University of Konstanz
Department of Economics

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Günter Franke, Markus Herrmann, and Thomas Weber

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Günter Franke*

Markus Herrmann**

Thomas Weber*

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* University of Konstanz, Department of Economics, D-78457 Konstanz, POB 147.

E-mail: guenter.franke@uni-konstanz.de. Phone ++49 7531 882545

** Landesbank Baden-Württemberg. E-mail: Markus.A.Herrmann@lbbw.de

*** Axpo corporation. E-mail: thomas.weber@axpo.ch

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Abstract

This paper analyses the loss allocation to First, Second and Third Loss Positions in European collateralized debt obligation transactions. The quality of the underlying asset pool plays a predominant role for the loss allocation. A lower asset pool quality induces the originator to take a *higher* First Loss Position, but, in a synthetic transaction, a *smaller* Third Loss Position. The share of expected default losses, borne by the First Loss Position, is largely independent of asset pool quality, but lower in securitizations of corporate loans than in those of corporate bonds. Originators with a good rating and low Tobin´s Q prefer synthetic transactions.

JEL classification: G 10, 21, 24

Keywords: Securitization, collateralized debt obligations, asset pool quality, First Loss Position, synthetic transactions.

I. Introduction

The global annual issuance volume of securitizations has grown from roughly 270 bn USD in 1997 to about 2100 bn USD in 2006 (Herrmann, Sun, and Jha (2007)). The recent financial crisis depressed it. Securitizations, in particular those of mortgage-backed loans, are viewed as one driver of this crisis (The Financial Crisis Inquiry Commission Report (2011)). Yet, there are now many attempts to revive securitization because, in principle, it allows a better allocation of default risks across banks and non-banks. A major impediment to the transfer of default risks are information asymmetries between the seller and the buyer of debt claims. In a securitization transaction credit enhancements such as First Loss Positions serve to protect the buyers of rated tranches against adverse selection and moral hazard of the originator. Improved alignment of incentives of originators and buyers is a crucial ingredient for financial stability (IMF (2011, Ch. III)). In a securitization transaction this alignment is closely related to the allocation of default risks to First Loss Positions, to rated securitization tranches (Second Loss Positions), and, in case of synthetic transactions, to the non-securitized super-senior Third Loss Positions.

This paper investigates the determinants of First Loss Positions in securitization transactions. Conventional wisdom suggests that the originator should retain the First Loss Position because it is the most information-sensitive tranche and sell the information-insensitive senior tranches (Boot and Thakor (1993)). Yet, we observe many synthetic transactions in which the super-senior tranche is not securitized. We also address this puzzle to find out, what drives the originator´s choice between true sale and synthetic transactions. Understanding loss allocation is crucial for the risk management of originators of securitization transactions and for asset allocation of investors buying rated tranches, but also for regulators trying to make banks less vulnerable to default risks embedded in securitizations. Moreover, studying loss allocation provides new insights into the mechanisms used in modern structured finance to deal with market imperfections.

We study the loss allocation in a subset of European securitization-transactions, called collateralized debt obligation (CDO)-transactions. In collateralized loan obligation (CLO)-transactions, also called balance sheet transactions, a bank securitizes part of its corporate loan portfolio. In collateralized bond obligation (CBO)-transactions, also called arbitrage transactions, the originator of the transaction, a bank or an investment manager, buys corporate bonds, pools them in a portfolio and securitizes it. Our data set does not include CDOs of mortgage-backed loans or bonds[1] which were at the centre of the recent financial crisis. Corporate loans and bonds underlying CLOs and CBOs turned out to be rather stable as will be argued later. Therefore, our findings should remain valid for the design of future securitization transactions.

Loss allocation in securitization transactions would be irrelevant in a perfect capital market. In imperfect markets, loss allocation is driven by balancing the interests of originators and investors, subject to various market imperfections such as regulation, information asymmetries, funding cost differentials and transaction costs. We attempt to find out how these drivers and the quality of the securitized asset pool affect loss allocation. The analysis is refined by comparing different types of transactions, such as true sale versus synthetic transactions and CLO- versus CBO-transactions.

First, we restate some basics about securitizations. The three players governing securitization are banks and investment managers as originators of these transactions, investors buying securitization tranches, and the rating agencies as information intermediaries. Given the models of the rating agencies, originators and investors determine the loss allocation in securitization transactions. The originator selects a set of loans and/or bonds[2] as

[1] This does not rule out that a corporate loan or bond is also partly collateralized by a mortgage or other types of collateral.

[2] The bonds may include a few tranches of other securitizations or structured finance products.

the underlying asset pool of the transaction. In all transactions, loss allocation is governed by strict subordination. Default losses are solely borne by the First Loss Position (FLP), also called equity tranche, until this tranche is completely absorbed by theses losses. Then the next losses are solely borne by the tranche with the lowest rating until it is fully absorbed, and so on. Strict subordination generates very strong quality differences between the tranches. In a *true sale transaction*, the originator sells all loans/bonds without recourse to the special purpose vehicle which issues the equity tranche and various rated bond tranches, usually including a large Aaa-tranche. The par values of all tranches add up to the par value of all loans/bonds securitized or slightly less. Therefore the transaction is fully funded. The originator can freely use the proceeds from tranche issuance. In a *synthetic transaction* the originator retains ownership of the loans/bonds and transfers part of the default risk through a credit default swap to the special purpose vehicle. This swap covers default risks beyond a threshold which defines the FLP; the coverage is limited by the par value of the issued tranches which is usually much smaller than the par value of the underlying asset pool (partially funded transaction). Investors buying these tranches take a Second Loss Position (SLP). Default losses beyond the FLP and SLP are borne by the non-securitized super-senior tranche, a Third Loss Position (TLP) held by the originator. She may insure its risk by buying a senior default swap. In a synthetic transaction the originator obtains no funding. The issuance proceeds need to be invested in Aaa-securities or other almost default-free assets, in order to provide strong collateral for the investors taking the SLP.

In a CLO-transaction the originator usually owns the loans to be securitized while in a CBO-transaction she buys bonds, pools them and securitizes the asset pool. In a CLO-transaction the originator acts as the servicer of the loans so that her monitoring and collection policies affect loan defaults. In a CBO-transaction the originator lacks this role so that her impact on defaults is very limited. The impact of the originator on the evolution of default losses of the asset pool also depends on whether the transaction is static or dynamic. In a static deal, the asset pool is determined from the outset; new assets cannot be added later on. In a dynamic (managed) deal, the originator may change the asset pool over time, subject to various restrictions in the securitization contract to preserve the quality of the asset pool.

This paper is, to our best knowledge, the first to empirically study the impact of the quality of the asset pool and originator characteristics on the loss allocation in securitization transactions. To measure the quality of the asset pool, we rely on the most important quality characteristics published by Moody´s, the assets´ weighted average default probability (WADP) and Moody´s diversity score (DS) resp. the more sophisticated adjusted diversity score (ADS). A lower WADP and/or a higher DS indicate a better asset pool quality. Relying on Moody´s assessment may be viewed as problematic. Rating agencies being important players in the securitization business have come under strong attack in the subprime-crisis. Their initial ratings of bonds issued in securitizations of subprime loans strongly underestimated the default risk. A huge wave of downgrades of these bonds followed in 2007. However, ratings of corporate bonds and of CDOs like those used in our sample escaped severe criticism. These ratings have been quite stable until the end of 2007[3]. This is also supported by the evidence in Newman et al (2008). Clearly, Moody´s quality assessments are subject to estimation error. We assume that they are unbiased indicators of default risk.

The new findings of the paper can be summarized as follows.

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[3] Worldwide, the percentage of Moody´s downgrades over the previous 12 months did not change significantly from the first to the last quarter of 2007, being around 9.5 %, compared to an average of 12.6 % over the years 1985-third quarter of 2008 (Moody´s (2008)). In the USA and Canada, there was even a slight decline in downgrades while in Europe there was some increase. Not surprisingly, corporate downgrades increased in 2008. Similar results are obtained for S&P as shown by Bloomberg and Fitch (Fitch (2008)).

- First, we show that ratings based on the probability of default imply the observed strict subordination of securitization tranches.

- Second, the empirical evidence strongly confirms an *inverse* relation between the quality of the securitized asset pool and the size of the FLP, but a *positive* relation between asset pool quality and the size of the TLP in synthetic transactions. Since information asymmetry is likely to be stronger for asset pools of lower quality, the inverse relation between the size of the FLP and asset pool quality suggests that the FLP grows with the perceived extent of information asymmetry[4]. The positive relation between the size of the TLP and asset pool quality suggests that loss allocation to the TLP is driven primarily by the originator´s risk and funding strategy.

- Third, we ask whether there exists a measure of investor protection against default losses which is invariant to asset pool quality. Such a measure of loss allocation might balance the interests of the originator and investors. Since the size of the FLP is a crude measure of protection, we investigate two other measures of investor protection, assuming a lognormal distribution for the default loss rate of the underlying asset pool. The first measure is the share of expected default losses absorbed by the FLP, called the *loss share*. The second measure is the probability that all default losses are exclusively borne by the FLP, i.e. investors are not hit by default losses. We denote it as the *support-probability* of the FLP.

Empirically, it turns out that the *loss share* is largely independent of the asset pool quality, in contrast to the support probability. The loss share is, on average, about 84 % for CLO-transactions and about 90 % for CBO-transactions. In CLO-transactions there is much room for the originator´s moral hazard, in CBO-transactions there is not. Hence one would

[4] Originators rarely announce to what extent they retain the FLP. The current financial market reforms require the originator to retain at least 5 percent of all default losses to mitigate adverse selection and moral hazard.

expect a higher loss share in CLO-transactions, in contrast to the empirical evidence. This suggests that moral hazard may lead to high reputation costs for the originator implying a strong monitoring effort. Therefore investors may accept a smaller loss share in CLO-transactions.

- Fourth, the attractiveness of a synthetic relative to a true sale transaction increases with asset pool quality. Better quality implies a lower default risk of the super-senior tranche, making it less attractive for the originator to sell this tranche. A TLP is in stark contrast to the literature which argues that the originator should sell the least information-sensitive tranche. The preference for synthetic transactions appears to be stronger for originators with a better rating. This may also be driven by funding costs. Highly rated originators can obtain cheaper funding issuing standard bonds rather than highly rated bonds in true sale securitizations.

- Fifth, the last important surprising finding is that characteristics of the originator such as her total capital ratio or Tobin´s Q which may proxy for her securitization motives, add little to the explanatory power of the regressions.

The paper is structured as follows. Section 2 reviews the literature. In section 3 we model the originator's choice problem and derive hypotheses. The empirical findings are presented and discussed in section 4. Section 5 concludes.

II. Literature Review

Several papers analyse the optimality of First Loss Positions. In the absence of information asymmetries, Arrow (1971) [see also Gollier and Schlesinger (1996)] analyses the optimal insurance contract for a setting in which the protection buyer is risk averse, but the protection sellers are risk neutral. If they bound their expected loss from above, then a FLP of the protection buyer is optimal. Townsend (1979) considers risk sharing between a risk averse entrepreneur and investors in the presence of information asymmetries about the entrepreneur's ability to pay. The optimal contract is a standard debt contract implying a FLP of the entrepreneur [see also Gale and Hellwig (1985)]. Malamud, Rui, and Whinston (2009) study optimal tranching in a securitization transaction, given a perfect market where agents have homogeneous expectations, but heterogeneous preferences. In their model, optimal risk sharing is achieved by issuing multiple tranches and investors buying different portfolios of tranches.

The literature on security design distinguishes between information-sensitive and -insensitive securities. Boot and Thakor (1993) argue that a risky cash flow should be split into a senior and a subordinated security. The senior information-insensitive security can be sold to uninformed investors while the information-sensitive subordinated security should be sold to informed investors. This should raise the sales revenue. Riddiough (1997) extends this reasoning by showing that loan bundling allows for asset pool diversification which softens information asymmetries.[5] DeMarzo and Duffie (1999) analyse the security-design assuming a tradeoff between the retention cost of holding cash flows and the liquidity cost of selling information-sensitive securities. They prove that a standard debt contract is optimal. DeMarzo (2005) shows that pooling of assets has an information-destruction effect since it prohibits the seller to sell asset cash flows separately. But pooling improves diversification. Tranching allows to sell more liquid, information-insensitive claims. Summarizing, these papers demonstrate the optimality of a FLP and argue that the senior information-insensitive tranches should be sold to investors. This is in strong contrast to synthetic transactions where the large least information-sensitive tranche, the TLP, is not sold.

Duffie and Garleanu (2001) discuss adverse selection and moral hazard in securitizations. They also discuss Moody´s diversity score and illustrate the sensitivity of the

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[5] Gorton and Pennacchi (1995) consider a bank which optimizes the fraction of a single loan to be sold and the guarantee against loan default through a repurchase agreement.

portfolio loss rate distribution to various parameters[6]. In a recent paper Duffie et al. (2009) argue that unobservable, non-stationary risk factors raise default correlations and imply higher tail risks for loan portfolios. This could explain the rather high credit spreads on Aaa-tranches in securitizations. Albrecher, Ladoucette, and Schoutens (2007) propose a generic one factor Lévy model to derive the portfolio loss rate distribution. Burtschell, Gregory, and Laurent (2009) compare models with one latent factor and different copulas to derive default intensities for CDOs. In an empirical study, Krekel (2008) proposes a Gaussian base correlation model with correlated recovery rates to improve the empirical model fit. Longstaff and Rajan (2008) estimate loss distributions of CDX-tranches with multiple factor models and find that a three factor model leads to a three-modal loss rate distribution where the second (third) mode has a much smaller density than the first (second). They interpret the second and third factor as default clustering factors.

Among the empirical studies of securitizations, Downing and Wallace (2005) find in commercial mortgage backed securities-transactions that FLPs are higher than what might be expected looking at the actual performance of mortgages. Downing, Jaffee, and Wallace (2009) observe that securitized assets have lower quality than non-securitized. Consistent with this, Piskorski, Seru, and Vig (2010) find a lower foreclosure rate associated with bank-held loans compared to similar securitized loans. Purnanandam (2010) observes significantly higher mortgage-related write-offs for banks that are more engaged in true sale securitizations, consistent with adverse selection and moral hazard. Loutskina and Strahan (2009) argue that securitization raises banks′ willingness to approve mortgages that are hard to sell. Cebenoyan and Strahan (2004) document that banks securitizing loans hold less

[6] Plantin (2003) shows that sophisticated institutions with high distribution costs buy and sell the junior tranches leaving senior tranches to retail institutions with low distribution costs.

capital than other banks and have more risky assets relative to total assets. Franke and Krahnen (2006) find that securitization tends to raise the bank's stock market beta indicating more systematic risk.

III. Hypotheses

A. Strict Subordination

In this section we present the hypotheses to be tested. Since strict subordination is perhaps the most striking property of loss allocation in securitization transactions, we first motivate it by the strong role played by the rating agencies. S&P and Fitch rate according to the probability of default (PD), while Moody´s rates according to the expected loss rate. The empirical evidence shows that Moody's ratings are similar to PD-ratings. The following lemma shows that under weak conditions PD-rating leads to strict subordination.

Lemma 1: Assume that a) the owner of a tranche enjoys limited liability, b) the issuer of securitization tranches minimizes the credit spreads to be paid, c) the credit spread paid on a tranche is inversely related to its rating, d) inverse loss sharing is ruled out. Then PD-rating implies strict subordination of tranches.

The first three assumptions of the lemma need no explanation. Inverse loss sharing is defined by a loss sharing such that at least one agent bears *less* default losses when the default loss of the underlying asset pool *increases*. This agent would benefit from higher losses of the asset pool and, thus, have an incentive to raise losses. So inverse loss sharing is ruled out. Then PD-rating implies strict subordination. The proof is straightforward. Consider a transaction with two tranches only. If both tranches share the first unit of default losses as well as additional units, then both tranches have the same PD. To minimize the PD of the second tranche, holding the PD of the first tranche constant, the latter has to exclusively bear all losses until it is exhausted. This maximizes the rating of the second tranche and, hence, minimizes the credit spread of this tranche. The same argument applies to multiple rated tranches, proving the lemma.

B. Information Asymmetry and Asset Pool Quality

The PD-based rating implies a minimum size of the FLP under the usual condition that the lowest rating of a rated tranche is B or better. While ratings provide important information to investors, they cannot remove information asymmetries completely. Originators usually have better information on loans and bonds underlying a transaction than investors. This creates room for adverse selection and moral hazard of the originator so that investors presumably demand higher credit spreads for rated securitization tranches. The originator may try to reduce this penalty by credit enhancements, in particular by a FLP. The stronger the information asymmetry, the higher the FLP should be.

To model information asymmetries, we distinguish between the published and the true quality of the underlying asset pool. Asset pool quality is measured by the weighted average default probability (WADP) of the loans/bonds in the asset pool and by asset pool diversification. Diversification is summarized by Moody´s Diversity Score (DS) or the improved Adjusted Diversity Score (ADS). This score can be interpreted as the diversification-equivalent number of equally sized loans whose defaults are uncorrelated. A third characteristic of the asset pool quality is the weighted average expected loss given default. To simplify modelling we assume that the loss given default λ is non-random. Then the expected loss rate of the asset pool is $\lambda\ WADP$. Given λ, we characterize asset pool quality by WADP and DS or ADS.

We assume that rating agencies publish unbiased information about the underlying asset pool quality[7]. The true quality differs from the published quality by a noise term ε,

$$\text{published asset pool quality} = \text{true asset pool quality} + \varepsilon.$$

The standard deviation of the noise term, $\sigma(\varepsilon)$, is a measure of quality uncertainty. It should be inversely related to the true asset pool quality. The intuition for this is that errors in estimating WADP are likely to be *proportional* to the true WADP. If the true WADP is very small (high), then errors in estimating WADP are likely to be small (high). Also $\sigma(\varepsilon)$ should be inversely related to the true DS. As pointed out by DeMarzo (2005) and others, a high DS reduces information asymmetries because the idiosyncratic risks of the assets tend to be diversified away. *Hence asset pool quality and quality uncertainty should be inversely related.*

Quality uncertainty creates room for adverse selection and moral hazard and therefore should be priced. One might argue that investors can buy tranches of many different transactions and thereby diversify their ε–risk. But buying a tranche incurs management and other transaction costs constraining diversification[8]. Moreover, there is a non-diversifiable risk that the rating models used by the rating agencies are flawed. Given only three relevant agencies which appear to use similar models, this creates a systematic risk. Therefore the ε–risk is likely to be priced.

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[7] As argued in the introduction, the criticism of rating agencies concerns their rating of securitizations of mortgage-backed loans, not that of corporate loans or bonds. In any case, our sample ends in 2005. At that time, confidence in ratings was still very strong.

[8] Gabaix, Krishnamurthy and Vigneron (2007) find that prepayment risk is priced in mortgage backed securities transactions, even though it is a pure redistribution risk. They attribute this to limits of arbitrage.

C. Allocation of Losses to the First Loss Position

As discussed before, the FLP should be higher, the stronger the information asymmetry. This and the inverse relationship between information asymmetry and asset pool quality motivate

Hypothesis 1: *The FLP is higher, the lower the quality of the asset pool.*

This hypothesis can also be motivated by the rating methodology. Given the rating of the lowest rated tranche, a lower asset pool quality requires a higher FLP. The size of the FLP[9] is a crude measure of loss allocation to the FLP because it does not take into account the loss distribution of the asset pool. In equilibrium, the loss exposure of the FLP *relative* to that of the rated tranches should be balanced. An intuitive measure for relative loss exposure is the *loss share.* It is defined as the expected loss borne by the FLP, divided by the expected loss of the asset pool. Investors might view the loss share as an important signal of balancing interests. Alternatively, consider the *support-probability* of the FLP. It is the probability that the asset pool-losses are smaller than the FLP. *(1-support probability)* is the probability that rated tranches are hit by default losses. According to S&P and Fitch, this probability determines the rating of the tranche with the lowest rating. It relates the loss allocation to quantile considerations as does the value at risk, which is commonly used to assess tail risk.

There is no equilibrium model which relates the loss share or the support-probability to the asset pool quality. Investors may pay more attention to their expected losses than to the support probability. Hence we conjecture that there might be an equilibrium loss share which is largely independent of asset pool quality. This motivates

[9] The FLP can take different forms. In a true sale transaction, the FLP is the most junior tranche. It may be supplemented by a reserve account in which interest surplus (interest revenue from the asset pool minus interest expense on tranches) accrues over time. Default losses are then absorbed first by the reserve account.

Hypothesis 2: *The loss share of the FLP is independent of the asset pool quality.*

Before testing this hypothesis, we present some theoretical properties. A decline in DS or ADS, holding WADP constant, is modelled as a mean preserving spread in the loss rate distribution of the asset pool. An increase in WADP, holding diversification constant, is modelled as a first order stochastic dominance shift in the loss rate distribution. Without loss of generality, we assume that the asset pool has a par value of 1 €. Then the default loss of the pool equals the portfolio loss rate. Lemma 2 presents comparative statics of the loss allocation measures with respect to asset pool quality, *given* the size of the FLP.

Lemma 2: *Consider a securitization transaction, given the size of the FLP.*

a) A decline in asset pool diversification

-- implies a lower expected loss for the FLP and a higher expected loss for the rated tranches (including the TLP in case of a synthetic transaction); hence it reduces the share of expected losses of the asset pool borne by the FLP,

-- reduces the support-probability of the FLP if the FLP is higher than the loss rate at which the two cumulative probability distributions intersect. This condition holds for a lognormal loss rate distribution and a non-random loss given default λ for each loan/bond if and only if

$$(1) \qquad FLP \geq \lambda \, WADP \sqrt{1 + \frac{\frac{1}{WADP} - 1}{DS}} \, .$$

b) An increase in the weighted average default probability of the asset pool

-- raises the expected loss of both, the rated tranches (including the TLP in case of a synthetic transaction) and the FLP,

-- reduces the support-probability of the FLP,

-- reduces the share in expected losses of the asset pool borne by the FLP, given a lognormal loss rate distribution, if

(2)
$$\left(1 - N(h+\sigma) - n(h+\sigma)\,\frac{1}{2\sigma}\,\frac{1}{1+WADP(DS-1)}\right) \geq 0\,,$$

$$\text{with } h = \frac{\ln \dfrac{FLP}{\lambda\, WADP}}{\sigma} - \frac{\sigma}{2} \qquad \text{and } \sigma^2 = \ln\left(1 + \frac{1/WADP - 1}{DS}\right).$$

N(.) and n(.) denote the standard normal distribution function resp. the standard normal probability density function.

Lemma 2a) and b) are well known except for the results regarding a lognormal loss rate distribution which are proved in Appendix 1.2 and 1.3[10]. By Lemma 2a), a decline in asset pool diversification redistributes default losses from the FLP to the rated tranches. Hence the loss share declines and the originator would benefit more from adverse selection and moral hazard. By Lemma 2 b), an increase in WADP raises the expected losses of the FLP and of the rated tranches, and it reduces the support-probability. This, again, might alert investors.

While these results are true for all probability distributions, the impact of DS on the support-probability and of WADP on the loss share depend on the probability distribution. While Longstaff and Rajan (2008) derive a three-modal loss rate distribution, we use a uni-modal distribution because the models used by the rating agencies to simulate the default losses of the asset pool generate uni-modal loss rate distributions. A distribution which approximates the probability distribution derived from simulation models reasonably well is

[10] The appendix is available from the first author on request.

the lognormal distribution. This was also used by Moody´s (2000)[11]. For each securitization transaction we translate the expected value and the standard deviation of the loss rate of the asset pool into the two moments of a lognormal distribution as shown in Appendix 1.1. For each claim in the asset pool we assume the same default probability WADP and the same loss given default λ. Using the Black-Scholes model, the loss share s is given by $s = N(h) + (FLP/\lambda\, WADP)\,(1- N(h+\sigma))$, the support-probability is $\gamma(FLP) = N(h+\sigma)$.

Lemma 2a) states the condition for a decline of the DS to lower the support-probability, Lemma 2b) the condition for an increase in WADP to lower the loss share. These conditions are mostly satisfied in our sample. Therefore, we start from the premise that a decline in asset pool quality reduces both, the loss share and the support probability, given the size of the FLP. Avoiding both effects requires an increase of the FLP as stated in Hypothesis 1. If the originator adjusts the FLP to asset pool quality so as to keep the loss share constant (Hypothesis 2), then the support-probability will change as stated in Lemma 3 which is proved in appendix 2.

Lemma 3: *Assume a lognormal loss rate distribution. Suppose that the loss share of the First Loss Position is independent of the asset pool quality. Then the support-probability of the FLP is inversely related to the weighted average default probability and to the diversity score, if and only if* $h < n(h+\sigma)/(1- N(h+\sigma))$. *Also,* $\partial \ln FLP/\partial \ln WADP < 1$.

Lemma 3 states a surprising testable result. Given a constant loss share and the condition on h, the support-probability of the FLP declines if one measure of portfolio quality,

[11] The lognormal distribution implies a positive probability of a loss rate above 1. But this probability is very small even for low quality asset pools. Consider a transaction in which the weighted average default probability of loans is very high with 20 percent and the diversity score is very low with 10. Then the probability of the implied lognormal distribution for loss rates above 1 is 0.1 percent. In typical transactions this probability would be much smaller.

the WADP, worsens, but it also declines if the other measure of portfolio quality, the DS, *improves*. This shows that given a *higher* WADP, the depressed support probability increases relatively more slowly than the depressed loss share with the FLP, but given a *lower* DS, the depressed support probability increases relatively faster than the depressed loss share with the FLP.

D. True Sale versus Synthetic Transactions

Our conjecture that information asymmetry plays a major role for the allocation of losses to the FLP can be checked by comparing true sale and synthetic transactions. In synthetic transactions, by strict subordination, the TLP does not serve as a credit enhancement for the rated tranches (SLP). Therefore information asymmetry should play a minor role for the allocation of losses to the TLP. The choice between true sale and synthetic transactions is, however, driven also by other considerations. For example, borrowers may not agree to a transfer of the loan to another creditor. A true sale transaction would then be infeasible. A synthetic transaction also avoids the operational risk associated with a property transfer in a true sale transaction. Moreover, a synthetic transaction permits the originator to short-sell default losses.

The originator may choose a synthetic transaction if she prefers to retain the TLP-risk and avoid the transaction cost of securitizing it. This preference should be stronger for a stronger asset pool quality because then the TLP-risk is smaller. Therefore we state

Hypothesis 3: *The preference for synthetic over true sale transactions increases with asset pool quality.*

A better asset pool quality reduces the attachment point of a Aaa-tranche. This is the contractually defined asset pool loss rate such that this tranche bears losses only when the loss rate exceeds this rate. Hence a better asset pool quality should raise the TLP (instead of lowering it as suggested for the FLP by Hypothesis 1). This motivates

Hypothesis 4: *In a synthetic transaction the non-securitized super-senior tranche (Third Loss Position) increases with the quality of the asset pool.*

Retaining the information-insensitive super-senior tranche is in stark contrast to the literature. One explanation of this puzzle may be the funding cost. In a true sale-transaction the originator may freely use the proceeds from issuing tranches, while synthetic transactions provide no funding. Hence, a bank´s choice between true sale- and synthetic transactions may also depend on the funding costs in a true sale-transaction versus those of standard bank bonds. We hypothesize that banks with a very good rating have little incentive to use CDO-transactions for funding purposes since they can obtain funds at low credit spreads anyway. This motivates

Hypothesis 5: *Synthetic [true sale] transactions are preferably used by banks with a strong [weak] rating.*

Interestingly, Hypotheses 3 to 5 can also be derived from optimal risk sharing in a model with heterogeneous investor preferences (Malamud, Rui, and Whinston (2009)).

E. CLO- versus CBO-Transactions

Next, compare CLO- and CBO-transactions. In a CLO-transaction, the originator should monitor the debtors so that a moral hazard problem exists. In a CBO-transaction the originator is, as any other bond investor, in a remote position vis à vis the bond obligors so that she cannot effectively monitor them. Therefore credit spreads of CLOs may include a higher penalty for moral hazard. Also, the potential for adverse selection may be stronger in CLO-transactions because more public information exists on bonds than on loans. These conjectures about adverse selection and moral hazard are confirmed by some of the empirical studies on mortgage-backed securities quoted above. Higher credit spreads in CLO-transactions should motivate the originator to mitigate this penalty through a higher FLP. This leads to

Hypothesis 6: *Given the same quality of the asset pool, the loss share of the FLP is higher in CLO- than in CBO- transactions.*

This hypothesis ignores reputation costs of the originator. Investors may react to default losses they have to bear by imposing higher credit spreads on the same originator in future securitizations. This generates a reputation cost. A high reputation cost may induce a strong originator effort which partially substitutes for the FLP. Hence, the FLP may be smaller in a CLO- than in a CBO-transaction. Higgins and Mason (2004) document various cases in which banks voluntarily absorbed default losses in credit card securitizations beyond the FLP so as to reduce their reputation cost. This cost might invalidate Hypothesis 6. Second, this hypothesis ignores the observation that default rates tend to be higher for bonds than for loans of the same debtor (Emery and Cantor (2005)). Therefore expected losses could be higher for securitized bonds than for loans. This difference would not show up in debtor ratings as opposed to debt claim ratings. Hence investors might insist on higher loss shares in CBO-transactions.

IV. Empirical Findings

These hypotheses will be tested on a set of 169 European CDO-transactions of corporate loans and bonds, excluding other types of collateral like mortgages. Our data set includes all European CDO-transactions from the end of 1997 to the end of 2005 for which we know Moody's DS and can derive WADP[12]. Information about transactions is taken from offering circulars, from pre-sale reports issued by Moody's and from the Deutsche Bank-Almanac. The sample represents about half of all European CDO-transactions issued in the observation period.

[12] We include a few transactions without a rating from Moody´s where the average quality of the underlying assets is known and also their diversification.

A. Derivation of Asset Pool Quality

Since asset pool quality is essential for our analysis, we provide information on how WADP and DS are derived. Rating agencies assign a rating to each asset in the pool. For publicly rated assets, such as corporate bonds, current bond ratings are used if derived in-house. The rating of another agency is lowered by a defined number of rating steps (notches), mainly to account for the uncertainty about the underlying rating model. For asset pools without publicly rated assets, such as corporate loans, three different rating approaches are typically employed as explained in a footnote[13]. Moody´s publishes a weighted average rating for the asset pool, based on the individual assets' ratings. We use Moody's tables to translate the weighted average rating of an asset pool into the weighted average default probability WADP.

The expected default loss rate of the asset pool equals λ *WADP*. Since we mostly do not have transaction specific information on loss given default, we assume λ to be 50 percent, with few exceptions. This is in line with Acharya et al (2007) who document recovery rates for various loans and bonds in the US. They find an average recovery rate slightly above 50 percent. For 2 transactions with secured loans we use λ = 25 percent. For mezzanine transactions with subordinated and unsecured underlying we use λ = 100 percent as the rating agencies do.

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[13] (1) The first approach relies on the quality of the originator's internal rating system. It maps the originator´s rating scale to the agency´s rating scale. Mappings are monitored regularly and adjusted if necessary. (2) Use of historical default loss data, often called the statistical/actuarial approach, in line with the agency's published recovery assumptions. (3) Use of proprietary credit risk information systems, i.e. a database/scoring model of corporate accounting data, in order to calculate an expected default rate for each obligor, using recovery assumptions. Examples include Moody's KMV RiscCalc™ and S&P's Credit Risk Tracker. The three approaches can be used in combination.

The loss allocation in a transaction also depends on the diversification of the asset pool. Moody's diversity score DS measures the diversification of the assets within and across industries, taking into account also variations in asset size. DS is defined as the number of claims of equal size and uncorrelated defaults, which gives the same standard deviation of the asset pool loss rate distribution as that actually observed. DS is defined by Moody´s as

$$DS = \sum_{k=1}^{m} G\left\{\sum_{i=1}^{n_k} \min\left\{1, F_i / \overline{F}\right\}\right\}.$$

m denotes the number of industries, n_k the number of claims against obligors in industry k, F_i the par value of claim i and $\overline{F}$ the average par value of all claims. $G(y)$ is an increasing concave function starting at $G(1) = 1$ with a maximum of 5 attained at $y = 20$. Hence, the maximum diversity score within an industry is 5. The diversity score ranges between 1 and 135. $DS = 1$ indicates "no diversification", $DS = 135$ "excellent diversification".

The DS has been criticized on various grounds (Fender and Kiff 2004). Therefore, in 2000 Moody´s started to use an *adjusted DS*. The adjusted DS (ADS) explicitly takes into account asset correlations of obligors within an industry, ρ_{in}, and between industries, ρ_{ex}. Given equally sized loans, Fender and Kiff (2004) show

$$ADS = \frac{n^2}{n + \rho_{ex} n(n-1) + (\rho_{in} - \rho_{ex})\sum_{k=1}^{m} n_k(n_k - 1)}.$$

For example, consider a transaction with 15 industries and 10 loans of equal size in each industry, assuming $\rho_{in} = 20$ percent. Then the adjusted DS with $\rho_{ex} = 0$ percent is about 39. But with $\rho_{ex} = 2$ resp. 4 percent it would be about 23 resp. 16, indicating the sensitivity of the adjusted DS to ρ_{ex}. Given 10 industries and 6 loans of equal size in each industry, the DS is similar to the ADS if $\rho_{in} = 20$ and $\rho_{ex} = 0$ (Fender and Kiff (2004)).

Deriving ADS with two correlation coefficients only is clearly a simplification. This shrinkage approach may have some merits in view of the difficulties of estimating correlations. An approach with two correlation parameters would follow from a KMV-portfolio model like that of *Gordy* (2003) in which the asset returns of the indebted companies are driven by one systematic macro-factor, by orthogonal industry factors and idiosyncratic factors. For each company, the correlation between the asset return and the macro-factor would equal ρ_{ex} and the (additional) correlation between the asset return and the industry factor would be (ρ_{in} - ρ_{ex}).

We know Moody´s DS for all 169 transactions. For 92 transactions we have enough information about industry diversification to carefully derive the adjusted DS. In line with Moody´s and S&P we derive the adjusted DS assuming an intra-industry asset correlation ρ_{in} of 20 percent and an inter-industry asset correlation ρ_{ex} of 2 percent. Alternatively, we use inter-industry correlations of 0 and 4 percent for a robustness check. We use Moody´s DS to analyse the full sample and, in addition, the adjusted DS to analyse the reduced sample of 92 transactions. We refer to this subset whenever we use the lognormal loss rate distribution.

B. Descriptive Statistics and Methodology

The first table shows the distribution of the 169 transactions across CLO/CBO- and true sale/synthetic transactions and across years. 57 percent of the transactions are CBO-transactions, 54 percent are synthetic. 136 transactions are arranged by banks and 33 by investment firms. The latter buy existing bonds and securitize them. 15 of these 33 transactions also include some loans. We classify these transactions as CBO-transactions. 1/3 of the CBO-transactions are originated by investment firms.

Insert Table 1 about here

Table 2 presents the means and standard deviations of WADP, DS, FLP and TLP in synthetic transactions. Using a loss given default of 50 percent with a few exceptions, the expected default loss of an asset pool is about half the WADP. The data are presented separately for the four subsamples of true sale/CLO, synthetic/CLO, true sale/CBO and synthetic/CBO-transactions. Table 2 indicates several interesting properties. The mean of the WADP is much higher for true sale than synthetic transactions. It is also clearly higher for synthetic CLO– than synthetic CBO-transactions. On average, CLO-transactions are much better diversified than CBO-transactions. In a CLO-transaction a bank can easily securitize many loans from its loan book to obtain a high DS. Buying bonds is often costly since the bond market is rather illiquid. Therefore the DS tends to be smaller in CBO-transactions.

The average size of the FLP is higher for true sale than for synthetic transactions, and within these subsets it is higher for CBO- than for CLO-transactions. The average size of the FLP exceeds the average expected loss which is about half of the WADP. Thus, the averages satisfy the condition in Lemma 2a). Also, the average size of the FLP is smaller than the average WADP except for synthetic CBO-transactions. The condition in Lemma 2b) and the condition $h < n(h + \sigma)/(1 - N(h + \sigma))$ in Lemma 3 always hold, based on an ADS with $\rho_{ex} = 2$ percent. The average TLP in synthetic transactions is about 87 % of the asset pool volume with a standard deviation of only 7 % if we exclude three atypical Geldilux-transactions. These are the only fully funded synthetic CLO-transactions, i.e. TLP is zero.

Insert Table 2 about here

In the following we test the hypotheses presented in section 3. We hypothesize that loss allocation depends on asset pool quality, on other characteristics of the securitization transaction and on exogenous factors such as the attitudes of investors and rating agencies, market imperfections and originator characteristics. The function relating loss allocation to all these factors is assumed to be the same for all CDO-transactions. We try to find out the properties of this function. One difficulty of this approach is that the originator simultaneously chooses asset pool quality and loss allocation. Asset pool quality cannot be viewed as an exogenous determinant of loss allocation, and vice versa. Yet, if a function exists which relates loss allocation to asset pool quality in equilibrium, then the best the originator can do is to adhere to this function. Originator characteristics are likely to affect loss allocation. Therefore we include various characteristics of originating banks as controls. Moreover, we run the regressions for loss allocation separately for the four subsets of true sale/CLO, true sale/CBO, synthetic/CLO and synthetic/CBO transactions to find out whether these subsets differ systematically.

Banks and investment firms are originators. While many characteristics of banks are known, those of investment firms are largely unknown. We include the following bank control variables, obtained from the Bank Scope Database. Basel ratios: the tier 1-capital ratio and the total capital ratio, capital structure: equity/total assets, asset structure: loans/total assets, profitability: return on average equity capital in the transaction year, the average return over the years 1994 to 2004, and the standard deviation of these returns as a proxy for profitability risk, Tobin´s Q to proxy for the bank´s growth potential, the bank´s rating to proxy for its funding cost. Rating is always captured by an integer variable which equals -1 for a Aaa-rating and declines by 1 for every notch, with -16 for a rating of B3.

For each characteristic we attach a residual dummy $RD = 1$ to those originators for whom the characteristic is not known, otherwise $RD = 0$. We use regressions of the type

(3) $$y = a + b\, x_1 + c\, (1-RD)\, \Delta x_2 + d\, RD + \varepsilon.$$

x_1 is the vector of explaining variables other than originator characteristics, Δx_2 the vector of (bank characteristics - its sample average) and ε the usual error term. This approach implies that for banks with a known characteristic the variation in this zero-mean characteristic is taken into consideration while for the other originators a fixed effect is assumed. If a variable does not add to the explanatory power of a regression, then we often eliminate it from the regression. We always run the regressions with constants, but we do not always report their values to save space.

C. The Quality of the Asset Pool

The quality of the underlying asset pool is a core variable. Asset pool quality and loss allocation may be interdependent. Therefore, we ask three questions. 1. Does the originator follow a homogeneous quality policy, i.e. is a low (high) weighted average default probability (WADP) associated with a high (low) diversity score (DS)? 2. Does loss allocation affect WADP and DS? 3. Do originator characteristics affect the choice of asset pool quality? Fig. 1 illustrates the relation between WADP and DS (Fig. 1a) resp. the adjusted diversity score ADS 2 (Fig.1b). Both figures do not indicate a strong relation between WADP and asset pool diversification. Hence the figures provide, at best, partial support for homogeneous quality choice.

Insert Figure 1 about here

Next, we run OLS-regressions to check the relation between WADP and DS. In Table 3, we first regress WADP for all 169 transactions on the inverse log diversity score and originator characteristics. DS turns out to be insignificant. Investment firms and banks with a higher total capital ratio tend to choose asset pools with higher WADP. Banks with a strong equity buffer might take higher default risks which they then securitize. Other originator characteristics have no significant impact. In accordance with Table 2, true sale-CBO transactions have significantly higher WADPs.

Since the choice of WADP might differ for subsets of transactions, we run the first regression also separately for ts/CLO, ts/CBO, syn/CLO and syn/CBO-transactions. The regression coefficient of the inverse log diversity score is significant only for the 30 true sale-CLO transactions ((2^{nd} regression in Table 3); a higher diversity score tends to lower WADP.

Insert Table 3 about here

Also loss allocation might affect the choice of asset pool quality. As Table 2 indicates, a higher WADP tends to lead to a higher FLP. When we include FLP in the regression, we find a strongly significant, positive regression coefficient (not shown). But due to endogeneity issues it would be dangerous to conclude that a higher FLP generates a higher WADP. The loss share and the support probability are less prone to endogeneity problems. Therefore we use them as regressors. Since both are sensitive to diversification, we use the subsample of 92 transactions for which we know the more reliable adjusted diversity score ADS 2, using an inter-industry asset correlation ρ_{ex} of 2 percent. Since loss sharing may differ for CLO- and CBO-transactions, we multiply the loss measures by the CBO-dummy resp. (1-CBO-dummy). The last two regressions in Table 3 show that the ADS 2-coefficient is insignificant while the investment firm-dummy has a positive and significant impact on WADP. The support probability-coefficient is strongly significant and negative for both, CBO- and CLO transactions. But the loss share is insignificant. By Lemma 3, one of these loss measures should have a clear impact if the other one does not. We defer a more detailed discussion of these findings to the next subsection.

Insert Table 4 about here

Table 4 reports regressions to explain DS resp. ADS 2. For the full sample of 169 transactions, the inverse log DS does not depend significantly on WADP, also the investment firm-dummy is insignificant. As suggested by Table 2, DS is lower for CBO-transactions, but higher for synthetic transactions. The total capital ratio-coefficient is only weakly significant. Other originator characteristics appear to be irrelevant. In separate regressions for each of the four subsamples, we only find a significant WADP-coefficient for the subsample of 30 true sale-CLO transactions (2^{nd} regression in Table 4), in line with the significant coefficient of DS on WADP in Table 3. We also check the subsample of 92 transactions to find out whether loss allocation has any relation to ADS 2 (last two regressions in Table 4). The support probability-coefficient is significant for the CBO-, but not for the CLO-transactions. The loss share-coefficient is weakly significant only in CBO-transactions. Hence, similar to Table 3, there is very little support for dependence between DS and WADP.

While DS is primarily driven by CLO- versus CBO-transactions, an endogeneity problem regarding the impact of DS on WADP might exist. Therefore, we run a two stage least squares regression (2SLS) to explain WADP. As the diversity score is much higher in CLO- than in CBO-transactions, we use the CBO-dummy as an instrumental variable for DS. The findings of this exercise do not support an endogeneity effect.

Summarizing, the choices of WADP and DS appear to be independent. Investment firms and banks with higher total capital ratios appear to prefer transactions with higher WADPs. Otherwise, originator characteristics do not seem to be relevant. While WADP is partly explained by the support probability, the loss share neither explains WADP nor ADS.

D. Loss Allocation to the FLP

1. Size of FLP

Now the core hypotheses on loss sharing will be tested. Hypothesis 1 states that the size of the FLP is inversely related to the quality of the asset pool. This hypothesis is strongly confirmed by the regressions in Table 5. The first two regressions are based on the full sample of 169 transactions using the DS, while the last regression is based on the subsample of 92 transactions using ADS. The results indicate that even for an asset pool with excellent quality, given by a WADP close to 0 and a DS of 135, the FLP is positive. Using the coefficients of the first regression, the estimated FLP equals $-8.5 + 46.6/\ln(135) = 1.00$ (%). This suggests that investors are concerned about information asymmetry and other potential problems of securitization transactions even if the published asset pool quality is very good. It may also explain why the FLP increases with WADP at a slope clearly below 1. Interestingly, the regression coefficient of the Synthetic dummy is significantly negative in the second regression, but insignificant in the last regression which uses the more sophisticated diversification measure.

We also regress the FLP-size on asset pool quality for the four subsets of transactions. The results (regressions 3 to 6) are very similar for true sale-CLOs and for true sale-CBOs. For synthetic CLOs and synthetic CBOs, WADP still remains strongly significant, but inverse ln DS turns insignificant. It might be that investors are less concerned about diversification in synthetic transactions because they interpret the TLP as a strong quality signal.

We also check whether the FLP is higher in a managed (dynamic) transaction than in a static transaction. In the second and the last regression the dummy being 1 for a managed transaction and 0 otherwise is insignificant. This may be due to the strict rules on replenishment /substitution. Also, originator characteristics have no impact on the size of the FLP. Originators with more valuable real options as indicated by Tobin´s Q do not seem to prefer a smaller FLP.

Insert Table 5 about here

We also run the FLP-regressions including the issuance date and the IBOXX spread as regressors. The IBOXX-spread is the difference between the IBOXX for BBB-bonds and the government-IBOXX for a maturity of 3 to 5 years. Both regressors have no significant impact (not shown). The insignificant issuance date-coefficient does not support the claim that the rating agencies relaxed their rating standards over time implying smaller FLPs. Finally, we run the regression for the subsample of 92 transactions for adjusted diversity scores based on inter-industry-correlations ρ_{ex} of 0 or 4 percent. We do not report the results because they are very similar to those for ρ_{ex} = 2 percent.

2. Loss share and Support Probability

Next, we analyse the relation between asset pool quality and sophisticated loss sharing measures. Using the inter-industry-correlation $\rho_{ex} = 2$ percent, the loss share of the FLP has a mean of 86.1 percent and a standard deviation of only 8.4 percent. This indicates that the FLP takes a high share of the expected default losses. For the support-probability the mean is 87.6 percent and the standard deviation 14.7 percent. This mean is also quite high. In accordance with Lemma 2a), the average loss share declines from 91.6 to 82.3 percent if ρ_{ex} increases from 0 to 4 percent, and the average support-probability declines slightly from 88.25 to 87.57 percent. Surprisingly, the support-probability is almost constant. This indicates that the cumulative lognormal distributions, generated by different inter-industry correlations, intersect at loss rates which are only slightly below the FLP.

Regressing the loss share on WADP and inverse log ADS 2 only, it turns out that WADP is completely insignificant, while the coefficient of the inverse ADS 2 is positive and significant (Table 6, 1st regression). However, the explanatory power of the regression is only about 5.6 percent. Adding the CBO-dummy as a regressor strongly weakens the significance of the ADS 2-coefficient. The CBO-coefficient is strongly significant, positive indicating a higher loss share in CBO-transactions. The average loss share is 83.7 % in CLO- and 90 % in CBO-transactions, invalidating Hypothesis 6. This is consistent with higher expected losses of securitized bonds versus loans as well as with a strong reputation cost for default losses in CLO-transactions. This cost might induce a strong (unobservable) monitoring effort of the originator in these transactions which partially substitutes for the loss share. But it also points to operational risk in CLO-transactions. If an originator does not intend future securitization transactions, she might not care about reputation costs and enjoy the private benefits of moral hazard. Again, the coefficients of the issuance date and the IBOXX spread are insignificant (not shown).

Insert Table 6 about here

We also run the first regression in Table 6 separately for the four subsets of transactions (regressions 3 to 6). For true sale-CLOs, synthetic CLOs and synthetic CBOs, WADP and inverse ln ADS 2 have no significance, the adjusted R^2s are negative or slightly above 0. Only for the small sample of 15 true sale-CBOs, we find a strongly significant negative effect of WADP, driven by 4 transactions with a WADP above 20 percent while all other transactions have a WADP below 6 percent (4^{th} regression in Table 6). Apart from these few transactions, the empirical evidence clearly indicates that the loss share is largely independent of portfolio quality. This conclusion is also supported by the regressions in Table 3 and 4, where the loss share adds nothing or little to the explanation of asset pool quality. Thus, Hypothesis 2 is clearly supported.

Next, we run similar regressions for the support-probability (right part of Table 6). For the full sample of 92 transactions, the WADP-effect is strongly significant and negative. ADS 2 is weakly significant, but insignificant if the CBO-dummy is included. These two regressions have an impressive explanatory power of about 60 %. These findings are not surprising in view of the previous finding that the loss share is independent of the asset pool quality. Lemma 3 then implies that the support-probability should react inversely to WADP and to ADS. Again, the issuance date and the IBOXX spread have no significant effects. Analysing the four subsets of transactions separately (last four regressions), WADP always has a strongly significant negative impact, while inverse ln ADS2 has a positive impact which, however, is significant only for synthetic CBOs. Hence we conclude that the support-probability varies with asset pool quality, in particular WADP, while the loss share does not. A loss share which is largely independent of the asset pool quality appears to be the market norm. These findings need not necessarily be driven by information asymmetry because we can only test for effects of asset pool quality.

Importantly, adding originator characteristics as regressors does not improve the explanatory power (not shown). Hence loss allocation appears to be driven by market forces, not by originator characteristics. This may be surprising if one believes in the cooperation of originators and rating agencies to maximize their joint benefit. As a caveat, our set of originator characteristics may miss some relevant characteristics.

The assumption of a lognormal loss rate distribution is sometimes criticised. If one simulates the loss rate distribution of a loan portfolio period by period, it turns out that the distribution is in some cases better approximated by a gamma distribution. Therefore we check robustness by using a two-parameter gammma distribution. For each transaction the expected loss rate and the loss rate-variance*,* based on ADS 2, are translated into the parameters of a gamma distribution. While for the 92 transactions the average loss share (average support-probability) assuming a lognormal distribution is 86.1 (87.6) percent, it is 84.3 (85.7) percent assuming a gamma distribution. Hence, it is not surprising that the regression results for loss shares and support probabilities based on the gamma distribution (not shown) are similar to those based on the lognormal distribution.

E. Loss Allocation to the TLP

Comparing true sale and synthetic transactions permits us to better understand the determinants of loss allocation. Hypothesis 3 claims that synthetic transactions are preferred for high quality asset pools. This hypothesis is clearly supported by the first probit-regression in Table 7. It is also supported if we analyse CLO- and CBO-transactions separately (2^{nd} and 3^{rd} regression). For CLO-transactions the DS-effect is insignificant, perhaps because these transactions tend to be well diversified.

Hypothesis 5 claims that originators with a good rating are less interested in funding through securitization. The fourth regression supports this hypothesis showing a significant, positive impact of the originator rating, while the originators without a rating, mostly investment firms, appear to prefer true sale transactions. Combining originator rating and portfolio quality in the fifth regression clearly improves the explanatory power of the regression.

Insert Table 7 about here

In the last regression the explanatory power is further improved by including the IBOXX spread, the originator´s Tobin´s Q and her total capital ratio. The IBOXX spread has a significant, positive impact on the preference for synthetic transactions. Hence it appears that originators are less interested in funding through securitization when credit spreads are high. The issuance date is insignificant (not shown). The significant, negative coefficient of Tobin´s Q suggests that it may not pay for originators with attractive outside options to retain the risk of a TLP. Originators with a high total capital ratio may prefer to retain the TLP-risk because their cost of retention may be smaller than that of selling.

We interpret the strong preference for synthetic transactions of originators with a good rating as evidence of a funding cost effect. This effect may dominate information-sensitivity effects and explain why the FLP, the most information-sensitive tranche, is at least partly sold while the TLP, the least information-sensitive tranche, is not. The left histogram in Fig. 2 shows credit spreads of European bank bonds with a maturity of at least 4 years, rated Aa3 and better, issued between 2000 and 2005. The right histogram shows the credit spreads of Aaa-rated CDO-tranches with a maturity of at least 4 years in our sample. The mean credit spread is 9.1 bp for the bank bonds and 40.6 bp for the Aaa-tranches. The minimum (maximum) spread of the bank bonds is -27 (+22) bp, while it is +1 (+100) bp for the Aaa-tranches[14]. Hence credit spreads of highly rated bank bonds are often lower than those of Aaa-tranches.

In Table 8, we regress the credit spreads of bank bonds and of CDO-tranches with a rating of at least Aa3 on the IBOXX-spread, negative rating, squared rating and bond maturity. Table 8 indicates that the spreads of bank bonds and of CDO-tranches are lower for a better rating and a shorter maturity. The tranche spreads increase with a higher IBOXX-spread while the bank bond spreads do not. To illustrate the funding decision, compare the estimated credit spread of a Aa2-bank bond and of a Aaa-tranche for a true sale transaction, given 5 years maturity and an IBOXX-spread of 2 percent. The estimated credit spread of the Aa2-bank bond is 7.9 bp, that of the Aaa-tranche is 42.7 bp. Thus, for highly rated banks funding through a large Aaa-tranche in a true sale transaction likely implies a higher funding cost than issuing standard Aa2-bonds. These banks may enjoy a strong reputation, which is not fully reflected in their bond rating, but in their credit spreads. Also investors may believe that big banks are too big to fail. Conversely, a Aaa-tranche in a securitization transaction may face some investor scepticism because securitization transactions are relatively new instruments with little performance history.

Insert Table 8 about here

Finally we analyse the size of the TLP. We exclude the three atypical fully funded Geldilux-transactions. In the first regression of Table 9, WADP has a strongly negative effect on the size of the TLP, while the impact of ln DS is u-shaped. For small diversity scores up to about 28 the estimated TLP declines with an increasing diversity score, for higher diversity scores it increases. There are only few transactions with a diversity score below 28. Therefore,

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[14] Similar to Aaa-tranches, standard bonds issued by large, well rated banks also represent well diversified risks. They predominantly default in very bad macro states, similar to Aaa-tranches.

the TLP mostly increases with the diversity score. Thus, Hypothesis 4 is clearly confirmed. Differentiating between CLO-and CBO-transactions (2nd and 3rd regression) shows similar results. But the diversity score turns insignificant in the strongly diversified CLO-transactions. The explanatory power of the first regression can be improved slightly by including the investment firm-dummy (last regression). The negative coefficient indicates that investment firms tend to retain smaller TLPs. Other originator characteristics do not appear to have a significant impact on the size of the TLP. Also, the issuance date and the IBOXX spread appear to be irrelevant.

Insert Table 9 about here

Comparing our findings for the FLP and the TLP, the differences are striking. While the FLP-size *reacts inversely* to asset pool quality, the TLP *increases*. This indicates that both choices are driven by different motives. Presumably, the FLP mitigates problems of information asymmetry; a lower asset pool quality induces a higher FLP providing more protection to investors. The TLP does not protect investors so that investor protection is irrelevant. Better asset pool quality lowers the Aaa-attachment point so that the TLP increases. Yet, the TLP should be sold since it is least-information sensitive. But funding through Aaa-tranches is not attractive for highly rated banks. This is reinforced in times of high credit spreads. Also, selling a large Aaa- tranche transfers little default risk so that banks may consider it a cost-ineffective tool for risk management.

F. Robustness Checks and Discussion

A potential critique of OLS-regressions to explain the FLP and the TLP is that these variables are constrained to the (0,1)-range. For a robustness check we transform the FLP and the TSP so that the transformed variable varies between plus and minus infinity. The regression results basically stay the same.

We already checked for potential endogeneity problems regarding the choice of asset pool quality. In the other regressions we see little potential for endogeneity. These regressions address loss allocation, given exogenous originator characteristics and attitudes of investors and rating agencies. While originator characteristics vary across transactions and are therefore used as controls, attitudes of investors and agencies should be similar for all transactions. Including a CBO-dummy as a regressor does not lead to endogeneity because CLO- and CBO-transactions represent two different types of transactions. Including a synthetic-dummy is more prone to endogeneity problems. But the findings of separate regressions for true sale and synthetic transactions are similar.

Our assumption that Moody´s quality assessments of the asset pool are unbiased, is difficult to test. Assessment biases might be driven by joint interests of originators and rating agencies, as suggested by the Congress hearings on MBS-securitizations of October 22, 2008. Our findings, however, indicate that the rating methods have been rather stable over the sampling period. We are not aware of any major changes in rating methodologies for corporate loans/bonds and CDO-transactions after our sampling period.

The discussion about the best way to measure the diversity score has led us not only to consider Moody´s DS, but also ADS based on inter-industry default correlations of 0, 2 or 4 percent. The regression results are similar. Sometimes the results are somewhat stronger for 4 percent. This may indicate that 4 percent was considered more realistic. If Moody´s over- or underestimated all WADPs by the same multiple, this would not affect our findings, apart from the level of the regression coefficients.

The assumption of a constant loss given default ignores that this parameter changes with business conditions which might impact loss allocation. Uncertainty in WADP and correlations should affect the results because the formulas for the loss allocation measures indicate non-linear effects as illustrated in Tarashew (2010) for the value at risk. For example, ADS is a declining convex function of correlation so that correlation uncertainty should upward-bias the expected ADS. Given an increasing convex function of the loss share in ADS, the expected loss share would also be upward-biased. Similarly, uncertainty in WADP should upward-bias the expected loss share since the loss share tends to be a declining convex function in WADP. Parameter uncertainty might also upward-bias the support-probability.

On a general level, our sample of 169 European CDO-transactions is modest even though it covers about half of the European transactions in the sampling period. This clearly limits the generality of our findings. The number of those transactions in the USA was much larger. It would be useful to compare our findings with those from the USA. It is dangerous to apply our findings to securitizations of other claims like mortgage-backed loans, credit card claims etc. Asset pool quality in these securitizations is measured by other criteria; often diversification of these pools is much stronger. This may lead to other loss allocations.

V. Conclusion

This paper investigates loss allocation to First, Second and Third Loss Positions in securitizations of corporate loans and bonds. The originator cooperates with investors and rating agencies to determine the quality of the underlying asset pool and the loss allocation. A sample of European securitization transactions of corporate loans and bonds shows that the size of the First Loss Position is strongly inversely related to asset pool quality while the Third Loss Position is positively related. The First Loss Position likely serves to mitigate information asymmetry problems, in contrast to the Third Loss Position. The general guideline for structuring transactions appears to be that the First Loss Position should cover a high share of the expected default losses, *largely independent* of the asset pool quality and of originator characteristics. The support-probability of the First Loss Position, i.e. the probability that the First Loss Position absorbs all losses, is inversely related to the weighted average default probability of the asset pool as predicted by theory.

The loss share is higher in CBO- than in CLO-transactions. In the latter, originators can mitigate default losses through their loan monitoring. The smaller loss share in CLO-transactions suggests that rating agencies and investors anticipate a strong monitoring effort of the originator in CLO-transactions, due to high reputation costs. Also, higher default rates of bonds relative to loans may motivate a higher loss share in CBO-transactions.

Asset pool quality *and* originator rating positively affect the originator´s preference for a synthetic transaction with a large Third Loss Position. Its size increases with the quality of the asset pool, in contrast to the First Loss Position. Retaining the Third Loss Position is also in conflict with the claim that the originator should sell the least information-sensitive tranche. Selling this tranche does not achieve a substantial risk transfer; moreover, credit spreads of Aaa-tranches tend to be higher than those of standard Aa-bank bonds so that an originator with a good rating may consider funding through Aaa-tranches too expensive.

Originator characteristics have a surprisingly small impact on loss allocation except for the choice between true sale and synthetic transactions. This indicates that choices are largely driven by attitudes of investors and rating agencies. We do not find evidence that rating standards declined over time.

The findings of this paper shed some light on the regulation of securitizations. Forcing the originator to retain 5 percent of all tranches would impose a loss share of the same percentage on her. Forcing her to retain 10 percent of the FLP would impose a loss share of 7 to 9 percent on her. Hence the latter is presumably more effective to constrain adverse selection and moral hazard. Clearly more empirical research is needed to better understand the various motives driving loss allocation in securitization transactions.

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Tables

	True sale	Synthetic	∑
CLO	30	43	73
CBO	48	48	96
∑	78	91	169

Year	997	998	999	000	001	002	003	004	005
number of transactions			2	6	0	2	6	9	2

Table 1: The upper part shows the number of transactions in the sample differentiating CLO- and CBO-transactions as well as true sale- and synthetic transactions. The lower part shows the annual distribution of transactions

	ts/CLO	syn/CLO	ts/CBO	syn/CBO
WADP – mean WADP – std.	7.5 % 7.5 %	3.8 % 3.1 %	13.2 % 9.8 %	1.9 % 3.2 %
DS – mean DS – std.	87 46	89 30	34 11	56 26
FLP – mean FLP std.	6.1 % 4.8 %	2.9 % 1.5 %	12.1 % 6.2 %	3.6 % 2.6 %
TLP – mean TLP – std.	- -	80 % (86%) 23 % (7%)	- -	87% 7%

Table 2: The table shows the means and standard deviations of transaction characteristics differentiating CLO and CBO-transactions as well as true sale (ts) and synthetic (syn) transactions. WADP and Moody´s DS are the weighted average default probability and Moody´s diversity score of the asset pool. FLP is the initial size of the FLP, TLP the non-securitized senior tranche as a percentage of the asset pool volume in synthetic transactions. The bracketed numbers for TLP in CLO-transactions are obtained if three fully funded synthetic Geldilux-transactions are excluded.

Explained variable	Weighted Average Default Probability (%)						
Sample of transactions	all 169	30 True sale, CLO	48 True Sale, CBO	43 SYN, CLO	48 SYN, CBO	92	92
Inverse ln diversity score	-4.7 (0.6860)	92.2 (0.0209)	3.0 (0.9096)	-17.2 (0.4890)	-0.54 (0.9582)	-	-
Inverse ln ADS 2	-	-	-	-	-	8.63 (0.3791)	-3.78 (0.6785)
Investment firm-dummy	9.5 (0.0000)	0.40 (0.9284)	13.17 (0.0000)	-	-0.26 (0.7481)	5.41 (0.0028)	8.57 (0.0247)
Loss share x CBO	-	-	-	-	-	-	-7.87 (0.2695)
Loss share (1-CBO)	-	-	-	-	-	-	-9.41 (0.2623)
Support Prob x CB0	-	-	-	-	-	-27.1 (0.0000)	-
Support Prob (1-CBO)	-	-	-	-	-	-28.9 (0.0000)	-
CBO-dummy (1- Synthetic dummy)	6.9 (0.0000)	-	-	-	-	-	-
ΔTotal capital ratio	1.2 (0.0021)	0.95 (0.1633)	3.056 (0.0000)	0.541 (0.1536)	0.306 (0.1649)	0.259 (0.2517)	0.898 (0.0951)
Adjusted R^2	0.508	0.221	0.602	0.0397	-0.0553	0.650	0.180

Table 3: The table displays the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions of WADP on various variables, without showing the regression constants. Inv ln ADS2 is the inverse log adjusted diversity score assuming a default correlation between industries of 2 percent. The investment firm-dummy is 1 if an investment firm is the originator and 0 otherwise. The CBO-dummy is 1 for a CBO-transaction and 0 otherwise. The Synthetic dummy is 1 for a synthetic transaction and 0 otherwise. ΔTotal capital ratio is the total capital ratio of the originating bank in the transaction year minus the average total capital ratio in the sample (see equation (3)). The adjusted R^2 is shown in the last row.

Explained variable	Inverse ln Diversity Score					Inverse ln ADS 2	
Sample of transactions	all 169	30 True sale, CLO	48 True Sale, CBO	43 SYN, CLO	48 SYN, CBO	92	92
Weighted average default probability (%)	4.85 (0.3376)	18.5 (0.0579)	1.27 (0.9069)	- 8.46 (0.5791)	-0.69 (0.9585)	- 0.017 (0.8475)	- 0.095 (0.2047)
Investment firm-dummy	0.004 (0.6763)	0.047 0.0141)	- 0.0118 (0.3448)	-	- 0.0155 (0.0358)	- 0.002 (0.7910)	- 0.0013 (0.8733)
Loss share x CBO	-	-	-	-	-	-	0.059 (0.0550)
Loss share (1-CBO)	-	-	-	-	-	-	0.042 (0.1243)
Support Prob x CB0	-	-	-	-	-	0.048 (0.0163)	-
Support Prob (1-CBO)	-	-	-	-	-	0.030 (0.1225)	-
CBO-dummy	0.040 (0.0000)	-	-	-	-	-	-
Synthetic dummy	- 0.018 (0.0645)		-	-	-	- 0.030 (0.0258)	- 0.029 (0.0225)
ΔTotal capital ratio	- 0.008 (0.0219)	- 0.001 (0.7187)	- 0.011 (0.0242)	- 0.0016 (0.2935)	- 0.019 (0.1355)	0.000 (0.9745)	- 0.000 (0.9821)
Adjusted R^2	0.347	0.472	0.049	- 0.013	0.209	0.182	0.186

Table 4: The table displays the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions of 1/ln DS resp. 1/ln ADS 2 on various variables, without showing the regression constants. The investment firm-dummy is 1 if an investment firm is the originator and 0 otherwise. The CBO-dummy is 1 for a CBO-transaction and 0 otherwise. The Synthetic dummy is 1 for a synthetic transaction and 0 otherwise. ΔTotal capital ratio is the total capital ratio of the originating bank in the transaction year minus the average total capital ratio in the sample (see equation (3)). The adjusted R^2 is shown in the last row.

Explained variable	Size of First Loss Position (%)						
Sample of transactions	169	169	30 TS, CLO	48 TS, CBO	43 SYN, CLO	48 SYN, CBO	92
Constant	-8.50 (0.0188)	-5.25 (0.1865)	-11.83 (0.0006)	-15.88 0.0611)	2.60 (0.1953)	4.76 (0.0341)	-15.0 (0.0421)
WADP of asset pool (%)	0.347 (0.0000)	0.296 (0.0000)	0.294 (0.0003)	0.237 (0.0027)	0.309 (0.0002)	0.447 (0.0159)	0.356 (0.0000)
Inverse ln diversity score	46.6 (0.0028)	40.5 (0.0117)	65.7 (0.0001)	79.5 (0.0056)	-4.19 (0.6068)	-8.15 (0.3278)	-
Inverse ln ADS 2	-	-	-	-	-	-	60.4 (0.0095)
Synthetic dummy	-	-2.07 (0.0029)	-	-	-	-	-1.03 (0.1345)
CBO-dummy	-	0.14 (0.7963)	-	-	-	-	0.82 (0.2022)
Managed-dummy	-	-0.49 (0.4417)	-	-	-	-	-0.68 (0.3263)
Adjusted R^2	0.546	0.574	0.766	0.343	0.393	0.328	.625

Table 5: This table displays the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions explaining the size of the FLP. WADP is the weighted average default probability of the asset pool. Inv ln ADS2 is the inverse log adjusted diversity score assuming a default correlation between industries of 2 percent. The synthetic-dummy is 1 for a synthetic transaction and 0 otherwise. The CBO-dummy is 1 for a CBO-transaction and 0 otherwise. The Managed-dummy is 1 for a managed transaction and 0 otherwise. The adjusted R^2 is shown in the last row.

	Share of expected losses (%)						
Sample of transactions	92	92	20 TS, CLO	15 TS, CBO	34 SYN, CLO	23 SYN, CBO	
Constant	67.3 (0.0000)	69.4 (0.0000)	71.3 (0.0532)	94.1 (0.0000)	120.9 (0.0018)	30.8 (0.4341)	(0.0000
WADP (%)	-0.124 (0.2950)	-0.121 (0.3556)	0.325 (0.1326)	-0.556 (0.0007)	-0.35 (0.6195)	0.187 (0.2308)	(0.0000
Inverse ln ADS2	61.7 (0.0145)	40.4 (0.0687)	36.5 (0.7537)	6.63 (0.7277)	-122 (0.3243)	187.9 (0.1432)	(0.0613
CBO-dummy	-	6.38 (0.0002)	-	-	-	-	
Date	-	0.14 (0.2680)	-	-	-	-	(0.6777
Adjusted R^2	0.056	0.166	-0.056	0.620	-0.023	0.014	

Table 6: This table displays the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions explaining the share of expected losses of the FLP resp. the support-probability of the FLP. WADP is the weighted average default probability of the asset pool. Inv ln ADS2 is the inverse log adjusted diversity score assuming a default correlation between industries of 2 percent. The CBO-dummy is 1 for a CBO-transaction and 0 otherwise. Date is the issuance date. The adjusted R^2 is shown in the last row.

Explained variable	Synthetic dummy					
Sample of transactions	169	73 CLO	96 CBO	151	151	151
Weighted average default probability (%)	-0.11 (0.0000)	-0.077 (0.0275)	-0.135 (0.0000)	-	-0.10 (0.0000)	-0.11 (0.0000)
Inverse ln diversity score	-6.71 (0.0050)	-3.47 (0.5212)	-11.43 (0.0014)	-	-6.86 (0.0085)	- 6.19 (0.0523)
IBOXX-spread (%)	-	-	-	-	-	0.879 (0.0098)
ΔOriginator's rating	-	-	-	0.225 (0.0033)	0.22 (0.0107)	0.33 (0.0013)
Originator rating-dummy	-	-	-	-1.54 (0.0000)	-1.29 (0.0002)	-0.77 (0.0631)
ΔTobin´s Q	-	-	-	-	-	-1.12 (0.0001)
ΔTotal capital ratio	-	-	-	-	-	0.198 (0.0947)
McFadden R^2	0.265	0.085	0.503	0.190	0.362	0.440

Table 7: This table shows the coefficients (with p-values in brackets) of binary probit regressions explaining the synthetic-dummy, without showing the regression constants. The synthetic-dummy is 1 for a synthetic transaction and 0 otherwise. IBOXX-spread is the spread between the BBB-IBOXX and the government–IBOXX for 3 to 5 years maturity. ΔOriginator's rating is the originator´s rating minus the average originator rating in the sample (see equation(3)). ΔTobin´s Q and ΔTotal capital ratio are defined analogously. The originator rating-dummy is 1 for originators without a rating and 0 otherwise. The last row shows the McFadden R^2.

Explained variable	Credit spread of bank bonds	Credit spread of CDO-tranches
Number of observations	118	226
constant	-7.99 (0.0273)	-21.3 (0.0419)
IBOXX-spread (%)	-0.695 (0.5545)	11.85 (0.0055)
- Rating	5.01 (0.0390)	32.46 (0.0011)
Rating²	-0.312 (0.5040)	-3.93 (0.0787)
Maturity of bond	1.002 (0.0000)	2.36 (0.0037)
Synthetic dummy	-	4.51 (0.2272)
Adjusted R²	0.286	.0.420

Table 8: This table displays the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions explaining the credit spreads of European bank bonds and CDO-tranches with a rating of AA- and better. Rating is -1 for Aaa, -2 for Aa1+, -3 for Aa2 and -4 for A1. IBOXX-spread is the spread between the BBB-IBOXX and the government–IBOXX for 3 to 5 years maturity. The Synthetic dummy is 1 for a synthetic transaction and 0 otherwise. The adjusted R^2 is shown in the last row.

Explained variable	Size of Third Loss Position (%)			
Sample of transactions	86	40 CLO	46 CBO	86
constant	- 0.066 (0.7861)	0.958 (0.6657)	- 0.162 (0.4871)	- 0.017 (0.9462)
Weighted average default probability (%)	- 0.015 (0.0000)	- 0.018 (0.0000)	- 0.014 (0.0000)	- 0.015 (0.0000)
Ln diversity score	0.14 (0.0000)	0.025 (0.9224)	0.16 (0.0000)	0.14 (0.0001)
Inverse ln diversity score	1.56 (0.0007)	-0.60 (0.8987)	1.73 (0.0001)	1.47 (0.0017)
Investment firm-dummy	-	-	-	- 0.06 (0.0007)
Adjusted R^2	0.576	0.592	0.544	0.588

Table 9: This table displays the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions explaining the size of the Third Loss Position in synthetic transactions. The investment firm-dummy is 1 if the originator is an investment firm and 0 otherwise. The sample contains 86 transactions. The adjusted R^2 is shown in the last row.

Figures

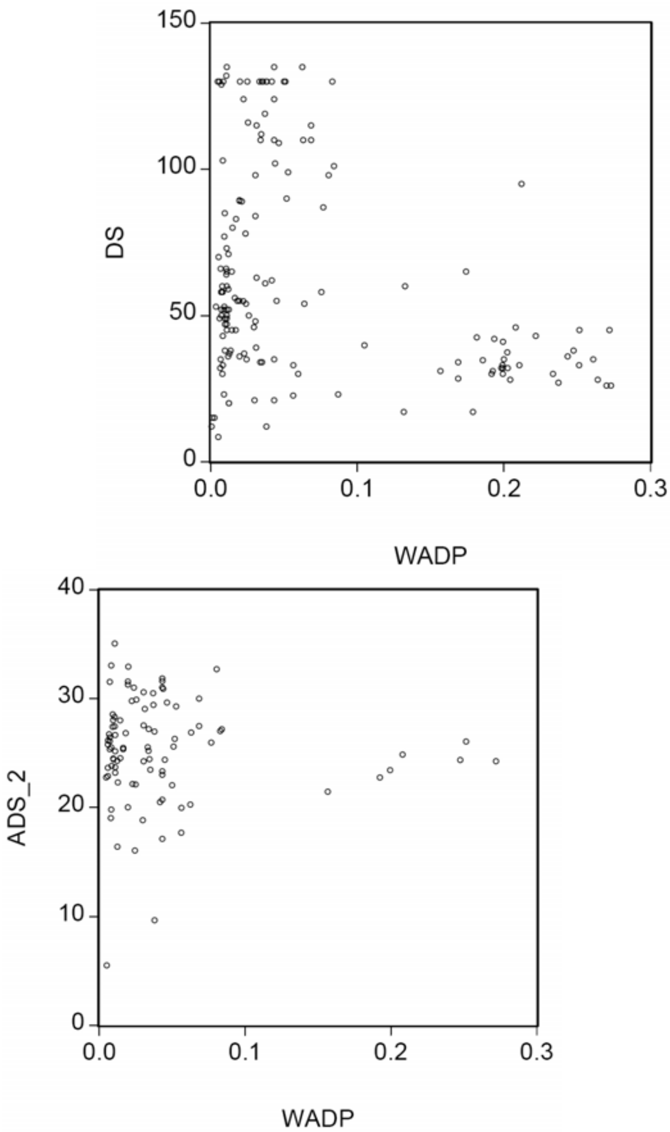

Fig 1.: Fig. a) shows for 169 transactions Moody´s diversity score DS and the weighted average default probability WADP. Fig. b) shows for 92 transactions the adjusted diversity score ADS with ρ_{ex} = 0.02 and the weighted average default probability WADP.

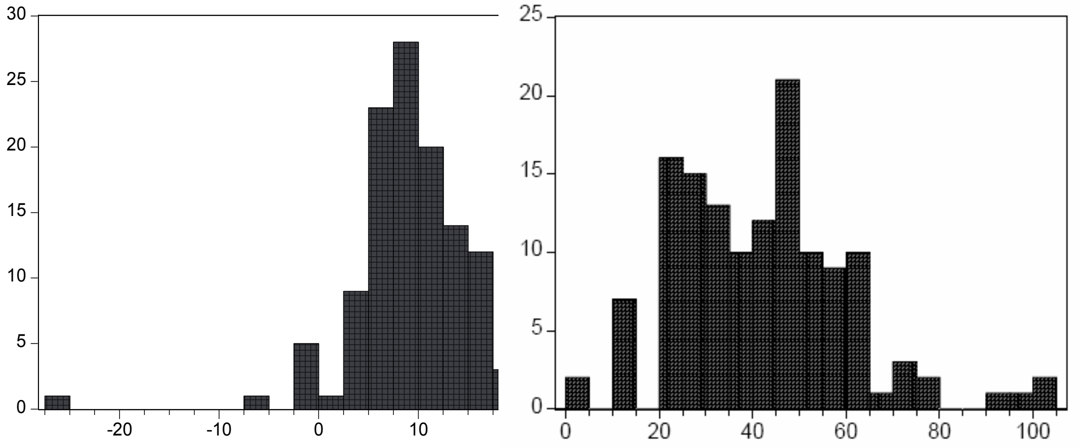

Fig. 2: The left histogram shows the credit spreads over EURIBOR/LIBOR of 118 European bank bonds with a maturity of at least 4 years, rated Aa3- or better, issued between 2000 and 2005. Data are obtained from DEALSCAN. The right histogram shows the credit spreads over EURIBOR/LIBOR of the 135 Aaa-rated CDO-tranches with a maturity of at least 4 years of our securitization sample.