ has a normal density: $\varepsilon_{i,j,t} \sim N(0, \sigma^2)$. This results in:

$$p_t(\varepsilon_{i,j,t}|\beta, x_t^*) = \frac{1}{\sigma\sqrt{2\pi}} \cdot \exp\Bigg(- \frac{1}{2\sigma^2} \cdot \Bigg(AL_{i,j,t} - LGD \cdot \Phi\Big(\frac{\Phi^{-1}(\pi_{i,t}) - \sqrt{\rho_{i,t}} \cdot \sqrt{1-\beta} \cdot \Phi^{-1}(PD_{i,j,t}^{Tr}(x_t^*)) - \sqrt{\rho_{i,t}} \cdot \sqrt{\beta} \cdot x_t^*}{\sqrt{1-\rho_{i,t}}}\Big)\Bigg)^2\Bigg) \quad (10)$$

and $\phi(x_t^*) = \frac{1}{\sqrt{2\pi}} \cdot \exp\Big(-\frac{1}{2}(x_t^*)\Big)$. The likelihood is optimized numerically following Patefield (2002).

3 Results

The results for our estimation for β are presented in Table 1 (column 1). The table additionally displays standard errors of estimation (SE; column 2), significance of estimation (p Values; column 3) and number of tranche observations (N; column 4).

[Insert Table 1 here]

Panel A shows that all asset classes of the structured products are significantly subject to systematic fluctuations. The β-estimates vary between 0.6048 and 0.8360. ABSs and CDOs are most sensitive to macroeconomic shocks. The results are in line with the theoretical and empirical findings by Coval et al. (2009) and Hamerle et al. (2009). The β estimates according to Panel B illustrate that tranches which are classified as non-granular are more sensitive to systematic risk than tranches that are classified as granular. Our β estimates for re-securitization exposures referring to Panel C also indicate a high macroeconomic sensitivity of tranches. [5]

Capital requirements are presented in Figure 2. The mean CEL capital ratios per year are calculated by applying Equation (3) and Equation (5) using all estimated parameters. The RBA capital ratios are determined by multiplying the RBA risk weight (RW) given a rating with 0.08: $RBA_{Ratio} = RW * 0.08$.

[Insert Figure 2 here]

[5] Note that all subsequent analysis is based on the estimates of Panel A.

The red dashed curve represents the CEL capital ratios based on the β estimation and the blue marked line the RBA capital ratios. The CEL capital ratios are significantly higher than the respective RBA ratios for each transaction class and for every year of the considered time period. This clearly supports our Hypothesis 1, that ratings do not capture systematic risk sufficiently.

Figure 3 presents the results of the rating-specific analysis:

[Insert Figure 3 here]

For the last year of our historical data, we plot RBA and CEL capital requirements as mean capital charges per rating grade for all asset classes. We have weighted CEL and RBA capital requirements by the thickness of the tranches. Each rating grade is represented by a colored bubble. The size of the bubble illustrates the number of tranches of an individual rating grade. For all asset classes, the capital charges for tranches B1-C in RBA are quite similar to CEL. Only for HEL and RMBS for the year 2008 the capital requirements are even lower for the CEL-formula, which may be limited by the small sample size. In contrast, it is quite striking that capital requirements for the high volume tranches AAA-Ba3 are significantly higher compared to the RBA. This underlines the assumption that the senior tranches are more sensitive to the macroeconomic conditions. These findings support a re-calibration of RBA risk weights for higher rated tranches. The following Table 2 summarizes the mean capital charges per rating grade for the RBA approach and the CEL formula respectively for the overall time period.

[Insert Table 2 here]

This confirms Hypotheses 2 for all asset classes. [6]

Figure 4 illustrates the capital ratios for all rating grades according to RBA approach and the CEL formula respectively. [7] The results are presented for all asset classes as mean capital ratios for the entire observation period. The RBA approach requires a 100% coverage for the lower rated tranches while mean CEL ratios fluctuate between 30% and 100%. In contrast, higher rated tranches generate mean CEL capital ratios up to 60% while RBA ratios hardly

[6] Please note that we have also analyzed in extensions capital charges per rating grade per year for all asset classes. The results are consistent with the consideration of mean values for the overall time period. In some years, the RBA capital charges exceed the CEL-capital charges for lower rating clases. However, even in those years the CEL-formula requires more capital for the higher rated tranches.

[7] Please note that contrary to Figure 3, the capital ratios are not weighted by tranche thickness.

cover 10% of tranche exposure.

[Insert Figure 4 here]

In Figure 2 we have already shown that the capital ratios are significantly higher for the CEL formula than under the RBA. We now compare both capital ratios with the default ratios (purple solid curve) for all asset classes. The Figures show that RBA capital ratios for the transaction types CDO, HEL and RMBS were lower than the default ratios for the year 2007 and in particular for the year 2008. The capital ratios have increased only marginally while the default rates rose rapidly from 2007 to 2008. Unlike RBA capital ratios the CEL ratios are even in the years 2007 and 2008 well above the default ratios and provide a sufficient cover during severe economic downturns.

In a next step we calculate those risks weights which are in fact needed to cover the high systematic risk and to meet the CEL capital requirements respectively for each rating grade (RG). Capital requirements under the RBA are calculated by: $RBA_{Capital} = RW * 0.08 * thickness$. We replace RBA capital by CEL capital as we are interested in those risk weights that match the CEL capital requirements and solve the equation for the risk weight which delivers our implied new risk weight ($RW_{Implied} = CEL/(0.08 * thickness)$).

In Table 3 we show the results of our calculation. We compare the average risk weights from the RBA approach for each rating grade with our implied new risk weights (column 3). Note that the mean RBA risk weights account for the seniority and granularity of our securitized tranches. This explains why RBA risk weights may in rare instances be non-monotone (mean risk weight for Aa2 is 0.20 and mean risk weights for Aa3 is 0.19). Please note that our implied new risk weights are also not monotone either. The reason for this phenomena is the distribution of risk characteristics of the tranches per rating class (in particular the thickness of the tranches). For regulation purposes risk weights need to be adjusted accordingly.

The new risk weights correspond to implied new rating grades according to column 4. The new rating grades were assigned as the original rating grade with a risk weight that is equal or higher to the new risk weight. It is striking that a AAA-rated tranche requires - based on the data given and the high systematic risk - an implied new rating grade of Baa3. All tranches with a rating grade of Ba3 or better require risk weights which are significantly higher than under the RBA. The remaining tranches B1-C, which require under the RBA already a 100% coverage may potentially obtain lower risk weights.

[Insert Table 3 here]

Table 4 represents the implied new risk weights for the individual asset classes.

[Insert Table 4 here]

The results are in general concordant with our previous findings. However, some differences between asset classes can be observed. ABS tranches do have the highest implied new risk weights due to their high sensitivity to macroeconomic changes. The other asset classes follow according to the estimation of their individual β.

Using the implied new risk weights which correspond to the implied new rating grades capital charges would have been sufficient to cover unexpected losses during the recent financial crisis.

4 Robustness Checks

In order to ensure the accuracy of our estimation procedure, we perform a simulation study. The model used to estimate β is based on the two following essential assumptions:

a) the default rates of the tranches per year and rating grade which we take from the given data history are a reliable proxy for the conditional default probability of the tranches $PD^{Tr}_{i,j,t}(x^*_t)$;
b) the impact of the assumptions of a LGD of 100% on our estimation results for β is marginal.

In our simulation study we follow the same 2-step estimation approach used in our empirical model. Based on a Monte-Carlo-Simulation, we generate a set of large credit portfolios. These portfolios are homogenous which means that all loans in the portfolio have the same probability of default. Credit risk is modeled according to the Gaussian one factor copula model in Equation (1) and Equation (2) where a common risk factor is driving the portfolio of loans. The simulation runs over 10 years and for 50 banks simultaneously. Every bank is affected by the same macroeconomic shocks. We now assume, following the results of our empirical study, that banks are highly dependent on realizations of macroeconomic shocks and therefore determine β to be 0.9. The portfolios are securitized into 8 tranches: AAA to an unrated first loss piece (FLP). The attachment levels are given as follows: (AAA: 22%, AA: 18%, A: 13%, BBB: 10%, BB: 8%, B: 6%, CCC: 3%, FLP: 0.00%) and are the same for each portfolio and every year. Under the assumption of infinitely granular bank portfolios,

a tranche experiences a loss if the conditional default probability (CPD) of the portfolio exceeds the relative attachment level of the particular tranche.

$$D_{i,j,t}^{Tr} = 1 \Leftrightarrow CPD_{i,t}(x_{i,t}) > AL_{i,j,t}^{Tr} \tag{11}$$

where $D_{i,j,t}^{Tr}$ is an impairment indicator variable.

$$D_{i,j,t}^{Tr} = \begin{cases} 1, & \text{if tranche } j \text{ is impaired} \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

The default probability of the pool conditional on the realization of the systematic risk factor ($CPD_{i,t}(x_{i,t})$) is given by the following expression:

$$CPD_{i,t}(x_{i,t}) = LGD \cdot \Phi\left(\frac{\Phi^{-1}(\pi_{i,t}) - \sqrt{\rho_{i,t}} \cdot x_{i,t}}{\sqrt{1-\rho_{i,t}}}\right) \tag{13}$$

Similar to our empirical study we use the information of securitized tranches to estimate parameters of the pool using the Maximum Likelihood method. In a first step the parameters $\rho_{i,t}$ and $\pi_{i,t}$ are estimated per bank and per year using the historical average of tranche default rates as proxies for the tranche-PD ($D_{i,j,t}^{Tr} = 1$) in line with the approach by Rösch & Scheule (2012):

$$\varepsilon_{i,j,t} = AL_{i,j,t} - LGD \cdot \Phi\left(\frac{-\sqrt{\rho_{i,t}} \cdot \Phi^{-1}(D_{i,j,t}^{Tr} = 1) + \Phi^{-1}(\pi_{i,t})}{\sqrt{1-\rho_{i,t}}}\right) \tag{14}$$

In a second step, the results of the first estimation are used in order to estimate the parameter β for the overall simulation period by applying again the Maximum Likelihood method (compare Equation (8)). The simulation is repeated 100 times to assure that results are

reliable.[8] The results are shown in Table 5.

[Insert Table 5 here]

Our proxy for the conditional default probability of the tranches generates a value for β which is fairly close to the assumed value of $\beta = 0.9$. Furthermore the results show that the variation of $LGD = 100\%$ instead of $LGD = 45\%$ has a very limited impact on the estimate β.

In a supplementary robustness test we assume that macroeconomic shocks follow an autoregressive process (AR-1) rather than being normal distributed:

$$X_t^* | x_{t-1}^* = x_{t-1}^* + \epsilon_t \tag{15}$$

with $E(\epsilon_t) = 0$, $Var(\epsilon_t) = 1$ and $E(X_t^* | x_{t-1}^*) = x_{t-1}^*$. Estimates for β prove to be robust under these conditions as well and are also presented in Table 5.[9]

5 Policy implications

This paper develops a framework to measure the exposure to systematic risk of asset securitizations. The paper measures empirically whether current ratings-based rules for regulatory capital of securitization reflect this exposure. The analysis is based on an US data set of asset securitizations for the time period between 2000 and 2008.

The paper finds that the shortfall of regulatory capital during the Global Financial Crisis is strongly related to ratings. In particular the most senior tranches of securitized exposures which count for high issuance volumes are highly sensitive to macroeconomic conditions and this exposure is not reflected in either (i) the ratings or (ii) the regulatory look-up tables, which map ratings to risk weights.

Furthermore, this paper is the first to calibrate risk weights which provide sufficient capital

[8] We are also performing the same study for other values of beta. The test results confirm the robustness of the approach.

[9] All simulations are performed for different time periods. The robustness assumption is confirmed through all simulation results.

charges to cover the exposure during economic downturns. As a consequence, the results from our investigation suggest that prudential regulators may consider a re-calibration of the risk weights given by the current RBA approach. Consequently, the re-calibration should focus on the higher rated tranches. Such a re-calibration may provide lower incentives to invest in higher rates securities with a higher systematic exposure and may contribute to the current efforts to re-establish sustainable securitization markets.

This re-calibration would have to be coordinated with rating agencies who may change their rating methodology in the future. Therefore it may be reasonable for regulators to provide rules with regard to the minimum standards for the generation of ratings and implement capital requirements consistent such rules.

In addition, the impact on financial markets, institutions and instruments of such a re-calibration would have to be quantified and transitionary regulations implemented to avoid larger market distortions.

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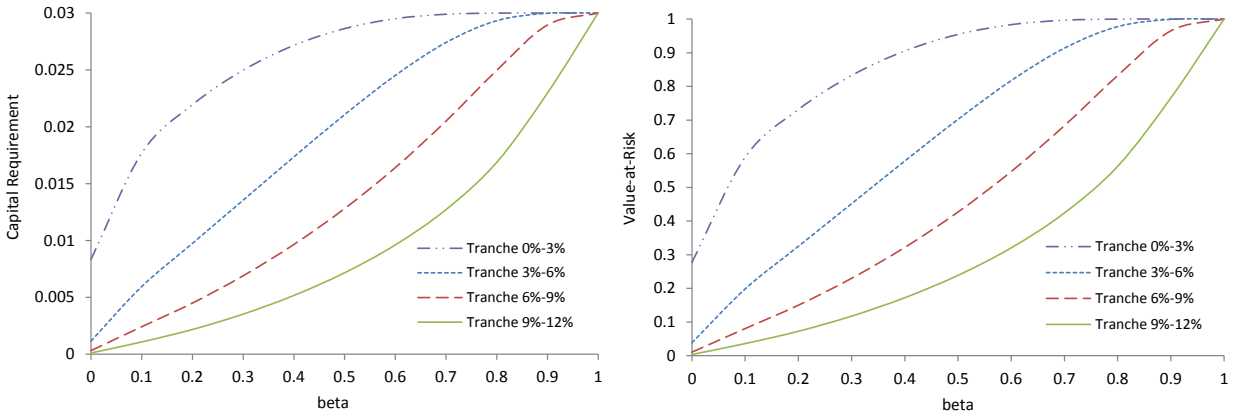
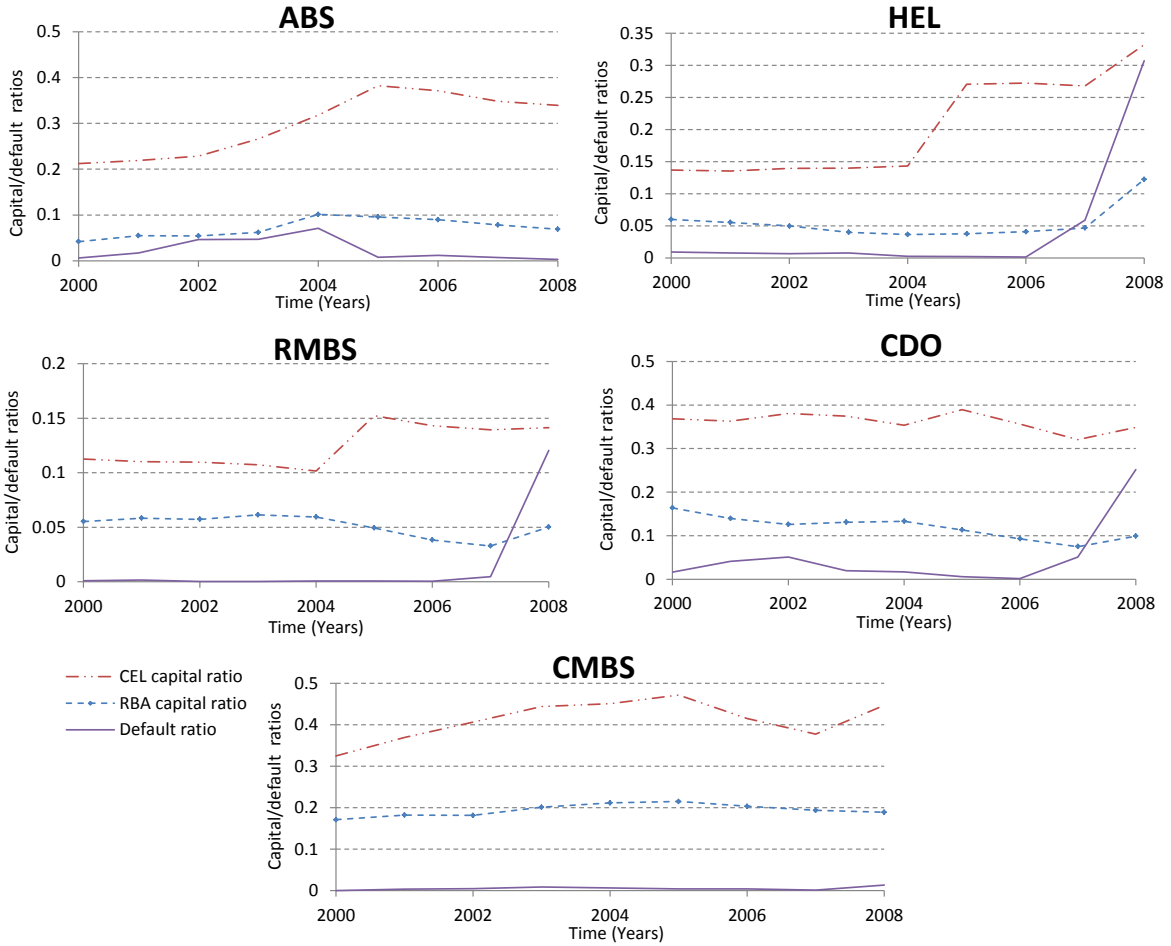
Figures

Fig. 1. Marginal Value-at-Risk, tranche capital and systematic risk variation



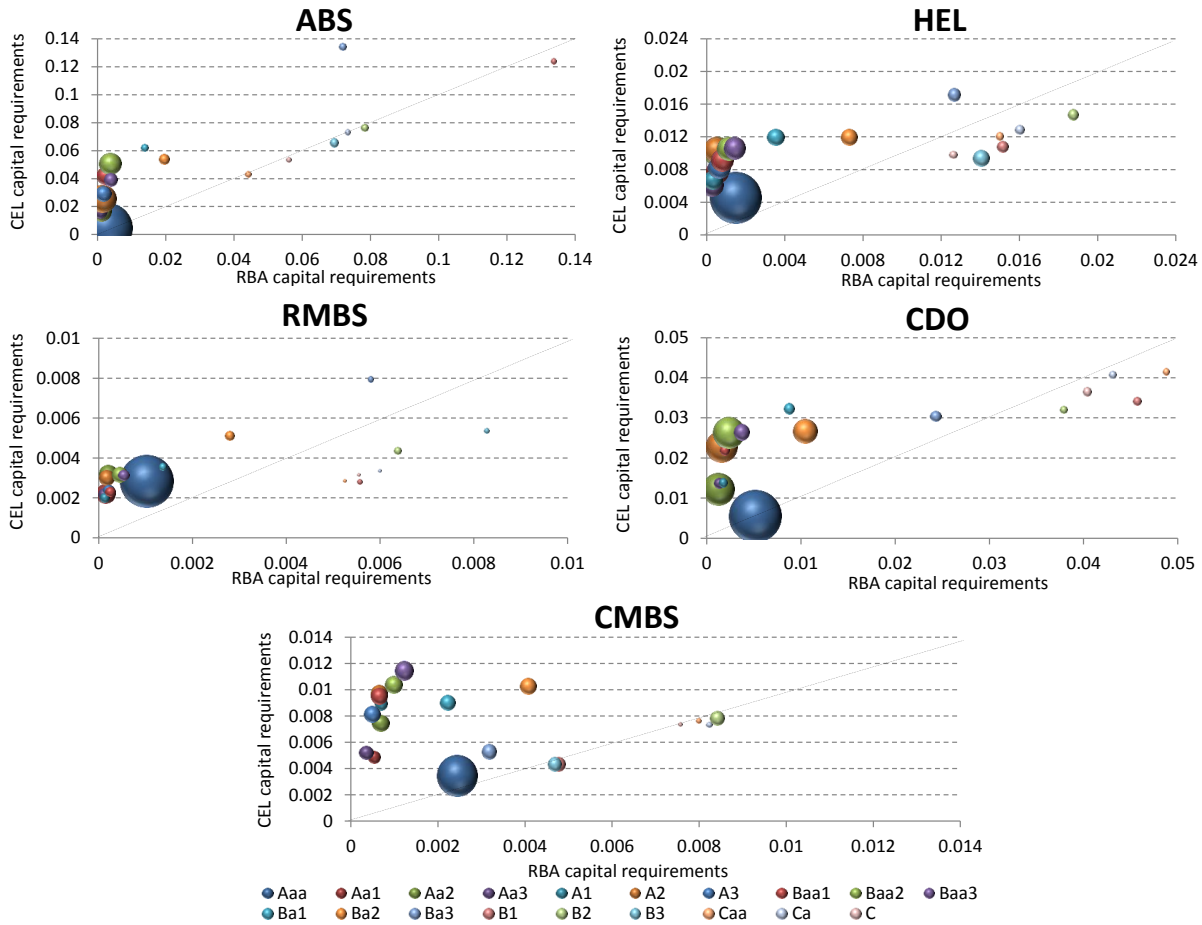
Notes: This figure shows the effect of β_i on the tranche capital (left graphic) and the Value-at-Risk (99.9th percentile) of the tranche (right graphic) respectively. We assume a LGD of 100%, a default probability of the pool of 1% and an asset return correlation of 20%. The parameters are held constant in order to illustrate the effect from a variation of β_i for the different tranches. Tranche capital requirements are calculated by Equation (3) and Equation (5) for different values of β_i and weighted by the thickness of the tranches (left graphic). The thickness of all tranches is equal and amounts to 3%. For $\beta_i = 1$, all tranches require 3% regulatory capital and are therefore fully covered by capital ($VaR = 100\%$).

Fig. 2. Empirical RBA and CEL capital and default ratios



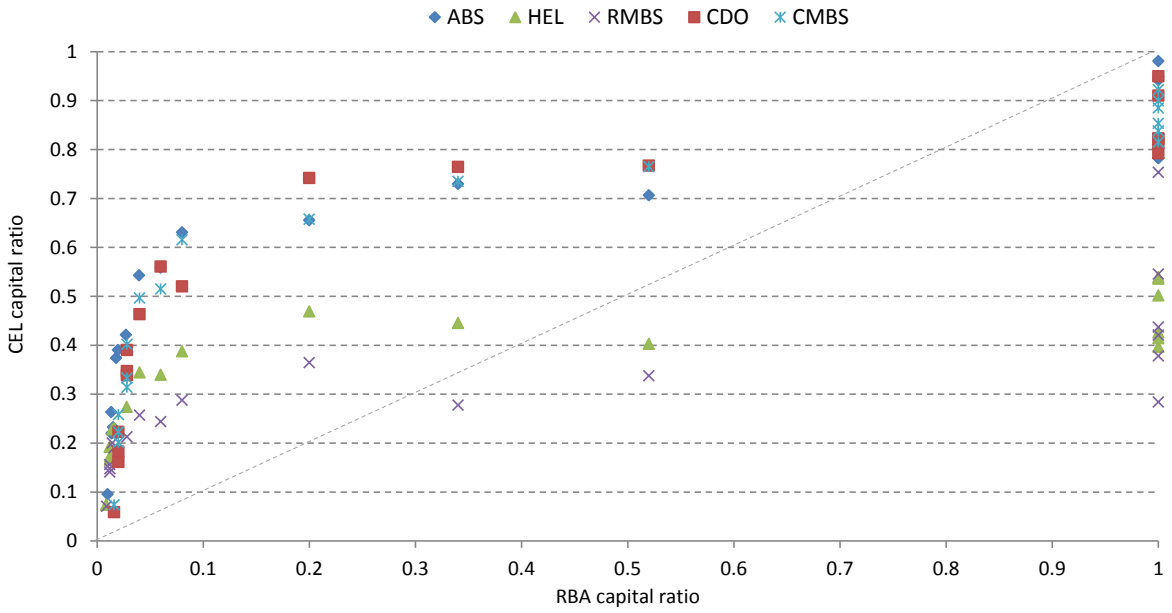
Notes: This figure shows the empirical RBA capital ratios (blue marked line), the CEL capital ratios based on our β-estimation (red dashed line) and the default rates (purple solid line) per transaction type for the time period 2000-2008. CEL capital ratios are significantly higher than the respective RBA capital ratios for each transaction type. Furthermore the default ratios exceed RBA capital ratios in the years 2007 and especially 2008 for the transaction types CDO, HEL and RMBS. In contrast, CEL capital ratios are above the default rates in all years including the economic downturn in 2007 and 2008.

Fig. 3. Empirical RBA and CEL capital requirements per rating-category, weighted by tranche thickness



Notes: This figure plots the relation between mean RBA capital requirements (x-axis) and mean CEL capital requirements (y-axis) per rating grade based on the empirical data for the year 2008 for each asset class. In this figure, CEL and RBA capital requirements have been weighted by the thickness of the tranches. Each bubble represents an individual rating grade and the size of the bubble indicates the number of tranches in each and every rating category. Evidently CEL capital requirements for the top-rated, high volume rating categories, are much higher than RBA capital requirements. In contrast, RBA capital requirements for the inferior rated, low volume tranches are similar or even higher compared to CEL capital requirements.

Fig. 4. Empirical RBA and CEL capital ratios per rating category and securitization class



Notes: This figure shows the relation between mean RBA capital ratios (x-axis) and mean CEL capital ratios (y-axis) per rating grade and securitization class and for the time period $2000 - 2008$. The RBA appraoch requires a 100% coverage for the lower rated tranches while mean CEL ratios fluctuate between 30% and 100%. In contrast, the higher rated tranches generate mean CEL capital ratios up to 60% while RBA ratios hardly cover 10% of tranche exposure. Mean RBA capital ratios increase for rating grade Aaa to Ba3 with deteriorating rating grades up to 52% tranche coverage. RBA capital ratios of tranches rated below Ba3 are by design 100%. On the contrary, the mean CEL capital ratios increase more continuously up to a maximum coverage of 98%.

Tables

Table 1
Empirical β estimation

This table denotes the results of our β estimation approach based on the empirical data for each asset class (Panel A), for the classification regarding granularity (Panel B) and for re-securitization exposures (Panel C). In our data set retail asset portfolios comprise a large number of exposures with small amounts. They are basically exposed to systematic risk and can be generally considered to be granular. In particular ABSs, HELs and RMBSs generally relate to retail assets (e.g., auto, credit cards and retail loans). Corporate/wholesale asset portfolios can generally be considered to be non-granular because they comprise a small number of exposures with large amounts. They are exposed to idiosyncratic and systematic risk. In particular CDOs and CMBSs comprise corporate/wholesale loan portfolios (e.g., unsecured or secured corporate loan exposures) and a part of ABSs exposures relates to corporate/wholesale asset portfolios (e.g., equipment loans and leases) as well. The table additionally displays standard errors of estimation (SE), significance of estimation (p Value) and number of tranche observations (N). Note that the values for β appear to be comparatively high. This indicates that securitized exposures are highly sensitive to macroeconomic risk. In Panel A, ABSs and CDOs are extremely sensitive as a result of our investigation. In Panel B it is remarkable that the tranches that are classified as non-granular are more sensitive to systematic risk than tranches classified as granular. The results in Panel C for our β estimation also confirm that re-securitization exposures are highly sensitive to macroeconomic changes.

	β	SE	p Value	N
Panel A: by securitization category				
ABS	0.8360	0.0064	<0.0001	16,313
HEL	0.6821	0.0071	<0.0001	64,681
RMBS	0.6048	0.0245	<0.0001	75,103
CDO	0.7176	0.0100	<0.0001	26,593
CMBS	0.6994	0.0107	<0.0001	30,874
Panel B: by granularity				
Granular	0.8618	0.0021	<0.0001	151,789
Non-granular	0.9462	0.0014	<0.0001	61,775
Panel C: for re-securitization exposures				
Re-sec.	0.8227	0.0051	<0.0001	1,499

Table 2
Mean capital requirements per rating grade and securitization class

This table presents the mean capital requirements per rating category for the RBA and CEL approach for the overall time period and for each securitization class. Evidently CEL capital requirements for the top-rated tranches are much higher than RBA capital requirements. In contrast, RBA capital requirements for the lower rated tranches are similar or even higher compared to CEL capital requirements. The figures basically confirm the results shown in Figure 3 for one year only (2008).

	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3	Caa	Ca	C
Panel A: ABS																			
RBA	0.0024	0.0014	0.0015	0.0010	0.0016	0.0014	0.0021	0.0027	0.0036	0.0057	0.0177	0.01740	0.0412	0.0871	0.0625	0.0641	0.0564	0.0654	0.0839
CEL	0.0175	0.0201	0.0198	0.0170	0.0247	0.0230	0.0283	0.0356	0.0367	0.0437	0.0604	0.0383	0.0634	0.0711	0.0501	0.0588	0.0431	0.0607	0.0825
Panel B: HEL																			
RBA	0.0017	0.0004	0.0006	0.0010	0.0005	0.0006	0.0011	0.0012	0.0014	0.0022	0.0045	0.0076	0.0148	0.0271	0.0173	0.0295	0.0378	0.0227	0.0258
CEL	0.0143	0.0051	0.0084	0.0065	0.0068	0.0082	0.0086	0.0098	0.0080	0.0087	0.0114	0.0104	0.0136	0.0112	0.0095	0.0150	0.0182	0.009	0.0127
Panel C: RMBS																			
RBA	0.0011	0.0004	0.0003	0.0003	0.0004	0.0003	0.0006	0.0004	0.0006	0.0011	0.0020	0.0022	0.0064	0.0088	0.0045	0.0272	0.0053	0.0048	0.0061
CEL	0.0085	0.0037	0.0029	0.0041	0.0037	0.0032	0.0043	0.0031	0.0027	0.0042	0.0044	0.0026	0.0072	0.0044	0.0023	0.0215	0.0029	0.0019	0.0048
Panel D: CDO																			
RBA	0.0064	0.0020	0.0028	0.0021	0.0022	0.0014	0.0017	0.0017	0.0025	0.0053	0.0095	0.0099	0.0183	0.0438	0.0375	0.0582	0.0662	0.0390	0.0363
CEL	0.0179	0.0143	0.0180	0.0152	0.0201	0.0187	0.0193	0.0200	0.0232	0.0354	0.0348	0.0223	0.0263	0.0344	0.0288	0.0447	0.0514	0.0368	0.0343
Panel E: CMBS																			
RBA	0.0038	0.0011	0.0011	0.001	0.0012	0.0014	0.0008	0.0011	0.0023	0.0018	0.0036	0.0075	0.0049	0.0105	0.0146	0.0074	0.0153	0.0071	0.0098
CEL	0.0107	0.0087	0.0105	0.0086	0.0120	0.0147	0.0099	0.0127	0.0189	0.0149	0.0121	0.0166	0.0069	0.0088	0.0126	0.0063	0.0135	0.0061	0.0091

Table 3
Implied new mean risk weights of all asset classes

This table denotes the mean RBA risk weights in comparison to implied new risk weights based on our estimation of β. The mean RBA risk weights account for the seniority and granularity of our securitized tranches (column 2), which explains that RBA risk weights may be non-monotone in rare instances (mean risk weight for Aa2 is 0.20 and mean risk weights for Aa3 is 0.19). The difference between mean RBA risk weights and implied new risk weights is substantial and indicates the considerable effect of the incorporation of our estimated systematic risk factor β. Finally, in the last column we show which rating grade would be attributable in order to meet the new risk weights.

Rating grade	mean RW	implied new RW	implied new RG
Aaa	0.15	0.88	Baa3
Aa1	0.19	2.70	Ba2
Aa2	0.20	2.69	Ba2
Aa3	0.19	3.18	Ba2
A1	0.26	4.01	Ba2
A2	0.27	4.16	Ba2
A3	0.35	4.65	Ba3
Baa1	0.50	5.80	Ba3
Baa2	0.75	5.97	Ba3
Baa3	1.00	6.64	B1 and worse
Ba1	2.50	7.86	B1 and worse
Ba2	4.25	7.79	B1 and worse
Ba3	6.50	8.12	B1 and worse
B1	12.50	8.95	B1 and worse
B2	12.50	8.58	B1 and worse
B3	12.50	9.4	B1 and worse
Caa	12.5	9.86	B1 and worse
Ca	12.5	10.13	B1 and worse
C	12.5	10.34	B1 and worse

Table 4
Implied new mean risk weights per individual asset class

This table gives an overview of the mean RBA risk weights in comparison to the implied new risk weights based on our estimation of β for each individual asset class. The implied new risk weights are the highest for ABS and CDO (highest estimated β) and the lowest for RMBS (lowest estimated β).

	ABS		HEL		RMBS		CDO		CMBS	
Rating	ø RW	implied RW	ø RW	implied RW	ø RW	implied RW	ø RW	implied RW	ø RW	implied RW
Aaa	0.12	1.19	0.11	0.81	0.11	0.75	0.20	0.69	0.20	0.98
Aa1	0.17	3.25	0.15	2.68	0.15	2.26	0.25	2.37	0.25	2.92
Aa2	0.19	2.91	0.15	2.59	0.15	2.31	0.25	2.74	0.25	2.91
Aa3	0.17	2.96	0.15	3.51	0.15	2.61	0.25	2.99	0.25	3.82
A1	0.22	4.79	0.18	3.86	0.18	2.96	0.35	4.11	0.35	4.31
A2	0.24	5.01	0.20	3.51	0.20	2.85	0.35	5.10	0.35	4.34
A3	0.34	5.56	0.35	4.60	0.35	3.34	0.35	4.42	0.35	5.33
Baa1	0.50	7.23	0.50	5.21	0.50	4.00	0.50	6.16	0.50	6.40
Baa2	0.75	6.95	0.75	5.29	0.75	3.67	0.75	7.28	0.75	6.68
Baa3	1.00	7.77	1.00	6.42	1.00	4.43	1.00	6.66	1.00	7.91
Ba1	2.50	9.46	2.50	7.18	2.50	5.04	2.50	9.06	2.50	8.55
Ba2	4.25	8.67	4.25	7.11	4.25	4.16	4.25	9.80	4.25	9.23
Ba3	6.50	8.64	6.50	8.00	6.50	4.81	6.50	9.58	6.50	9.55
B1	12.5	10.39	12.50	8.37	12.50	5.76	12.50	10.27	12.50	9.97
B2	12.5	10.32	12.50	7.71	12.50	4.20	12.50	10.27	12.50	10.41
B3	12.5	11.59	12.50	8.57	12.50	6.01	12.50	10.34	12.50	10.47
Caa	12.50	11.78	12.50	9.24	12.50	6.82	12.50	10.26	12.50	11.18
Ca	12.50	12.17	12.50	9.22	12.50	6.74	12.50	11.27	12.50	11.24
C	12.50	12.26	12.50	9.19	12.50	6.93	12.50	11.61	12.50	11.71

Table 5
Robustness test

This table shows the results of the robustness checks for the estimation for β, which is robust with respect to our assumption for the CPD proxy and the assumption of a LGD of 100%. In the table below SE denotes the empirical standard deviation. The table also presents the results for our assumption that macroeconomic shocks follow an autoregressive process (AR-1) rather than being normal distributed. The robustness supposition is confirmed for this assumption as well.

	LGD = 45%		LGD = 100%	
	β-Estimate	SE	β-Estimate	SE
Without AR(1) process				
$PD^{Tr}(x_t^*)$	0.820	0.108	0.877	0.079
proxy $PD^{Tr}(x_t^*)$	0.926	0.044	0.946	0.035
With AR(1) process				
proxy $PD^{Tr}(x_t^*)$	0.803	0.138	0.889	0.080