Information asymmetries and securitization design++

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Abstract

The strong growth in collateralized debt obligation transactions raises the question how these transactions are designed. The originator designs the transaction so as to maximize her benefit subject to requirements imposed by investors and rating agencies. An important issue in these transactions is the information asymmetry between the originator and the investors. First Loss Positions are the most important instrument to mitigate conflicts due to information asymmetry. We analyse the optimal size of the First Loss Position in a model and the actual size in a set of European collateralized debt obligation transactions. We find that the asset pool quality, measured by the weighted average default probability and the diversity score of the pool, plays a predominant role for the transaction design. Characteristics of the originator play a small role. A lower asset pool quality induces the originator to take a *higher* First Loss Position and, in a synthetic transaction, a *smaller* Third Loss Position. The First Loss Position bears on average 86 % of the expected default losses, independent of the asset pool quality. This loss share and the asset pool quality strongly affect the rating and the credit spread of the lowest rated tranche.

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1. Introduction

Over the last 20 years the volume of securitizations has grown tremendously. The global volume of securitization issuance was estimated to be roughly 270 bn USD for 1997 and about 2100 bn USD for 2006 (HSBC (2007)). The recent subprime-crisis depressed the issuance volume. Securitizations were accused of fostering intransparancy of bank risks which dried out the liquidity in the interbank market. Whether the intransparancy was generated by the securitizations or by the complexity of structured investment vehicles investing in securitization bonds, is an unsettled empirical question. It is also controversial whether securitizations have positive or negative effects on financial stability. In any case, many financial intermediaries use securitizations for their management of default risks. Despite of this, there is amazingly little research on securitizations. This paper looks at a subset of securitization-transactions, called collateralized debt obligation (CDO)-transactions which can be collateralized loan obligation (CLO)- or collateralized bond obligation (CBO)- transactions. In the former case a bank typically securitizes part of its loan portfolio. In the latter case the originator of the transaction, a bank or an investment manager, buys bonds, and sometimes in addition some loans, pools them in one portfolio and sells the portfolio to investors.

This paper analyses important aspects of the design of CDO-transactions. Given information asymmetries between banks and investors about the quality of securitized loans or bonds, investors are concerned about buying lemons and, therefore, insist on credit enhancements in securitizations which mitigate potential problems of information asymmetry. If a bank, for example, securitizes the payment claims of many loans granted to small and medium sized enterprises, then investors know little about these obligors, relative to the bank. This provides room for adverse selection and moral hazard of the bank. Since investors penalize the bank for information asymmetries, she therefore attempts to mitigate their effects. In a perfect capital market these problems would not exist. Therefore securitization research needs to focus on market imperfections to understand the design of securitization transactions. Information asymmetries, costs of financial distress, costs of equity capital, other regulatory costs and liquidity premiums appear to be important as well as transaction and management costs. The latter include the costs of setting up (internal costs of the originator, fees of lawyers, rating agencies, custodians etc.) and managing the transaction after the setup. They are incurred by the originator and the investors buying the securities. Thus, various costs pose a barrier to securitization. It makes sense only if these costs are overcompensated by benefits. These may come from better risk allocation across agents, a reduction of the bank's cost of required equity capital, other regulatory costs and funding costs. Moreover, the transfer of default risks in a securitization gives the bank the option to take other risks.

The purpose of this paper is to add to the understanding of the design of securitization transactions by analysing credit enhancements. The most important credit enhancements are contractual obligations of the originator and third parties to bear default losses of the asset pool underlying the transaction. In all transactions there exists a First Loss Position (FLP). It absorbs all default losses up to a limit, equal to its volume. Investors only bear default losses beyond the FLP. The higher the FLP, the more are investors protected against default losses and, hence, against problems of information asymmetries. In synthetic transactions, investors usually bear only part of the default losses beyond the FLP. They take a limited second loss position (SLP) and the originator takes the third loss position (TLP) by not selling the super-senior tranche. She may buy protection against the losses of the TLP through a senior credit default swap. Similarly, the originator need not retain the FLP, but may sell part or all of it to third parties. It is not publicly known to what extent the originator retains the risks of the FLP and the TLP.

The market imperfections mentioned above pose a challenge to the originator of a transaction. How should she design the transaction so as to maximize her net benefit? In particular, given the quality of the underlying asset pool (loans/bonds) serving as collateral for a transaction, how large should the FLP be so as to mitigate problems of information asymmetry? Should the transaction be structured as a true sale- or a synthetic transaction so as to allow for a TLP? How large should be the TLP? These questions can only be answered taking into consideration the needs of the originator and those of investors. They insist on a solid design of the transaction so as to protect them against potential losses due to information asymmetries. We try to answer these questions by, first, analyzing the optimization problem of the originator and deriving hypotheses about an optimal design. Second, we investigate a set of European securitization transactions to test these hypotheses. In the empirical analysis, we also investigate the lowest rated bond tranche sold to investors. This tranche can be viewed as the mirror of the FLP since the FLP determines the protection of the lowest rated tranche against default losses. Therefore the characteristics of the lowest rated tranche help to understand the choice of the FLP.

To our best knowledge, this study is the first to analyse the impact of the quality of the securitized asset pool and originator characteristics on the transaction design. The design is the outcome of an optimization model. *The optimal design of a transaction is a function of the asset pool quality, of the attitudes of investors and rating agencies and of the characteristics of the originator.* This function is investigated in this paper. We assume that this function is the same for all CDO-securitization transactions and, thus, exogenous to the originator. Her job is to design the transaction according to this function because there is no way for her to do better.

The main findings of the paper can be summarized as follows. First, a theoretical model shows that the FLP should be inversely related to the quality of the securitized asset portfolio. The FLP should increase when the portfolio quality declines. The quality of the securitized asset portfolio is measured by its weighted average default probability (WADP) and by Moody´s diversity score (DS). A lower WADP and/or a higher DS improve the asset pool quality. The empirical evidence confirms that the FLP increases when the asset pool quality declines. We interpret this as evidence that a lower portfolio quality reinforces problems of asymmetric information which are mitigated by a higher FLP.

Second, the qualitative finding that a lower asset pool quality raises the FLP does not tell us how the FLP is quantitatively determined. Therefore, we investigate two transformations of the asset pool quality into loss sharing characteristics, assuming a lognormal distribution for the default loss rate of the underlying portfolio. The first characteristic is the share of expected default losses absorbed by the FLP, called the loss share. The second characteristic is the probability that all default losses are fully borne by the FLP, i.e. investors are not hit. We denote it as the support-probability of the FLP. (1-the support-probability) is the probability that investors are hit by default losses. In particular, it is the probability that the lowest rated tranche, i.e. the tranche with the lowest rating, is hit. Its rating is determined by this probability according to S&P.

A simple optimization model illustrates how the loss share and the support-probability react to changes in asset pool quality. Empirically, it turns out that the share of expected default losses, with a mean of 86 %, is independent of the asset pool quality. This indicates that a share of 86 % is the guideline for the market which may be influenced to some extent by other considerations. A constant share of the expected default loss implies for the lognormal model that the support-probability of the FLP depends inversely on the WADP and, surprisingly, also inversely on the DS. This is confirmed by the empirical findings. These findings gives us a rather precise understanding of how the market copes with information asymmetries in securitizations.

Third, the FLP resp. its loss share together with asset pool quality are quite powerful in explaining empirically the rating and the credit spread of the lowest rated tranche. But the credit spread of the lowest rated tranche is better explained by its rating, its maturity and the date at which the transaction is arranged. This underlines the important role of the rating agencies.

Fourth, the attractiveness of a synthetic relative to a true sale transaction increases with the portfolio quality. Hence, TLPs are more likely for transactions with better portfolio quality. Better quality implies a lower default risk of the super-senior tranche, given its size, making it less attractive for the originator to buy protection on this tranche through selling it or buying a

super-senior default swap. The preference for synthetic transactions is stronger for originators with a better rating. Presumably, for highly rated originators funding through standard bonds is cheaper than through true sale transactions. Retention of the super-senior tranche is in strong contrast to the literature which argues that the originator should sell the least information-sensitive tranche. The size of the super-senior tranche, i.e. the size of the TLP, *increases* with the portfolio quality, in contrast to the size of the FLP which is *inversely related* to portfolio quality. This indicates the different nature of the FLP and the TLP. The FLP appears to be important for investor protection while the TLP does not and, therefore, is driven by other considerations.

Fifth, surprisingly, characteristics of the originator like her total capital ratio, Tobin´s Q and other variables which proxy for her securitization motives, add little to the explanatory power of the regressions. This indicates that the design of securitization transactions depends little on these characteristics. Essentially, rating agencies and investors appear to be the dominant forces.

The paper is structured as follows. In section 2 the relevant literature is discussed. In section 3 we model the originator's optimization problem and derive hypotheses about her choice of the transaction design. The empirical findings are presented in section 4 and discussed in section 5. Section 6 concludes.

2.   Literature Review

The design of a CDO-transaction regarding the handling of information asymmetries is a complex task. In order to relate it to the literature, we first characterize CDO-transactions. Depending on her motives, the originator selects a set of loans or/and bonds[1] as the underlying asset pool of the transaction. In a static deal, this set is determined at the outset. In a dynamic (managed) deal, this set changes over time depending on the originator's policy. In a true sale transaction, all loans/bonds are sold without recourse to the special purpose vehicle which issues an equity tranche (=FLP) and various tranches of bonds to investors. The originator can freely use the proceeds from issuing the tranches including the sold part of the equity tranche. In a synthetic transaction the originator retains ownership of the loans/bonds and transfers part of the default risk through a junior credit default swap to the special purpose vehicle. This swap covers default risks beyond a threshold, excluding the default risk of the TLP. This threshold implies a FLP of the originator. The coverage of default risks by the swap is limited by the face value of the bonds issued by the SPV. Often the issued bond-tranches cover only a small fraction of the nominal value of the underlying portfolio so that

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[1] The bonds may include a few tranches of other securitization transactions or structured finance products.

the originator retains a large super-senior tranche and its associated default risk unless this risk is protected through a super-senior credit default swap. Hence, the super-senior tranche represents a TLP which is only hit if the SLP of investors is fully exhausted by default losses. In contrast to a true sale transaction, the originator does not receive the issuance proceeds in a synthetic transaction. These need to be invested in AAA-securities or other almost default-free assets. In all transactions, the originator decides about the choice of the asset pool, the size of the FLP, the tranching of the bonds to be issued. If the originator opts for a synthetic transaction, he also decides about the TLP. These decisions are taken by the originator in close collaboration with the involved rating agencies and leading investors.

In the following we summarize the literature related to these issues. There exists a variety of papers modelling the optimal design of financial contracts. Several papers show the optimality of first loss positions (FLP). 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 the protection sellers bound their expected loss from above, then a FLP of the protection buyer is optimal. This follows because optimal risk sharing entails an upper limit of the realized loss borne by the risk averse protection buyer. *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. If the entrepreneur fully pays the investors' claim, then she incurs no other costs. If she does not fully pay claiming that she lacks the necessary funds, then this claim needs to be verified. If the state verification cost is borne by the entrepreneur, the optimal contract is a standard debt contract: The entrepreneur fully pays the fixed claim when her company earns sufficient funds. Otherwise she prefers to pay the lower state verification cost and impose some loss on the investors. This is basically the same as taking a FLP.

In a related model of *Gale* and *Hellwig* (1985), both, the entrepreneur and investors, are risk neutral. However, the entrepreneur can only bear limited losses in order to stay solvent. Again, a standard debt contract turns out to be optimal implying a FLP of the entrepreneur.

In the previous two papers information asymmetries are resolved through state verification. The more recent literature distinguishes between information-sensitive and -insensitive securities. Information-insensitive securities are subject to little information asymmetries, in contrast to information-sensitive securities. *Boot* and *Thakor* (1993) argue that a risky cash flow should be split into a senior and a subordinated security. The senior security is information-insensitive and can be sold to uninformed investors while the subordinated security is information-sensitive and should be sold to informed investors. This allows the seller of the cash flow to raise the sales revenue. *Riddiough* (1997) extends this reasoning by showing that loan bundling allows for pool diversification which softens information

asymmetries. Moreover, the holder of the junior security should control changes in the loan portfolio because she primarily bears the consequences.[2]

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 also prove that a standard debt contract is optimal and that an issuer with very profitable investment opportunities retains little default risk in a securitisation transaction. In a recent paper *DeMarzo* (2005) shows that pooling of assets has an information destruction effect since it prohibits the seller to sell asset cash flows separately and, thereby, optimize asset specific sales. But pooling also has a beneficial diversification effect. Tranching then allows to create more and also less information-sensitive claims and to sell the more liquid information-insensitive claims. This model is generalized to a dynamic model of intermediation. Summarizing these papers, they 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 in which the least information-sensitive tranche, the TLP, is not sold.

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. *David* (1997) asks how many tranches should be issued. Tranches are sold to individual and institutional investors. The latter buy tranches to hedge their endowment risk. Hence tranches should be differentiated so as to allow the different groups of investors an effective hedging.[3]

There are only a few empirical studies related to securitizations. *Childs, Ott and Riddiough* (1996) investigate the pricing of Commercial Mortage-Backed securities and conclude that the correlation structure of the asset pool and the tranching are important determinants of the launch spreads of the tranches. *Higgins* and *Mason* (2004) find that credit card banks provide implicit recourse to asset-backed securities to protect their reputation. *Cebenoyan* and *Strahan* (2004) document that banks securitizing loans hold less capital than other banks and have more risky assets relative to total assets. *Downing* and *Wallace* (2005) analyse securitizations of commercial mortgage backed securities and find that FLPs are higher than what might be expected looking at the actual performance of mortgages. According to *Downing, Jaffee* and *Wallace* (2006) participation certificates sold to special purpose vehicles are on average

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[2]   *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.

[3]   *Glaeser and Kallal (1997*) show that more information may increase information asymmetries. Hence limiting information disclosure may improve liquidity of asset-backed securities in the secondary market.

valued less than those not sold. *Franke* and *Krahnen* (2006) find that securitization tends to raise the bank's stock market beta indicating more systematic risk taking. *Cuchra* and *Jenkinson* (2005) analyse the number of tranches in securitizations and conclude that the number increases with sophistication of investors, with information asymmetry and with the volume of the transaction. Finally, *Cuchra* (2005) analyses the launch spreads of tranches in securitizations and finds that ratings are very important determinants besides of general capital market conditions. He also finds that larger tranches command a lower spread indicating a liquidity premium.

3.   The Originator's Optimization and Hypotheses

The focus of this paper is the design of CDO-transactions in the presence of information asymmetries and other market imperfections. If the originator would ignore the reactions of investors and rating agencies to information asymmetries in the design of securitization transactions, then she might end up paying very high credit spreads. Therefore she prefers to mitigate information asymmetry induced problems by credit enhancements, in particular by setting up a First Loss Position. The optimal design of a transaction depends on the quality of the underlying asset pool, the originator characteristics and the attitudes of investors and rating agencies. While the originator chooses asset pool quality, her characteristics, attitudes of investors and those of rating agencies are exogenously given. The function relating the *optimal* design of a transaction to asset pool quality is driven by these exogenous factors. We assume that this function is the same for all CDO-transactions and exogenously given. Every originator chooses the optimal transaction design according to this function. The purpose of this paper is to find out important properties of this function. We, therefore, analyse a simple model to determine these properties theoretically and then a set of European CDO-transactions to determine them empirically.

In this section, first, we relate information asymmetries to asset pool quality. Second, we present some general results on the relationship between asset pool quality and loss sharing between investors and the holders of the FLP. Third, we present a simple optimization model of the originator to derive her optimal monitoring effort and her choice of the FLP. Fourth, we derive various hypotheses about the optimal transaction design which are tested later on a set of European transactions.

3.1 Information Asymmetries and Asset Pool Quality

Transferring default risks through a securitization transaction is always subject to problems of information asymmetries between the originator and investors. The originator knows more about the quality of the loans underlying the transaction because she has close contact to the obligors. Moreover, she decides about her effort of monitoring the obligors and enforcing her

loan claims. This effort is not observable by investors adding to the information asymmetry. Therefore credit spreads include a penalty for adverse selection and moral hazard problems. To model these information asymmetries, we distinguish between the published and the true quality of the underlying asset pool.

Asset pool quality is measured in different dimensions. One measure of the average quality of the loans is the weighted average default probability (WADP) of the loans. The higher WADP, the higher are the expected default losses of the asset pool. The second measure of asset pool quality is a measure of asset pool diversification. The intra- and interindustry-diversification of the loan portfolio can be summarized in a diversity measure as done in Moody´s Diversity Score (DS). 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 loss given default of the loans. Loss given default is measured by (1-recovery rate). The recovery rate of a loan is the fraction of its par value denoting the present value of all future payments on this defaulted loan discounted to the date of default. Initially the par value of the loan approximately equals its market value so that the loss given default applies equally to the par and the market value. Since we cannot get reliable data on the weighted average loss given default for most CDO-transactions, we assume that this characteristic is the same across all CDO-transactions[4]. Moreover, to simplify modelling we assume that the loss given default is non-random. Hence we characterize asset pool quality by the two determinants WADP and DS.

The rating agencies publish information on the asset pool quality. We assume that rating agencies do their best to publish unbiased information. Investors believe this so that they consider the published information as the best predictor of the true asset pool quality. But they know that the true quality differs from the published quality by a noise term ε,

published asset pool quality = true asset pool quality + ε.

We define the standard deviation of the noise term, $\sigma(\varepsilon)$, as quality uncertainty and assume that it is 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). We also assume that $\sigma(\varepsilon)$ is 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

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[4] Only for a few Spanish transactions we have some data which we then use in our empirical study.

be diversified away[5]. The lower the DS, the stronger is idiosyncratic default risk relative to systematic default risk. The effects of idiosyncratic risks are almost by definition harder to analyse and to predict than those of systematic risk, because idiosyncratic risks are much more diverse and less well understoood. Hence we believe that there are good reasons to assume an inverse relation between asset pool quality and quality uncertainty.

Higher quality uncertainty creates more potential for adverse selection and moral hazard, because these activities are more difficult to discover when the quality risk is stronger. For example, moral hazard of the originator in monitoring loan performance which adds to $\sigma(\varepsilon)$, is harder to discover for loans of low quality because these loans often are more exposed to hardly observable, idiosyncratic risk factors than high quality loans. Therefore, higher uncertainty about asset pool quality should reinforce problems of information asymmetries.

In the following, the two asset pool characteristics WADP and DS are always understood as the published characteristics. Investors assume that these characteristics are unbiased estimates of the true characteristics, but are aware of the quality uncertainty-dependent potential for adverse selection and moral hazard.

3.2 General Relationship between Asset Pool Quality and Loss Sharing

Investor scepticism, driven by information asymmetries, can be reduced by raising the FLP. The economic rationale behind the FLP is similar to that behind the deductible in insurance business. The higher the deductible, the more damages are borne by the insured, the weaker are her incentives for adverse selection and moral hazard, the less important are problems of information asymmetries for the insurer.

The FLP can take different forms. In a true sale transaction, the originator may retain, for example, all or part of the most junior tranche of the securities, i.e. the equity tranche, which is most information-sensitive. The FLP may be an initial FLP which is a fixed commitment of the originator to absorb the first default losses up to a given limit. The initial FLP 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 and which then serves to absorb default losses. Hence an originator may substitute part of the initial FLP by a reserve account. This would reduce regulatory equity capital requirements. In a synthetic transaction, the FLP equals the threshold of the junior credit default swap between the originator and the investors.

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[5] *De Marzo* (2005) argues that stronger diversification makes securitization of asset pools more attractive relative to liquidating assets separately because diversification reduces information asymmetries.

The latter being protection sellers cover only default losses exceding the threshold, up to the limit given by the face value of issued tranches. The SPV is the intermediary of this swap.

In the following, we discuss the relation of loss sharing between investors and the holders of the FLP to asset pool quality. Without loss of generality, we analyse securitization transactions with an underlying asset pool of a par value of 1 €. Hence the default loss of the pool equals the loss rate.

Loss sharing between investors and the holders of the FLP can be measured in a naive way by the size of the FLP. This measure does not take into account the asset pool quality. We would like to know more precisely the functional relationship between the FLP and the two main determinants of the quality of the asset pool, WADP and DS. This would improve our understanding of how the capital market copes with information asymmetries. We search for an empirically testable model which maps WADP and DS into an economically meaningful loss sharing characteristic. Ideally speaking, this loss sharing characteristic should describe the equilibrium loss sharing as a function of WADP and DS. Since investors are concerned about risk and expected return, it is natural to look at two loss sharing characteristics, one being a measure of sharing expected losses and the other one being related to the probability that investors are hit by default losses.

The first measure, the share of expected default losses borne by the FLP, s, is defined as the expected loss borne by the FLP, divided by the expected loss of the asset pool. s is called the *loss share.* The higher this share is, the smaller are the potential effects of information asymmetries on investors. Although this measure does not consider risk explicitly, the risk of the loss rate distribution is implicitly taken into account as it determines the loss share (see the following Lemma 1 a).

The second measure of loss sharing is the probability that all losses are fully covered by the FLP. (1- this probability) is the probability that investors are hit by default losses. We define the *support-probability of the FLP* as the cumulative probability of the asset pool-loss rate distribution at the loss rate which equals the FLP (in percent of the par value of the asset pool). If, for example, the FLP is 4 percent and the associated cumulative probability of the loss rate distribution is 80 percent, then with 80 percent probability the FLP fully absorbs all losses. Investors then incur losses with 20 percent probability. According to S&P, this probability determines the rating of the tranche with the lowest rating. The higher this probability, the lower is the rating of this tranche, the more investors are exposed to default risks, the more afraid investors may be of information asymmetry. This measure of loss sharing addresses default risk by quantile considerations as does the value at risk which is commonly used by banks to assess tail risk.

First, we analyse the relationship between the loss share and true portfolio quality. As a primer, we characterize the impact of a change in asset pool quality on the loss share. This impact depends on the direct impact of the asset pool quality on loss allocation and on the indirect impact through the originator´s adjustment of her monitoring effort and of the FLP. The following lemma characterizes the direct impact of a change in WADP resp. DS on the loss allocation. A decline in DS, holding WADP constant, can be perceived as a mean preserving spread in the loss rate distribution of the asset pool so that the two cumulative probability distributions intersect once. An increase in WADP, holding DS constant, can be perceived as a first order stochastic dominance shift in the loss rate distribution. Lemma 1a) and b) are proved in Appendix 1, Lemma 1c) in Appendix 2.

Lemma 1: *Consider a securitization transaction, given the size of the FLP and the originator´s effort.*

a) A mean preserving spread of the loss rate distribution, induced by a decline in asset pool diversification, implies a lower expected loss for the FLP and a higher expected loss for the sold tranches (including the TLP in case of a synthetic transaction). Hence it reduces the share in expected losses of the asset pool borne by the FLP.

b) A first order stochastic dominance shift in the loss rate distribution, induced by an increase in the weighted average default probability of the asset pool, implies a higher expected loss for the sold tranches (including the TLP in case of a synthetic transaction) and for the FLP.

c) Given a lognormal loss rate distribution, an increase in the weighted average default probability reduces the share in expected losses of the asset pool borne by the FLP if the FLP is equal or greater than the expected loss of the asset pool.

The lemma shows that a decline in asset pool diversification redistributes the expected loss from the FLP to investors (and the TLP in case of a synthetic transaction) while an increase in the weighted average default probability hurts both, the FLP and the investors (including the TLP in case of a synthetic transaction). Whether the loss share increases with WADP, depends on the shape of the probability distribution. A simple probability distribution is the lognormal distribution. This was also used by Moody´s (2000). It implies a positive probability of a loss rate above 1 which in reality is impossible. But this probability is very small for realistic assumptions. Consider a transaction in which the average default probability of loans is high with 20 percent and the DS is low with 10. Then the cumulative probability of the implied lognormal distribution at a loss rate of 1 is 99.9 percent. In typical transactions this probability would be higher. Therefore the lognormal approximation should be quite good.

For each securitization transaction we derive the lognormal distribution as follows (see Appendix 2.1). The expected loss rate of the asset pool is λ WADP with λ being the loss

given default of the loans. λ is assumed to be exogenously given and non-random. We assume that all claims in the asset pool have the same loss rate variance S² derived from a binomial model of default or non-default,

$S² = λ² WADP (1-WADP)$.

We divide S² by the DS to derive the variance of the loss rate of the asset pool. Given this variance and the expected loss of the asset pool, we derive the mean and the standard deviation σ of the lognormal distribution as shown in Appendix 2.1. Then applying the Black-Scholes methodology, for each transaction the share of expected losses, borne by the FLP, *s*, is given by

$s = N(h) + (FLP/ λ WADP) (1- N(h +σ))$ (1)

with $h = \dfrac{\ln \dfrac{FLP}{λ\,WADP}}{σ} - \dfrac{σ}{2}$ and

$σ^2 = \ln\left(1 + \dfrac{1/WADP - 1}{DS}\right)$.

The support-probability of the FLP, *γ(FLP),* is given by the value of the normal distribution function at the standardized *ln FLP*,

$γ(FLP) = N(h +σ)$. (2)

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

Returning to Lemma 1c), an increase in WADP reduces the loss share if the FLP is equal to or greater than the expected loss rate. This is a weak condition which is mostly satisfied. Hence, given the FLP and the originator´s effort, the loss share usually goes down when WADP increases.

Second, we analyse the support-probability of the FLP associated with the loss rate distribution as another measure of loss sharing. Again we state a lemma which describes the effects of changes in the asset pool quality on this support-probability, given the FLP and the originator´s effort. For changes in WADP, the proof follows immediately from a graph of the respective cumulative probability distributions. For changes in DS, look at Figure 4 in the appendix.

Lemma 2: *Consider a securitization transaction, given the size of the FLP and the originator´s effort.*

a) A mean preserving spread of the loss rate distribution, induced by a decline in asset pool diversification, reduces (increases) the support-probability of the FLP if the FLP is higher (smaller) than the loss rate at which the two cumulative probability distributions intersect. Given a lognormal loss rate distribution, the latter condition holds if and only if [6]

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

b) A first order stochastic dominance shift in the loss rate distribution, induced by an increase in the weighted average default probability of the asset pool, reduces the support-probability of the FLP.

Not surprisingly, Lemma 2 states that a higher WADP lowers the support-probability of the FLP. Also a deterioration of the asset pool quality given by a lower DS lowers the support-probability if the FLP is higher than the loss rate at which the two cumulative probability distributions intersect. For a lognormal distribution, the latter condition is satisfied if the FLP clearly exceeds the expected loss rate of the underlying portfolio. As will be shown later in the empirical part, the FLP usually satisfies the condition in Lemma 2. Therefore Lemma 2 implies that a deterioration of the asset pool quality has similar qualitative effects on the support-probability of the FLP as on the share of expected losses (Lemma 1).

Since the loss share and the support-probability are two different loss measures which might govern the size of the FLP, it is important to understand the relationship between both. This is given by the next lemma proved in appendix 3.

Lemma 3: *Assume a lognormal loss rate distribution. Suppose that upon a change in the portfolio quality, the First Loss Position is changed so that its loss share remains the same. Then, given the originator´s effort, 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, $\partial FLP/ \partial WADP < 1$ if $FLP \leq WADP$.*

Lemma 3 gives a surprising result. Given a constant loss share and the condition $h < n(h +\sigma)/(1- N(h +\sigma))$, the support-probability of the FLP declines if one measure of portfolio quality, the WADP, worsens, but it also declines if the other measure of portfolio quality, the DS, *improves*. The condition $h < n(h +\sigma)/ (1- N(h +\sigma))$ clearly holds if the FLP does not exceed

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[6] For proof see Appendix 2.3.

the expected loss rate because then $h < 0$. But for a very high FLP h would be rather high while $n(h +\sigma)/(1- N(h +\sigma))$ converges to 0. Then the support-probability of the FLP would increase with the DS. As will be shown in the empirical part, the condition $h < n(h +\sigma)/ (1- N(h +\sigma))$ is always satisfied in opur sample.

From Lemma 3 it is easy to derive the effects of changes in WADP and DS on the loss share holding the support-probability of the FLP constant. Since the loss share and the support-probability increase with the FLP, we have the following

Corollary 1: *Given the conditions in Lemma 3, but holding the support-probability instead of the loss share constant, a higher weighted average default probability and a higher diversity score raise the loss share.*

3.3 Modelling the Optimal First Loss Position

3.3.1 The Model Setup

Next we present a simple model for the originator´s optimization problem and derive her optimal effort and the optimal FLP. When structuring a securitization transaction, the originator maximizes her net benefit. Her gross benefit in a CLO-transaction may be summarized by the decline in the costs of required equity capital and other regulations and possibly the decline of funding costs. The decline in default risks enables the originator to take new risks. Then the value of these new activities contributes to the gross benefit. The costs of securitization transactions include the setup and management costs, the credit spreads paid to investors, the costs of credit enhancements and reputation costs. The latter costs are incurred if investors suffer from default losses and attribute them to bad management of the originator. Investors would then charge higher spreads in future transactions.

In a CBO-transaction, the originator also maximizes her net benefit. However, often she purchases the asset pool and securitizes it simultaneously, retaining part of the risks through a FLP. Apart from these risks, the net benefit in such a transaction is an arbitrage profit. This explains why these transactions are often called arbitrage transactions.

The preferred size of the FLP depends on the benefits and costs of a FLP incurred by the originator. First, consider the benefits. If the originator retains the most junior tranche, she saves the high credit spread including, perhaps, a complexity premium on this tranche due to high costs of required sophisticated management. A higher FLP may also strengthen investor confidence in the overall transaction so that they charge a lower penalty for information asymmetry on all sold tranches. This is likely to be true because a higher FLP reduces the investors´ share in default losses. Therefore, investors may be more confident in the overall

transaction, the higher is the FLP. Second, the cost of the FLP is the cost of the required regulatory/economic capital, apart from management costs.

We illustrate the originator´s choices by a simple model. To motivate this model, first we argue why we *do not* use a signalling model. Signalling models help to analyse the behavior of economic agents in the presence of adverse selection problems. These problems also exist in securitization transactions. Hence it would be natural to explore a signalling model explaining the choices of the originator such that she would be motivated to signal the true properties of the transaction[7]. The main properties from the perspective of the investors are the portfolio quality, the FLP and the originator´s effort in monitoring and servicing the underlying loans. The latter is unobservable, but it is important for the evaluation of the portfolio quality. The FLP is specified in the offering circular. Hence the crucial properties are the WADP (and the loss given default) and the DS of the underlying portfolio describing its quality. But these are estimated by the rating agencies, not by the originator. They are responsible for estimating and communicating the portfolio quality. They should also forecast the orginator´s effort and incorporate it in their estimates of the portfolio quality. Therefore a signalling model would have to model the behavior of the rating agencies. This is beyond the scope of this paper.

Instead, this paper analyses a simple model of the originator which ignores strategic behavior of investors and of the originator. She faces a cost function and chooses FLP and effort to minimize the overall cost in a true sale-transaction. The cost function is

$$E(l(e)) + C(FLP) + (a+r) (1- s) E(l(e)) + g(e) \qquad (3)$$

This cost is composed of the expected loss of the asset pool, $E(l(e))$, the regulatory/economic cost of the FLP-risk, $C(FLP)$, the penalty imposed on the originator for problems associated with information asymmetry, $(a+r) (1- s) E(l(e))$, and the cost of the originator´s effort, $g(e)$. e denotes the originator´s effort in monitoring obligors and collecting debt claims. Effort is scaled such that $g(e)$ is a linearly increasing function. We assume that there is a minimal effort e_{min} such that $e \geq e_{min}$. The higher the effort is, the smaller is the expected loss. $E(l(e))$

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[7] A signalling model might provide a hypothesis quite different from our hypothesis. We shall show that the size of the FLP should be higher, the *lower* the quality of the asset pool is. *Bester* (1987) showed that borrowers may signal their quality to lenders through the amount of collateral. Since the expected cost of the collateral, borne by the borrower, is inversely related to her default probability, the expected cost of a collateral is inversely related to the borrower quality. Therefore high quality borrowers are ready to provide large collateral while low quality borrowers are not. Applying the same logic to the FLP in a securitization transaction, the signalling model would indicate that the size of the FLP *increases* with the quality of the asset pool.

is a declining, convex function since losses can never become negative. Its negative slope increases with WADP because then there is more to be gained through more effort. For modelling, we assume that a higher effort reduces the expected loss such that the loss distribution improves by first order stochastic dominance. Investors and rating agencies cannot observe the effort. But they are assumed to correctly predict the originator´s effort. Therefore in equation (3) *e* is the correctly anticipated effort.

In the cost function the expected loss *E(l(e))* is fully attributed to the originator. The motivation for this is that even though the investors bear part of the losses, they charge the orginator for these losses so that eventually she has to bear these losses. We assume that investors base their behavior on the asset pool quality communicated by the rating agencies, but they are aware of quality uncertainty.

Investors charge the originator a penalty for problems of information asymmetries. Since investors are only exposed to default losses according to their loss share, it is assumed that the penalty is based on the expected loss borne by investors, *(1- s) E(l(e))*. The penalty factor is composed of an *ex-ante* penalty factor *a* and an *ex-post* penalty factor *r*. *a* and *r* are known to investors and the originator. Splitting the penalty factor into two parts is motivated by the sequential decision making of the originator. After the sale of the tranches the originator decides about her effort. Investors may provide an incentive for a strong effort by charging ex post a reputation cost if they actually have to bear default losses. We model the actual reputation cost as *r max(0, l(e)-FLP)* so that the expected reputation cost is *r(1-s)E(l(e))*. The originator can reduce this cost through a higher effort which, however, generates a higher effort cost. *r* is constant, irrespective of portfolio quality, because investors are assumed to charge reputation costs proportional to their realized loss.

Before the tranches are sold, the originator decides about the FLP. The credit spreads charged by the investors include the ex-ante penalty *a(1- s) E(l(e))*. The ex-ante penalty factor *a* is also assumed to be constant. Since the penalty is charged on the investors´ loss, a high *a* motivates the originator to choose a high FLP which, however, raises her cost of economic capital. Overall, the model includes two mechanisms by which investors can reduce their expected loss, the ex ante-penalty and the ex post-reputation cost. The higher *a* and *r* are, the stronger are the incentives for the originator to reduce the investors´ expected loss through the choice of FLP and effort.

The cost of the equity capital required by the FLP, *C(FLP)*, depends on the regulatory/economic capital associated with the FLP. In the new banking regulation of Basle II the regulatory capital required for the FLP is equal to the FLP. In our model the bank as an originator uses economic capital, defined as the value at risk of the FLP. If the originator sells

part of the equity tranche, then the buyer would also use economic capital as a measure of risk. The value at risk equals for a standardized par value of 1 € of the transaction volume,

VaR(FLP) = l(q) – expected loss of the FLP

with *l(q)* being the loss rate quantile associated with the exogenously given quantile probability *q*, used for the VaR. This probability is usually below 1 percent. In all CDO-transactions the probability that the FLP is fully absorbed by losses is higher than 1 percent. Therefore *l(q)* equals FLP. Hence,

VaR(FLP) = FLP – expected loss of the FLP.

The cost function, *C(FLP)*, starting in the origin, is assumed to be linear in the *VaR(FLP)*. This is supported by the observation that banks often require a fixed rate of return on economic capital, for example, 20 percent. Since most CDO-transactions have a maturity of 5 to 7 years, the cost of the FLP has to be aggregated and discounted over these years. For simplicity, we assume that the present value of this cost equals 100 percent per € of the *VaR(FLP)*. Then the cost function (1) simplifies to

E(l(e)) + FLP - s E(l(e)) +(a+r) (1- s) E(l(e)) + g(e)

= FLP +(1+a+r) (1- s) E(l(e)) + g(e)   (4)

In the cost function, we ignore transaction costs because we assume for simplicity that they are independent of the transaction design. Moreover, we ignore potential benefits of funding costs for the originator because these do not exist in synthetic transactions and are of little relevance for the optimal choice of effort and FLP in true sale transactions. We will address the funding cost issue later on when discussing true sale versus synthetic transactions.

3.3.2 The Optimal Effort

Given the quality of the asset pool, the originator faces two choices, the size of the FLP and her effort to monitor the obligors and collect the outstanding debt claims. Since the effort is chosen after the setup of the transaction and the sale of tranches, we first consider the optimal effort choice. *e** mininizes the subsequent cost function (5), given the asset pool quality and the FLP. Hence *e* = e*(FLP)*. Knowing this function, before the sale of tranches the originator optimizes the FLP which translates into an optimal loss share *s**.

The originator optimizes her effort after the setup of the transaction and the sale of the tranches. Then the cost of the originator, still dependent on her effort choice, equals her expected loss, *s E(l(e))*, the variable part of the cost of economic capital, *-s E(l(e))*, her

expected reputation cost, *r (1- s) E(l(e))*, and the effort cost *g(e)*. The first two terms cancel. Hence the originator minimizes

$$r (1- s) E(l(e)) + g(e) .$$
(5)

This equation shows that the optimal effort is determined by its impact on the expected loss of the investors, not by its impact on the expected loss borne by the FLP. This rather surprising result is driven by the assumption that the present value of the equity cost declines 1 to 1 with the expected loss borne by the FLP. Hence, if *r = 0,* there is no reputation cost and the originator´s effort is minimal. Now assume *r > 0.* Let *g´* denote the constant marginal effort cost. Then the FOC for the effort, given an interior solution, is

$$r \frac{\partial (1-s)E(l(e))}{\partial e} + g' = 0 .$$
(6)

The higher *r,* the higher is the optimal effort. Actually, *r* could be set so that the optimal effort would equal the first best effort, given by the FOC, *∂ E(l(e))/ ∂e + g´ = 0.*

How does the optimal effort depend on the FLP and on the quality of the underlying portfolio? By definition,

$$(1-s)E(l(e)) = \int_{FLP}^{1} (l - FLP) f(l(e)) \, dl$$
(7)

with *f(l(e))* being the probability density function of the portfolio loss rate *l ,* given effort *e.*

Hence from the FOC,

$$g' = -r \int_{FLP}^{1} (l - FLP) \frac{\partial f(l(e))}{\partial e} \, dl$$
(8)

For an interior solution of the optimal effort, the sensitivity of the optimal effort with respect to some parameter *p, ∂e*/∂p,* is given by

$$\frac{\partial e *}{\partial p} = \frac{-\frac{\partial}{\partial p} \int_{FLP}^{1} (l - FLP) \frac{\partial f(l(e*))}{\partial e} \, dl}{\frac{\partial^2}{\partial e^2} \left[(1-s))E(l(e)) \right]}$$
(9)

with the denominator being positive.

First, consider the effect of an increase of the FLP on the optimal effort. From (9) it follows that the numerator on the right hand side of (9) then equals - *∂F(FLP, e*) /∂e* with *F(FLP, e*)*

being the cumulative probability of the loss rate distribution at $l = FLP$, given effort e^*. Hence $F(FLP, e^*)$ is the support-probability of the FLP. Since a higher effort implies a first order stochastic dominance improvement of the loss rate distribution, by Lemma 2b), $\partial F(FLP, e^*)/\partial e > 0$ so that the optimal effort is *inversely related* to the FLP. This surprising result is again due to the fact that a higher effort serves to reduce the expected loss borne by investors. This loss is, ceteris paribus, smaller, the higher is the FLP. If $FLP \rightarrow 0$, then the expected loss borne by investors approaches $E(l(e))$. Hence the originator´s effort would be maximal.

Second, consider an increase in WADP. Given WADP, $- \int\limits_{FLP}^{1} (l - FLP)\dfrac{\partial f(l(e^*))}{\partial e}\, dl$ is positive since an effort increase lowers the expected loss of investors. If WADP increases, then there is more to be gained from an effort increase. Hence the numerator of (9) is positive and the optimal effort increases. Third, if the diversity score declines, then from Lemma 1a) *(1- s) E(l(e))* also increases so that the same reasoning applies and the optimal effort increases. This proves

Proposition 1: *The optimal effort of the orginator declines, ceteris paribus, if the First Loss Position increases. It increases if the quality of the asset portfolio declines.*

3.3.3 The Optimal First Loss Position

Next, we analyse the choice of the FLP. Since the optimal effort is chosen in a subsequent step, *e* = e*(FLP)*. Therefore the optimization of the FLP has to take into consideration the impact of the FLP on the optimal effort. The originator minimizes the overall cost

FLP + (1+ a+ r) (1- s) E(l(e*)) + g(e*)

s.t. e* = e*(FLP) .   (10)

First, suppose *r = 0*. Then the originator chooses the minimal effort. Differentiating (10) with respect to FLP gives the optimal size of the FLP

$0 = 1 - (1+a)(1 - F(FLP^*, e_{min}))$.   (11)

The higher the adverse selection penalty parameter *a* is, the higher is the optimal FLP. This is intuitive because a higher FLP reduces the loss borne by investors and hence the adverse selection penalty. Moreover, for *r = 0,* from (11) it follows that the support-probability of the optimal FLP is independent of the portfolio quality. By Lemma 2, given the FLP and effort and the condition in Lemma 2a), this support-probability goes down if WADP increases or DS declines. Hence in order to retain the same support-probability of the optimal FLP, the optimal FLP has to go up. This is also in line with intuition. A lower portfolio quality induces a higher FLP.

For a lognormal distribution it follows from Corollary 1 that an increase in WADP or DS raises the loss share *s* if the support-probability of the FLP is held constant and if the conditions in Lemma 3 hold.

These results are summarized in

Proposition 2: *Assume that the reputation cost parameter r is zero. Then*

   a) *the support-probability of the optimal FLP is independent of the portfolio quality,*

   b) *the optimal FLP increases if the weighted average default probability of the asset pool increases or, given the condition of Lemma 2 a), the diversity score declines,*

   c) *the optimal loss share s increases if the weighted average default probability or the diversity score increases, subject to the conditions in Lemma 3.*

It should be noted that according to statement b) the optimal FLP increases if portfolio quality declines, but according to statement c) the optimal loss share increases with WADP, but also increases if the DS increases. Hence, Proposition 2 shows that in the absence of reputation costs the optimal loss share does not react unanimously to a deterioration in portfolio quality.

Now suppose $r > 0$. Given an interior solution for the optimal effort, the FOC (6) applies. Hence, the optimal FLP is given by

$$0 = 1 - (1 + a + r)(1 - F(FLP^*, e^*) - \frac{g'}{r} \frac{\partial e^*}{\partial FLP}) + g' \frac{\partial e^*}{\partial FLP} \quad . \tag{12}$$

This can be rewritten as

$$(1 + a + r)(1 - F(FLP^*, e^*) + \left| \frac{\partial e^*}{\partial FLP} \right| g'(\frac{1 + a}{r} + 2) = 1 \tag{13}$$

This FOC shows the interaction effect between effort and FLP. $\partial e^*/\partial FLP$ is negative (Proposition 1). Hence the more sensitively the optimal effort reacts to the FLP, the smaller $F(FLP^*, e^*)$ must be, implying ceteris paribus a smaller optimal FLP. But a smaller FLP implies a higher optimal effort. Hence the more sensitively effort reacts to the FLP, the smaller is the optimal FLP and the higher is the optimal effort. The intuition for this result is the substitution between FLP and effort for investor protection. Investors are protected by a high FLP, but also by strong effort. Both mechanisms substitute for each other such that a high FLP induces a low effort and vice versa.

In order to get some insight into the reaction of $\lvert\partial e^*/\partial FLP\rvert$ to asset pool quality, first, consider a very good asset pool quality. Then the optimal effort equals the minimal effort so that the sensitivity $\partial e^*/\partial FLP = 0$, regardless of the level of the reputation cost parameter r. Second, assume a low portfolio quality and a high reputation cost parameter, then the optimal effort will be high indicating a high sensitivity $\lvert\partial e^*/\partial FLP\rvert$. Hence we observe a sensitivity increase, moving from high to low asset pool quality. Whether there exists a monotonic relation between $\lvert\partial e^*/\partial FLP\rvert$ and asset pool quality, depends on effort productivity and the cost parameters a and r. In any case, Proposition 2c) no longer holds. From the FOC (13), a lower asset pool quality reduces the support-probability of the FLP if it raises the sensitivity. If this increase is strong enough, then the decline in the support-probability of the FLP is strong enough to reduce the optimal loss share s^*. This proves

Corollary 2: *The optimal loss share of the originator is inversely related to the quality of the asset pool if the absolute sensitivity of the optimal effort to the First Loss Position is strongly inversely related to the asset pool quality.*

3.4 Hypotheses For Loss Sharing

From the preceding analysis, we now derive testable implications. Proposition 2 b) shows that the optimal FLP is inversely related to asset pool quality, given no reputation costs. This relation remains true if the reputation cost parameter r is positive, but the effort increase following a deterioration of asset pool quality does not fully compensate for the increase in problems of information asymmetry. Therefore we state the general hypothesis

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

Regarding the more refined measures of loss sharing, Corollary 2 shows that the optimal loss share may be positively or negatively related to asset pool quality, depending on marginal effort productivity and on the cost parameters a and r. Since we neither know marginal productivity nor the cost parameters, we state the null-hypothesis

Hypothesis 2: The optimal share of expected losses, borne by the FLP, is independent of WADP and DS.

The alternative null-hypothesis 3 rests on the assumption that there are no reputation costs. Then we obtain from Proposition 2a)

Hypothesis 3: The optimal support-probability of the FLP is independent of the quality of the asset pool.

The optimization model discussed in the previous subsection is based on true sale-transactions. In a synthetic transaction the originator retains the super-senior tranche and thus has a TLP.

This tranche would also be affected by changes in the DS or the WADP. But since the probability is very small that the super-senior tranche incurs a loss, the preceding results for true sale transactions are likely to remain valid also for synthetic transactions. Therefore hypotheses 2 and 3 are equally tested on synthetic transactions.

Hypotheses 1 to 3 are the core hypotheses on loss sharing. In the following we derive hypotheses about the impact of some other transaction characteristics on loss sharing. Hypotheses 1 to 3 are based on the conjecture that loss sharing is driven by the extent of information asymmetries. These might be stronger in CLO- than in CBO- transactions, controlling for WADP and DS. Loans are often given to small or medium sized firms whose identity is not revealed to investors while bond issuers are revealed and often are big firms or governments with publicly available information. Therefore CLO-transactions might offer more potential for adverse selection than CBO-transactions, controlling for WADP and DS. Also moral hazard problems might be stronger in CLO- than in CBO-transactions. In a CLO-transaction the originator remains the servicer of the loans so that the loan sale generates a moral hazard problem. In a CBO-transaction, the originator is not the servicer of the bonds eliminating the associated moral hazard on her side. Yet there may exist a moral hazard problem of the trustees in the bond issues. But these risks are diversified given many different bond trustees while the servicer risk in the CLO-transaction is not diversified (see also deMarzo (2005)). Therefore CLO-transactions may invoke more investor skepticism than CBO-transactions, given the same WADP and DS. Originators may respond to this by higher FLPs in CLO-transactions. This motivates

Hypothesis 4: *Given the same quality of the asset pool, loss sharing through the FLP is higher in CLO- than in CBO- transactions.*

Hypothesis 4 makes a statement on the optimal FLP in CLO- and CBO-transactions, given the *same* asset pool quality. This qualification may be problematic. If investors charge higher credits spreads for portfolios with lower diversification, then it pays for the originator to put together a well diversified asset portfolio. In a CLO-transaction this is easy for a bank with a large loan portfolio. Therefore we conjecture that the loan portfolio in a CLO-transaction will show a high DS. The situation is different for CBO-transactions. In a CBO-transaction the originator has to buy the bonds for the asset pool. This is often costly since the bond market is rather illiquid. Therefore we hypothesize that loan portfolios are better diversified.

Hypothesis 5: *The diversity score of the asset pool is higher in CLO- than in CBO-transactions.*

If Hypothesis 5 is correct, then the better diversification of CLO-transactions may render FLPs in CLO-transactions smaller than in CBO-transactions.

The originator faces the choice between a static and a dynamic (managed) transaction. In a static transaction the original asset pool cannot be changed subsequently by the originator. In contrast, the originator may change the asset pool in a dynamic transaction subject to constraints specified in the offering circular. She may replenish the pool after repayment of some assets or substitute new for existing assets. This induces another moral hazard problem which can be mitigated by a higher FLP. This motivates

Hypothesis 6: *Given the same quality of the asset pool, loss sharing through the FLP is higher in managed than in static transactions.*

A higher FLP retained by the originator reduces her opportunities for taking new risks. Therefore an originator with better investment opportunities should take a smaller FLP. As argued by *De Marzo* and *Duffie* (1999), she would transfer more default risks, the more valuable her real options are.

Hypothesis 7: *Banks with more valuable real options reduce loss sharing through the FLP.*

3.5 Hypotheses about the Lowest Rated Tranche

Closely related to the loss sharing through the FLP are the properties of the lowest rated tranche, i.e. the most subordinate tranche sold to investors. This tranche is hit by default losses only if FLP[8] is completely exhausted by default losses. The higher the FLP, the higher is the loss sharing of the FLP. According to S&P, (1-support probability) determines the launch or initial rating (= rating at the issue date) of the lowest rated tranche. According to Moody´s, the expected loss per invested € of a tranche determines its rating. Therefore not only the loss sharing of the FLP matters, but also the size (thickness) of the tranche. Given the FLP, a thicker tranche implicitly includes part of better tranches so that the expected loss per invested € is lower. Therefore, the size of a tranche might also matter for its rating. Hence, given the loss rate distribution of the asset pool, the rating (credit spread) of the lowest rated tranche should be related positively (inversely) to the loss sharing of the FLP and the size of the tranche. This motivates

Hypothesis 8: *The rating (the credit spread) of the lowest rated tranche is positively (inversely) related to the quality of the underlying asset pool, the loss sharing of the FLP and to the size of this tranche.*

Cuchra (2005) finds that credit spreads of tranches are strongly determined by their ratings relative to other factors like capital market conditions and type of collateral asset. In order to

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[8] In some transactions, there exists more than one non-rated junior tranche. Then all these tranches together define the size of the FLP.

find out whether investors rely more on the factors given in hypothesis 8 than on the rating, we test

Hypothesis 9: *The credit spread of the lowest rated tranche is better explained by its rating and its maturity than by the factors given in hypothesis 8.*

Maturity of the transaction should also matter because the credit spread is paid annually while the rating is based on the lifetime of the transaction.

Cuchra (2005) also finds that the credit spread of a tranche is inversely related to its $-volume indicating an inverse relation between the tranche´s liquidity premium and its volume. Therefore we also test

Hypothesis 10: *The credit spread of the lowest rated tranche is inversely related to its €-volume.*

3.6 Hypotheses about the Choice Between a True Sale- and a Synthetic Transaction

While loss sharing in a true sale-transaction is determined by the FLP, in a synthetic transaction the FLP *and* the TLP determine loss sharing. Usually a synthetic transaction is partially funded, i.e. the volume of securities sold is only a (small) fraction of the volume of the asset pool. The originator often retains part of the FLP *and* a large super-senior tranche being a TLP. If she does not buy protection against the default risk of the super-senior tranche, then she takes this TLP. Investors take a second loss position (SLP) through their tranches. The TLP reduces the default losses borne by the SLP. But in contrast to the FLP, the TLP does not reduce the probability that investors are hit by default losses. Since the TLP is only hit by default losses, when the SLP is completely exhausted by default losses, there is little protection of investors through the TLP. Conversely, the SLP provides strong protection for the TLP. Therefore, investors should neither care much about the existence of a TLP nor about whether the originator retains the risk of the super-senior tranche. The latter is anyway not publicly known. Hence the previous discussion about the choice of the FLP does not apply to the choice of the TLP.

The choice between a true sale- and a synthetic transaction involves a choice between a) selling vs. not selling the super-senior tranche, and b) funding vs. no funding[9]. In a true sale-

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[9]   Another aspect relates to balance sheet effects. Until 2004, in a true sale transaction the securitized assets disappear from the originator's balance sheet while they do not in a synthetic transaction. Thus, a true sale transaction allows to "improve" the balance sheet. The new

transaction the originator may freely use the proceeds from issuing tranches, while in a synthetic transaction the proceeds need to be invested in almost default-free bonds. Thus, synthetic transactions in general provide no funding for the originator.

Whether it pays for a bank to sell the super-senior tranche, depends on the quality of this tranche and the credit spread required by investors. The quality depends on the size of the super-senior tranche. The smaller it is, the larger are the subordinated tranches, the better is the quality of the super-senior tranche. Holding its size constant, the better the quality of this tranche, the smaller is its risk, making it more attractive for the originator to retain this tranche. The tranche–quality is positively related to the asset pool quality. Hence, strong asset pool quality would support retention of the super-senior tranche. This motivates

Hypothesis 11*: Synthetic transactions are preferred to true sale transactions for asset pools with high quality.*

Similarly, holding the risk of the non-securitized super-senior tranche constant, its size grows with the quality of the asset pool. Hence, the bank can retain a larger super-senior tranche, the better is the asset pool quality. This motivates

Hypothesis 12: *In a synthetic transaction the size of the non-securitized super-senior tranche (Third Loss Position) increases with the quality of the asset pool.*

If this hypothesis is correct, then investors may interpret the size of the non-securitized super-senior tranche as a positive signal about the quality of the underlying portfolio.

Retaining the super-senior tranche is, however, in strong contrast to some papers discussed in section 2 which argue that the originator should sell the least information-sensitive tranche because it suffers least from information asymmetries. The super-senior tranche is the least information-sensitive tranche. Hence synthetic transactions pose a puzzle. The explanation of this puzzle may hinge on the funding cost. The originator may consider the credit spread on a super-senior tranche as high relative to its default risk so that she prefers not to sell this tranche. This is plausible, in particular, if the bank regards the asset pool quality as very high, but rating agencies do not share this view[10]. 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 is impossible for banks with a weak rating.

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accounting standards imply for many true sale transaction that the assets need to be shown on the originator´s consolidated balance sheet.

[10]   The originator may buy protection against default losses of this tranche through a super-senior credit default swap. Casual observation suggests that banks often do not buy this protection because they feel that it is too expensive.

For them it may be cheaper to obtain funds through a true sale transaction than through stand alone-borrowing. In a true sale transaction the strong collateralisation and the bankruptcy-remoteness of the special purpose vehicle render the bank's rating rather unimportant. These arguments support

Hypothesis 13: *Synthetic [true sale] transactions are preferably used by banks with a strong [weak] rating.*

These hypotheses will be tested in the following.

4. Empirical Findings

The hypotheses stated above will be tested on a set of European CDO-transactions. We only consider multi tranche-transactions because single tranche-transactions are usually initiated by investors. The quality of the asset pool plays a pivotal role in our hypotheses. Therefore it is essential to have the same type of quality measure for all transactions. Moody's uses two important measures of asset pool quality, one being the weighted average rating factor of the assets in the pool and the other one being their diversity score (DS). We include in our data set all European CDO-transactions from the end of 1997 to the end of 2005 for which we know Moody's DS and can derive the WADP[11]. Most transactions were completed in the years 2000 to 2005. Information about transactions is taken from offering circulars, from pre-sale reports issued by Moody's and from transaction reports of the Deutsche Bank-Almanac. Our European CDO-sample of multi-tranche deals includes 169 observations. This sample represents a fraction of about 50 % of all European CDO-transactions in the observation period.

4.1 Measuring Asset Pool Quality

The expected default loss of the asset pool equals the weighted average default probability times the loss given default. Since we mostly do not have transaction specific information on loss given default, we assume λ to be 50 percent with exceptions mentioned subsequently. In a recent study Acharya et al (2007) document recovery rates for various loans and bonds in the US. They find an average recovery rate of 81 percent for bank loans, 59 percent for senior secured, 56 percent for senior unsecured, 34 percent for senior subordinated and 27 percent for subordinated debt instruments, each figure with a standard deviation of more than 26 percent. The average recovery rate is slightly above 50 percent. For 2 transactions with

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[11] 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.

secured loans we use λ = 25 percent. For some recent mezzanine transactions in which the underlying loans are subordinated and unsecured, we use λ = 100 percent as the rating agencies do.

Moody's assigns each asset a rating factor and then takes a weighted average. This rating factor equals 1 for all AAA-claims regardless of maturity. For claims with another rating, the rating factor depends on the maturity and denotes the idealized probability of default for this rating class divided by the idealized probability of default for AAA-claims of the same maturity. We use Moody's tables to translate the weighted average rating factor into the weighted average default probability (WADP). If Moody's does not publish a weighted average rating factor, we use the published average rating of the asset pool and translate it into the WADP using Moody´s tables.

Moody's diversity score (DS) measures the diversification of the assets within and across industries, taking into account also variations in asset size. The DS is defined as the number of claims of equal size and uncorrelated defaults which gives the same standard deviation of the loss rate distribution as that actually observed. The 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 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. Thus, a DS of 1 indicates "no diversification" and a DS of 135 indicates "excellent diversification".

The DS has been criticized on different grounds (see *Fender* and *Kiff* 2004). The main weaknesses of the formula are, first, that the industry specific diversity scores are added, and second, that there is no transparent derivation of the G-formula. The first weakness implies that implicitly Moody´s DS assumes that defaults of obligors of different industries are uncorrelated. Therefore, in 2000 Moody´s started to use an *adjusted DS*. The adjusted DS explicitly takes into account asset correlations between industries. We also use the adjusted DS if we have enough information to derive it. We use the information on the par values of claims across industries to take into account the diversification across industries. This allows us to use the following formula for the adjusted DS (see *Fender* and *Kiff* 2004)

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

As argued by *Fender* and *Kiff,* the ADS is quite close to Moody´s DS if $\rho(in)$ = 20 percent and $\rho(ex)$ = 0 percent. The formula for the adjusted DS shows that a positive $\rho(ex)$ clearly reduces the adjusted DS. Therefore the adjusted and Moody´s DS can be quite different. 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 equals about 54. But the adjusted diversity score with $\rho(ex)$ = 2 resp. 4 percent would be about 27 resp. 18. This is just ½ resp. 1/3.

In their simulation tools for deriving loss rate distributions of asset pools Moody´s and S&P usually assume that the asset correlation of obligors of the same industry is around 20 percent while the asset correlation of obligors of different industries is around 5 percent or below. Therefore when we use the adjusted diversity score, we assume an intra-industry asset correlation $\rho(in)$ of 20 percent and an inter-industry asset correlation $\rho(ex)$ of 2 percent. Alternatively, we also use inter-industry correlations of 0 and 4 percent.

We know Moody´s DS for all 169 transactions. But we have information about industry diversification only for 92 transactions. This is mainly due to the managed transactions. For these transactions various criteria for replacing existing claims through new claims are specified in the offering circulars, but mostly not industry specific. Therefore we cannot derive the adjusted DS for these transactions. Hence we use Moody´s DS for analysing the full sample and, in addition, the adjusted diversity score for analysing the reduced sample.

4.2   Descriptive Statistics and Methodology

First, we present some descriptive statistics. The sample includes 169 transactions. The first table shows their distribution across CLO/CBO- and true sale/synthetic transactions and the distribution across years. In the sample 57 percent of the transactions are CBO-transactions, 54 percent are synthetic. This is an astonishing percentage in view of the literature which argues that the least information-sensitive tranches should be sold. This tranche is the super-senior tranche which is rarely sold in synthetic transactions.

From the 169 transactions, 136 are arranged by banks and 33 by investment firms. The latter buy existing bonds and securitize them. 15 of these 33 transactions are classified as CLO-transactions, although the originating investment firms buy bonds and existing loans and securitize them. Therefore we reclassify these 15 CLO-transactions as CBO-transactions. Thus, 33 CBO-transactions, i.e. 1/3 of the CBO-transactions, are originated by investment firms, all other transactions by banks.

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

Year	1997	1998	1999	2000	2001	2002	2003	2004	2005
number of transactions	1	1	12	26	40	42	16	19	12

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 distribution of transactions across years.

Table 2 presents the means and standard deviations of

--   WADP, the weighted average default probability of the assets in the pool,

--   DS, Moody's diversity score of the asset pool,

--   FLP, the initial size of the first loss position as a percentage of the volume of the asset pool,

--   TLP, third loss position, i.e. the volume of the non-securitized senior tranche as a percentage of the volume of the asset pool in synthetic transactions,

--   the ra ting of the lowest rated tranche. 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 B-. A higher integer indicates a better rating.

--   CSL, the initial (= launch) credit spread on the lowest rated tranche[12],

The data are presented separately for true sale-/synthetic and CLO/CBO-transactions.

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[12] Most tranches are floating rate notes. In the few cases of fixed rate notes we take the difference between the coupon and the swap rate of the same maturity as the credit spread.

	CLO – ts	CLO – synth	CBO – ts	CBO – synth
WADP – mean	7.5 %	3.8 %	13.2 %	1.9 %
WADP – std.	7.5 %	3.1 %	9.8 %	3.2 %
DS – mean	87	89	34	56
DS – std.	46	30	11	26
FLP – mean	6.1 %	2.9 %	12.1 %	3.6 %
FLP std.	4.8 %	1.5 %	6.2 %	2.6 %
TLP – mean	-	80 % (86%)	-	87%
TLP – std.	-	23 % (7%)	-	7%
Ratinglast– mean	-9.4	-11.7	-9.1	-8.0
Ratinglast – std.	2.8	1.9	3.8	3.0
CSL– mean	244 bp	475 bp	373 bp	270 bp
CSL – std.	184 bp	206 bp	254 bp	150 bp

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 (synth) 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, ratinglast and CSL the launch rating resp. the launch credit spread of the most junior rated tranche. The bracketed numbers for TLP in CLO-transactions are obtained if three fully funded Geldilux-transactions are excluded.

Table 2 indicates several interesting properties. The mean weighted average default probability is much higher for true sale than synthetic transactions. Also the mean is clearly higher for synthetic CLO– than synthetic CBO-transactions. On average, CLO-transactions are much better diversified than CBO-transactions supporting hypothesis 5. The average size of the FLP is higher for true sale than for synthetic transactions, and within these subsets the FLP is higher for CBO- than for CLO-transactions.

Comparing the average size of the FLP with the average expected loss which is about half of the WADP, the average FLP clearly exceeds the average expected loss as assumed in Lemma 1c). Also the averages satify the condition in Lemma 2a). The condition $h < n(h +\sigma)/(1- N(h +\sigma))$ in Lemma 3 always holds, based on an adjusted diversity score with $\rho(ex) = 2$ percent. The average size of the FLP is smaller than the average WADP except for synthetic CBO-transactions, suppporting the last condition in Lemma 3.

The TLP in synthetic transactions is, on average, about 87 % of the asset pool volume with a standard deviation of only 7 % for CLO **and** for CBO-transactions if we exclude three atypical Geldilux-transactions. These transactions are the only fully funded synthetic CLO-transactions, i.e. TLP is zero. Including these transactions lowers the average TLP of synthetic CLO-transactions to 80 %.

The overall mean of the rating of the lowest rated tranche is between BBB and BBB-. There is one transaction with only one rated tranche (AAA) and also one transaction with a tranche rated B-. Thus, there is strong variability in the rating of the lowest rated tranche. The rating (credit spread) of the lowest rated tranche is, on average, lowest (highest) for synthetic CLO-transactions which have underlying portfolios with strong quality.

In the following we test the hypotheses derived in section 3. Originator characteristics may affect loss sharing. Therefore we distinguish banks and investment firms as originators, and, include various characteristics of originating banks in our empirical analysis. These characteristics are largely unknown for investment firms, but they matter presumably litte for the design of transactions originated by them. These firms arrange transactions solely for arbitrage purposes. The involved choices should be largely determined by market conditions imposed by investors and rating agencies, not by characteristics of the investment firm.

Banks pursue different objectives in their securitization activities. A bank may want to reduce its default risk and, hence, the equity capital requirements. The need for such a transaction may depend on the level of its equity capital relative to its risk-weighted assets, on its profitability and on its options for taking other risks. Therefore these characteristics might affect the transaction design. Similarly, a bank may want to lower its funding costs through a true sale-securitization. The need for doing this may be related to its funding opportunities using standard debt instruments. Since the costs of these instruments depend on the bank´s rating, this should also be true for the strength of the funding motive in securitizations.

 In order to account for the impact on securitization decisions of these bank-internal considerations, in the regressions we include as additional regressors data on the originating banks which proxy for these considerations. These data are

- data on equity capital relative to risk weighted assets: the tier 1-capital ratio and the total capital ratio,

- capital structure data: equity/total assets,

- asset structure data: loans/total assets,

- profitability data: the 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 profitability and also for its growth potential as evaluated by the capital market,

- the bank´s rating to proxy for its funding motive.

These bank characteristics are obtained from the Bank Scope Database.

Since these characteristics are not available for investment firms and also for some banks, for each characteristic we attach a residual dummy RD of 1 to those originators for whom the characteristic is not known and a residual dummy RD of 0 otherwise. Then the regression is of the type

$$y = a + b\,x_1 + c\,(1\text{-}RD)\,\Delta x_2 + d\,RD + \varepsilon. \tag{14}$$

x_1 denotes the vector of explaining variables not being originator characteristics, b the vector of regression coefficients, Δx_2 the bank characteristic minus its average in the sample and ε the usual error term. This approach implies that for the banks with a known characteristic the variation in this zero-mean characteristic is taken into consideration while for the other originators no variation is assumed. d can be interpreted as the product of the average (unknown) characteristic and the corresponding "true" regression coefficient. Hence a higher average would be automatically compensated by a lower "true" regression coefficient and, thus, is irrelevant. If Δx_2 or RD does not add to the explanatory power of the regression, then it is eliminated.

4.2   The Quality of the Asset Pool

The quality of the underlying asset pool is a core variable in most hypotheses. Therefore, we first try to improve our understanding of what drives the quality of the asset pool. In particular, we ask two questions. First, 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)? Second, do originator characteristics affect the choice of asset pool quality? Under a homogeneous quality policy, both quality indicators would be highly correlated. Regressing ln Moody´s DS only on WADP shows a negative, highly significant regression coefficient. But the explanatory power, measured by R^2, is only 9.3 %. The reason is evident from Fig. 1 a). It appears that for asset pools with WADP below 0.1 there is no relation between WADP and Moody´s DS. For asset pools with WADP above 0.1, Moody´s DS is rather low indicating low quality of the pool. Hence there is partial support for homogeneous quality choice. Looking at the adjusted DS and WADP in Fig. 1 b) confirms even more that there is no systematic relation between both quality measures.
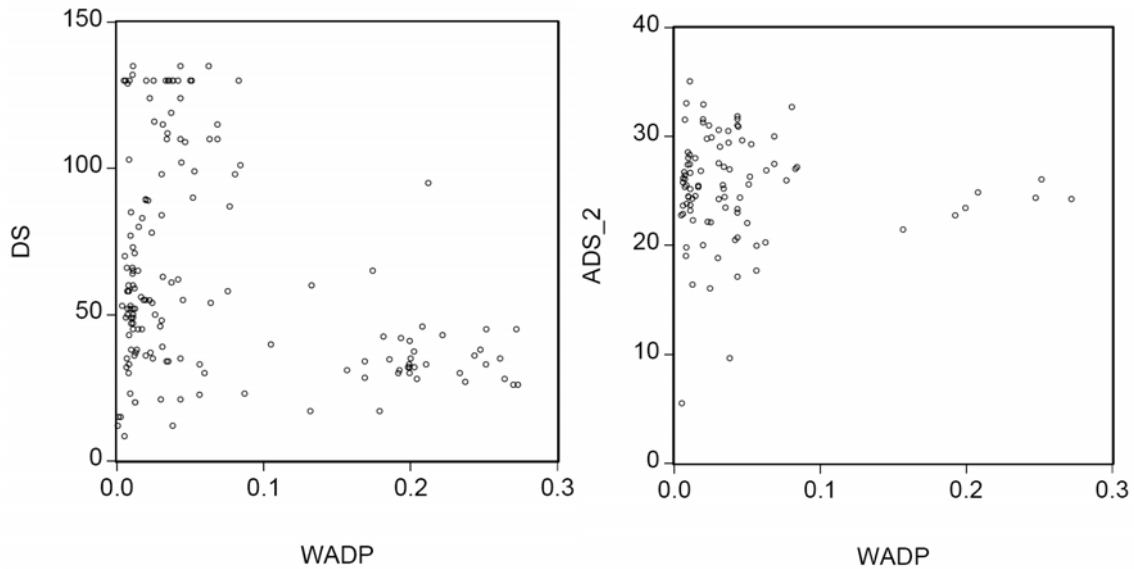
Fig 1.: Fig. a) shows for 169 transactions Moody´s diversity score DS and the weighted average default probability WADP. Fig. b) shows for 92 transactions the adjusted diversity score DS with ρ(ex) = 0.02 and the weighted average default probability WADP.

Therefore, we now check which originator characteristics affect WADP and DS. In each subsequent regression we include a constant, but we never show it in the following tables which display the regression results. The first column of table 3 shows that WADP depends strongly on the originator type represented by a dummy of 1 if the originator is an investment firm and 0 otherwise. On average, investment firms clearly choose a higher WADP than banks. Possibly asset pools with a higher WADP offer more potential for arbitrage profits in a CBO-transaction. As shown in the second column, WADP tends to be lower in synthetic transactions represented by a dummy of 1 if the transaction is synthetic and 0 otherwise. Finally, WADP tends to increase with the bank´s total capital ratio indicating that banks with a strong equity buffer take more default risks. Tobin´s Q has no significant impact.

Looking at the characteristics explaining Moody´s diversity score, remember that WADP explains only very little. Hence the third column of table 3 indicates that a substantial part of the variation in DS can be explained by the CBO-dummy which is 1 for a CBO-transaction and 0 otherwise. CBO-transactions tend to be much less diversified as can be seen already in the descriptive statistics in table 2. This might, however, be driven more by the relative ease to put together a large loan portfolio than by information asymmetries. Hypothesis 5 is clearly supported by the data.

Explained variable	Weighted average default probability (%)		Inverse ln Diversity Score	
Weighted average default probability (%)	-	-	0.001 (0.0079)	0.0006 (0.17)
Inverse ln diversity score	17.0 (0.17)	16.7 (0.19)	-	-
Investment firm-dummy	11.6 (0.0000)	8.83 (0.0000)	-	-
CBO-dummy	-	-	0.043 (0.0000)	0.040 (0.0000)
Synthetic dummy	-	-5.37 (0.0000)	-	-0.018 (0.0580)
ΔTotal capital ratio	-	1.41 (0.0014)	-	-0.008 (0.0188)
ΔTobin´s Q	-	-1.20 (0.126)	-	-
Adjusted R^2	0.371	0.486	0.265	0.350

Table 3: The table displays the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions explaining the weighted average default probability (WADP) and log diversity score of the asset pool. 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 (14)). The adjusted R^2 is shown in the last row.

For the DS it does not matter whether the originator is a bank or an investment firm. As indicated by the last column in table 3, high diversity scores tend to be observed in synthetic transactions indicating a low risk of the super-senior tranche with a given size. The regression coefficient is weakly significant. Finally, DS tends to increase with the total capital ratio of the originating bank. The explanation of this finding may be that well capitalized banks lend to more obligors so that their loan portfolio is better diversified. Other bank characteristics do not appear to affect the choice of WADP and DS. This indicates that the choice of the asset pool is largely driven by market factors and less by internal considerations of the originator.

These findings are partly confirmed by the subsample of 92 transactions for which we can derive the adjusted diversity score with $\rho(ex) = 2$ percent. The overall explanatory power of the subsample is smaller regardless of whether Moody´s DS or the adjusted DS is used. If we use the inverse ln adjusted DS to explain WADP, then its coefficient is negative and significant, however. The other explanatory variables in the second regression of Table 3 retain their coefficient signs, but are less significant. Regressing the inverse ln adjusted DS on WADP and the CBO-dummy shows no significant coefficient of WADP, but a significant positive coefficient of the CBO-dummy. The synthetic dummy is significant as before but ΔTotal capital ratio loses significance.

4.3   The Extent of Loss Sharing

Now the main hypotheses of the paper on loss sharing will be tested. First, we look at the size of the FLP. Hypothesis 1 states that the size of the FLP is inversely related to the quality of the asset pool. First, we OLS-regress the size of the FLP on the WADP and 1/ln DS. The reason for including 1/ln DS is that the relationship between the FLP and diversification is likely to be nonlinear since the marginal benefit of diversification should decline. The first regression in Table 4 confirms this conjecture. The WADP of the asset pool has a strongly significant positive impact on the FLP, its regression coefficient is smaller than 1. This is expected if the loss share is independent of the asset pool quality and FLP is smaller than WADP (Lemma 3).The impact of the diversity score on FLP is clearly negative. Given the high adjusted R^2 of 54.5 %, Hypothesis 1 is strongly supported.

Next, we include in the regression the Synthetic dummy. Its coefficient is significantly negative indicating that synthetic transactions have smaller FLPs. Investors may view the synthetic structure as a signal of low risk because the super-senior tranche is not sold. This may allow the originator to choose a smaller FLP retaining the same published portfolio quality. In order to test hypotheses 4 and 6, we add the CBO- and the dynamic-dummy. The latter is 1 for a managed (dynamic) transaction and 0 otherwise. Results are not shown in Table 4. Both dummies turn out to be insignificant so that hypotheses 4 and 6 are falsified. The lack of significance of the dynamic-dummy may be due to the strict rules on replenishment/substitution of loans/bonds in offering circulars. Also it does not matter for the size of the FLP whether a bank or an investment firm is the originator.

Hypothesis 7 claims that originators with more valuable real options should prefer lower FLPs. Including Tobin´s Q as a proxy for the bank´s real options does not add to the explanatory power of the regression, thus falsifying the hypothesis. The same negative results are obtained for other bank characteristics.

Explained variable	First Loss Position (%)		
WADP of asset pool (%)	0.387	0.303	0.293
	(0.0000)	(0.0000)	(0.0000)
Inverse ln diversity score	49.80	43.40	43.34
	(0.0015)	(0.0033)	(0.0035)
Synthetic dummy	-	-2.82	-2.87
		(0.0004)	(0.0004)
Adjusted R^2	0.545	0.587	0.593

Table 4: 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. The synthetic-dummy is 1 for a synthetic transaction and 0 otherwise. The adjusted R^2 is shown in the last row.

Next, we look at other loss sharing measures. Hypotheses 2 and 3 claim that the share of expected losses borne by the FLP resp. the support-probability of the FLP are invariant to the asset pool quality. In order to test these hypotheses, we assume that the loss rate distribution is lognormal (for details see Appendix 2).

This parametric approach to estimating the lognormal loss rate distribution is done for each of the 92 transactions for which we can derive the adjusted diversity score. For the 92 transactions we, first, derive the adjusted DS 2, i.e. the adjusted DS with $\rho(ex) = 2$ percent. Then the implied share of expected losses, *s,* has a mean of 86.1 percent and a standard deviation of only 8.4 percent. This indicates that the FLP takes a very high share of the expected losses. It also indicates that the loss share varies only little. For the support-probability $\gamma(FLP)$ the mean is 87.62 percent and the standard deviation 14.7 percent. This mean is also quite high. Since the inter-industry correlation is controversial, we add the figures for $\rho(ex) = 0$ percent and for 4 percent. In accordance with Lemma 1, the average share of expected losses declines from 91.6 to 82.3 percent if $\rho(ex)$ increases from 0 to 4 percent. In accordance with Lemma 2, the average support-probability declines from 88.25 to 87.57 percent if $\rho(ex)$ increases from 0 to 4 percent. Surprisingly, the average loss share clearly reacts to the assumed inter-industry correlation, while 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 smaller than the FLP.

We now run linear regressions to explain s resp. $\gamma(FLP)$ by the explanatory variables we used before. The results are shown in Table 5. Regressing the share s on WADP and on the inverse

log adjusted DS 2 it turns out that WADP is completely insignificant, while the coefficient of the inverse adjusted DS 2 is positive and significant. However, the explanatory power of the regression is only about 5.6 percent. *Hence we conclude that neither WADP nor DS can explain the variation in the share s.* This finding supports Hypothesis 2 claiming that the loss share is independent of asset pool quality. In terms of Proposition 2 and Corollary 2 this suggests that the originator faces both, adverse selection and reputation costs. The second column of Table 5 shows the regression results adding the CBO-dummy. The regression coefficient is positive and significant indicating that in CBO transactions the FLP absorbs a higher share of expected losses. Since CBOs tend to be less diversified, the adjusted DS 2 turns almost insignificant. Even though the explanatory power of the regression increases, it it still modest.

	Share of expected losses (%)		Support probability (%)	
WADP (%)	-0.124 (0.30)	-0.128 (0.34)	-1.99 (0.0000)	-2.00 (0.0000)
Inverse ln ADS2	61.7 (0.0145)	41.1 (0.0718)	64.1 (0.0625)	43.2 (0.15)
CBO-dummy	-	5.91 (0.0006)	-	5.99 (0.0002)
Adjusted R²	0.056	0.164	0.596	0.632

Table 5: This table displays the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions explaining the share of expected losses taken by 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. The sample is restricted to 92 transactions for which ADS2 can be derived. The adjusted R^2 is shown in the last row.

Next, we run the same regressions for the support-probability of the FLP, *γ(FLP)*. Using only WADP and the adjusted DS 2 for explanation, both turn out to be highly significant. And this regression has a rather impressive explanatory power of 60 %. Thus, Hypothesis 3 is invalidated. 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 clearly react to the asset pool quality. Comparing this support-probability regression with that of the expected loss share shows that the latter much better characterizes the market norm. The support-probability depends on the asset pool quality, while the loss

share does not. Thus, the market norm appears to mitigate information asymmetry problems not through a constant support-probability, but much more through a constant share of expected losses borne by the FLP.

Returning to the first regression of the support-probability, surprisingly both regression coefficients have different signs. While a higher WADP reduces the support-probability *γ(FLP)*, a deterioration in the adjusted DS raises the probability. The explanation for this surprsing result is also provided by Lemma 3. It states that given a constant loss share, the support-probability of the FLP declines if the WADP or the DS increases. Thus, this finding corroborates the finding that the loss share is independent of the portfolio quality. Adding the CBO-dummy turns the DS insignificant while the dummy coefficient is significantly positive. Summarizing, the observation that the support-probability can be explained much better than the share of expected losses through the regressions, indicates that originators much closer adhere to the constant loss share-strategy than to the constant support-probability strategy. The constant share strategy appears to be a good approximation to what is actually observed in the market.

It should be noted that a loss share which is independent of asset pool quality does not imply that the share is constant. The originator may still vary the rating of the lowest rated tranche within close limits. This would raise the explanatory power of the regressions, but also create an endogeneity problem. Adding originator characteristics as regressors in the regressions of Table 5 does not improve explanatory power. Hence loss sharing appears to be driven by market factors, not by originator characteristics.

The assumption of a lognormal loss rate distribution is sometimes criticised. If one simulates the loss rate distribution of a loan portfolio, often the distribution is slightly better approximated by a gamma distribution than by a lognormal distribution. Therefore we run a robustness check using a two parameter gammma distribution. For each transaction the expected loss rate and the variance $σ^2(l)$, based on the adjusted DS with $ρ(ex) = 2$ percent, are translated into the parameters of a gamma distribution. While the share of expected losses assuming a lognormal distribution has a mean of 86.1 percent, this mean is 84.3 percent assuming a gamma distribution. A linear regression of the lognormal-based share on the gamma-based share shows an R^2 of 93.5 percent. Regarding the support-probability of the FLP, *γ(FLP)*, its lognormal-based mean is 87.6 percent, while its gamma-based mean is 85.7 percent. A linear regression of the gamma-based *γ(FLP)* on the lognormal-based *γ(FLP)* has an R^2 of 98.9 percent.

Hence it it not surprising that the regression results are similar. Regarding the share of expected losses taken by the FLP, the same coefficients are significant/insignificant taking the gamma distribution instead of the lognormal distribution. The significant coefficients have the

same sign. And also there is no dominance of one over the other distribution in terms of the R²s. The same statements are true comparing the regressions of the gamma-based *γ(FLP)* and the lognormal-based *γ(FLP)*. Hence we conclude that in terms of the regression results there is no noticeable difference between a lognormal and a gamma distribution.

4.4 Properties of the Lowest Rated Tranche

The lowest rated tranche should clearly reflect the loss sharing of the FLP and the asset pool quality. Hence we want to know which measure of loss sharing best explains the properties of the lowest rated tranche. Therefore we now analyse two important properties of the lowest rated tranche, its launch rating and its launch credit spread. Since we can derive the adjusted diversity score for only 92 transactions, the sample is again based on 92 observations for the regressions explaining the rating of the lowest rated tranche. The regressions explaining the launch credit spread of the lowest rated tranche are based on 82 observations, since we do not know the credit spread of the lowest rated tranche for all 92 transactions.

First, we try to explain the rating of the lowest rated tranche. Hypothesis 8 states that the rating of this tranche should be driven by the quality of the asset pool, the loss sharing of the FLP and the size of the tranche. Although rating is a discrete variable, we use OLS since we have 16 rating classes. The first regression in table 6 strongly supports hypothesis 8 using FLP itself as a measure of loss sharing. Since the FLP strongly depends on WADP and ln ADS2, we include in the regression FLP-residual, i.e. the residual from an OLS-regression of FLP on WADP and ln ADS2. This assures that the coefficients of WADP and ln ADS2 are not biased through the impact of these variables on FLP. The coefficients of WADP, FLP-residual and tranche size have the expected signs and are strongly significant. The explanatory power of this regression is quite high with 70 percent. Replacing FLP by the share of expected losses lowers the explanatory power somewhat, this effect is stronger using instead the support probability of the FLP. As the second regression in table 6 shows, FLP appears to be an incomplete measure of loss sharing. Adding the share of expected losses-residual raises the explanatory power to 73 percent. This residual is from am OLS-regression of the share of expected losses on the FLP because the share is determined by the FLP, while WADP and ADS2 are largely irrelevant. The high explanatory power indicates that the rating of the lowest rated tranche is affected by both, the FLP and the loss share. In both regressions the coefficient of *ln ADS2* is negative. This can be explained by Lemma 3. Controlling for the share of expected losses, the support-probability of the FLP is inversely related to the DS. The same is true of the rating of the lowest rated tranche reflecting that the rating of S&P depends on the support-probability. Originator characteristics appear to be irrelevant.

Explained variable	rating of the lowest rated tranche		credit spread of the lowest rated tranche (bp)	
Weighted average default probability (%)	-0.13 (0.0000)	-0.08 (0.0175)	12.21 (0.0000)	-
Ln ADS2	-3.78 (0.0006)	-3.93 (0.0000)	-	-
FLP - Residual	0.70 (0.0000)	0.60 (0.0080)	-	-
Ln size of lowest rated tranche	0.91 (0.0000)	0.90 (0.0000)	-69.4 (0.0003)	-
Share of expected losses - Residual	-	0.10 (0.0216)	-	-
Share of expected losses (%)	-	-	-9.24 (0.0012)	-
Squared Rating of lowest rated tranche	-	-	-	-3.00 (0.0000)
Maturity	-	-	-	22.2 (0.0219)
Date of issue	-	-	63.4 (0.0001)	57.2 (0.0000)
Date of issue squared	-	-	-1.68 (0.0000)	-1.43 (0.0000)
Adj. R²	0.700	0.732	0.494	0.650

Table 6: This table displays the results from OLS-regressions explaining the rating and the credit spread of the lowest rated tranche (p-values in brackets, heteroskedasticity adjusted in OLS regressions). WADP is the weighted average default probability of the asset pool. Ln ADS2 is the log adjusted diversity score assuming a default correlation between industries of 2 percent. FLP-Residual is the residual of an OLS regression of FLP on WADP and ln ADS2. Ln size of lowest rated tranche is the logarithm of the percentage size of this tranche. Share of expected losses-residual is the residual of an OLS regression of Share of expected losses on FLP. Maturity is the maturity of the transaction. Date of issue refers to the date at which the transaction is launched. Regarding the rating, the sample is restricted to 92 transactions for which ADS2 can be derived. Regarding the credit spread the sample is restricted to 82 transactions for which ADS2 can be derived and the credit spread of the lowest rated tranche is known. The adjusted R^2 is shown in the last row.

Next, we analyse the determinants of the credit spread of the lowest rated tranche. As regressors we use the same variables that we used to explain the rating of the tranche. In addition, we include the maturity of the transaction and also the issue date because the ratings are usually "through the cycle ratings", i.e. they do not change with the current phase of the business cycle. Therefore the date may proxy for this phase and for changes in the market´s risk aversion. Since the business phase moves up and down in the sample period, we include the date and its square in the regressions. The date is an integer variable equal to 0 for the last quarter of 1997 and increases by 1 for each successive quarter. The third column of table 6 shows the regression results. The adjusted diversity score turns out to be irrelevant, as does the FLP once we include the share of expected losses. The maturity of the transaction is also irrelevant. This is not surprising given its correlation with WADP of 62.4 %. The regression explains almost 50 percent of the variation in the credit spread. As expected, the signs of the regression coefficients are precisely opposite to those in the rating regressions supporting hypothesis 8. The strong impact of the issue date is given by a parabola with a maximum around 2002 which represents a trough in the business cycle. One would expect the IBOXX-spread, defined by the average yield of BBB-bonds over government bonds, to better reflect market sentiment than the mechanical date. Substituting for the date by the IBOXX-spread reduces the explanatory power of the regression considerably, however.

The negative coefficient of the tranche size seems consistent with hypothesis 10 supporting a liquidity premium effect in line with the findings of *Cuchra* (2005). But this conclusion is presumably misleading because the explanatory power of the regression shrinks to 41.7 % if we replace the size of the lowest rated tranche (in percent of the transaction volume) by its €-amount. Hence we conclude that thickness drives the negative sign, not €-volume. Hypothesis 10 is not supported.

Hypothesis 9 claims that the credit spread of the lowest rated tranche can be better explained by its rating and its maturity than by the characteristics analysed so far. This claim is strongly supported by the fourth regression in Table 6. Squared rating, maturity and issue date explain 65 % of the variation in the credit spread, much more than the third regression. We use squared rating instead of rating because there is a strong convexity relating the credit spread to rating. Maturity has a significant, positive coefficient as expected. Including other regressors in the last regression does not improve explanatory power. This is perhaps not surprising given that the rating itself depends strongly on the portfolio quality, loss sharing of the FLP and the size of the tranche. Overall, hypothesis 9 is supported by the findings. Again, originator characteristics appear to be irrelevant.

4.5   The Choice Between True Sale- and Synthetic Transactions

As discussed above, the choice between true sale- and synthetic transactions is a joint choice of a funding strategy and of taking/not taking a TLP. Hypothesis 13 claims that originators with a good rating are not interested in funding through securitization. A probit regression of the synthetic-dummy on the originator's rating supports this hypothesis. We include two regressors, the originator rating minus the average originator rating in the sample, and a dummy for those originators for which we do not have a rating. The first regression in Table 7 shows that the originator rating has a significant, positive impact on the probability of synthetic transactions, while the originators without a rating appear to prefer a true sale transaction. For them refinancing through true sale appears to be preferable. These findings provide strong support for hypothesis 13.

Explained variable	Synthetic dummy			
Weighted average default probability (%)	-	-0.11 (0.0000)	-0.10 (0.0000)	-11.69 (0.0000)
Inverse ln diversity score	-	-6.71 (0.0050)	- 6.86 (0.0085)	- 3.39 (0.24)
ΔOriginator's rating	0.225 (0.0033)	-	0.22 (0.0107)	0.30 (0.0020)
Originator rating-dummy	-1.54 (0.0000)	-	-1.29 (0.0002)	-1.33 (0.0001)
ΔTobin´s Q		-	-	-0.93 (0.0010)
ΔTotal capital ratio				0.211 (0.0570)
McFadden R^2	0.190	0.265	0.362	0.424

Table 7:   This table shows the coefficients (with p-values in brackets) of binary probit regressions explaining the synthetic-dummy, This variable is 1 for a synthetic transaction and 0 otherwise. ΔOriginator's rating is the originator´s rating minus the average originator rating in the sample (see equation(14)). 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.

Hypothesis 11 states that synthetic transactions are preferred for high quality asset pools. This hypothesis is strongly supported as can be seen from the second regression in Table 7. The explanatory power of the regression can be clearly improved by including also the originator rating and the corresponding dummy for those originators for which a rating is not known (third regression).

In the last regression we test for the effects of other variables. It turns out that the explanatory power can be improved by also including the originator´s Tobin´s Q and her total capital ratio. But now DS is no longer significant. This may be explained by the correlations between ln DS and the new regressors, Tobin´s Q (-0.19) and the total capital ratio (0.24). A high total capital ratio indicates a low cost to the originator of retaining the super-senior tranche. The negative coefficient of Tobin´s Q tells us that it may not pay for originators with attractive outside options to retain the risk of a TLP.

Explained variable	Size of the third loss position (%)	
Weighted average default probability (%)	- 0.015 (0.0000)	- 0.015 (0.0000)
Ln diversity score	0.14 (0.0000)	0.14 (0.0001)
Inverse ln diversity score	1.56 (0.0007)	1.47 (0.0017)
Investment firm-dummy	-	-0.06 (0.0007)
Adjusted R^2	0.576	0.588

Table 8:   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 adjusted R^2 is shown in the last row.

Next we analyse the size of the TLP in synthetic transactions. Since we only look at synthetic transactions, the determinants of the TLP-size are not necessarily the same as those of the choice between synthetic and true sale transactions. We exclude here the three fully funded Geldilux-transactions which are atypical. For two other transactions we do not know the TLP-size leaving us with 86 observations. According to hypothesis 12, the TLP-size increases with the quality of the asset pool. This is clearly true for the WADP. The WADP alone explains already 48 % of the variation in the TLP-size (not shown in Table 8). Including DS clearly

improves the explanatory power as shown in the first regression of Table 8. The impact of ln DS is u-shaped. For small diversity scores up to about 28 the TLP-size declines with the diversity score, but for higher diversity scores it increases[13]. There are only a few transactions with a diversity score below 28. Therefore, the general picture is that the TLP-size increases with the diversity score. Thus, hypothesis 12 is clearly confirmed. The explanatory power of the regression can be improved slightly by including the investment firm-dummy (last column in Table 8). The coefficient is negative indicating that investment firms tend to retain smaller TLPs.

Comparing our findings for the size of the FLP and of the TLP, the differences are striking. While the FLP-size reacts inversely to asset pool quality, the TLP increases with asset pool quality. This indicates that both are driven by different motives. The FLP serves to mitigate problems of information asymmetries, but the TLP does not. The TLP-size appears to be driven by the effects of the TLP on the originator´s risk and return. The originator prefers a large TLP if its default risk is low. Then it does not pay to sell this risk to investors because they would charge a relatively high credit spread.

4.6 Robustness Tests

A potential critique of OLS-regressions to explain the FLP and the TSP is that these variables are constrained to the (0;1)-range. The distribution of the regression residuals turns out to be fairly symmetric, with little excess kurtosis. As a robustness test 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. Therefore we do not present the results of the transformation.

The discussion about the best way to measure the diversity score has led us not only to consider the DS published by Moody´s, but also to consider the adjusted DS based on default correlations between industries of 0, 2 resp. 4 percent. The regression results are similar even though our sample shrinks to 92 observations. Sometimes the results are stronger for the adjusted DS with 4 percent inter-industry correlation. This is surprising but may indicate that in former years 4 percent inter-industry correlation was assumed to be realistic.

There might exist an endogeneity problem regarding the choice of asset pool quality as analysed in Table 3. The choice of WADP and DS might be interdependent. We check for

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[13] For $Z(DS) = 0.14 \ln DS + 1.56 / \ln DS$ we get $Z(20)=0.940$, $Z(28)=0.935$, $Z(60)=0.954$, $Z(90)=0.977$, $Z(120) = 0.996$. Hence, the non-securitized senior tranche would increase on average by 4.2 % of the par value of the asset pool if the DS increased from 28 to 90.

endeogeneity through a two stage least squares regression (2SLS). First, consider the dependence of *WADP on DS*. As shown before, the diversity score is much higher in CLO- than in CBO-transactions while WADP is similar in both types of transactions. Therefore, we use the CBO-dummy as an instrumental variable. In a 2 SLS inverse ln diversity score is regressed, first, on the CBO-dummy, the synthetic dummy *Syn, ΔTobin´s Q* and Δ*total capital ratio* (see equation (14)). Second, WADP is regressed on the estimate of *inverse ln DS, e(1/ln DS),* the investment firm dummy *ID* and the same other variables except for the CBO-dummy. The estimation results are

WADP = 29.9 e(1/ln DS) + 8.86 ID– 5.05 Syn + 1.54 Δtot cap ratio – 1.39 ΔTobin´s Q

$\qquad$ (0.29) $\qquad$ (0.0000) (0.0004) (0.0015) $\qquad$ (0.102)

This result is very similar to that of the second regression in Table 3 in which the WADP is OLS regressed on the same variables. Hence, even though the originator chooses WADP and DS simultaneously, this does not appear to significantly affect the explanation of WADP.

Then we turn the exercise around to explain ln diversity score. As shown above, transactions originated by investment firms clearly have a higher WADP, without having a clear impact on the diversity score. Therefore we use the investment firm-dummy as an instrumental variable for WADP. Hence in a 2SLS, we first regress the WADP on the investment firm-dummy, the CBO dummy, the synthetic dummy and Δtotal capital ratio. Second, ln diversity score is regressed on the estimate of WADP and the same other variables except for the investment firm-dummy. The estimation results are

1/ln DS =0.0009 e(WADP)+ 0.04 CBO - 0.015 Syn - 0.009 Δtot cap ratio

$\qquad$ (0.294) $\qquad$ (0.0000) $\qquad$ (0.2073) (0.0130)

This result is very similar to that of the fourth regression in Table 3 in which *inverse ln DS* is OLS regressed on the same variables. Hence, the simultaneous choice of WADP and DS by the originator also does not appear to significantly affect the explanation of *inverse ln DS.*

In the other regressions, we see little potential for endogeneity. The regressions try to answer the question how asset pool quality affects loss sharing through FLP and TLP, given exogenous originator characteristcs and attitudes of investors and rating agencies. These attitudes together with asset pool quality determine the choice of the loss sharing. Including a CBO-dummy as regressor does not create endogeneity because CLO- and CBO-transactions represent two different types of transactions. Including a Synthetic-dummy is more prone to endogeneity problems. But as Table 7 indicates, the choice between true sale and synthetic transactions itself is driven by asset pool quality and originator characteristics. Regarding the rating and the credit spread of the lowest rated tranche, any reasonable economic model needs to take into consideration its size and loss sharing as explaining variables.

5   Discussion

The general presumption of this paper is that information asymmetries are stronger for asset pools with lower quality. Therefore the originator faces penalties for information asymmetries which are mitigated by her choice of effort and of the FLP. In synthetic transactions the originator also takes a TLP. Lemmas 1 to 3 characterize the impact of asset pool quality on default losses borne by investors and the holders of the FLP. Propositions 1 and 2 characterize the optimal effort and the optimal FLP. While a lower asset pool quality induces a higher FLP, its impact on the loss share and on the support-probability of the FLP depends on the size of the adverse selection and reputation cost parameters a and r as well as on the marginal productivity of effort.

This paper investigates the impact of asset pool quality on some important aspects of the transaction design, given the attitudes of investors and rating agencies and originator characteristics. In almost all regressions asset portfolio quality, measured by the weighted average default probability and the diversity score, plays a strong role. Originator characteristics play only a weak role if at all. In the following, we discuss the empirical findings. The impact of both asset pool quality variables on other originator choices is not homogeneous in the sense that a higher WADP always has the same impact as a lower DS. Therefore we discuss both quality measures separately. The main empirical findings are summarized in Fig. 2. The arc relating two variables indicates which variable has an impact on the other one. (+), (-) indicates a positive resp. a negative impact.

Asset pool quality has an impact on all choices shown in Fig. 2 except for the share of expected losses borne by the FLP. As stated in Hypothesis 1, low asset pool quality makes it attractive for the originator to offer a high FLP to mitigate problems of information asymmetries. This is clearly supported by the findings. The two more refined measures of loss sharing between the originator and the investors are the share of expected losses borne by the FLP and the support-probability of the FLP. The share of expected losses, derived from WADP and DS, turns out to be largely independent of both quality measures, supporting Hypothesis 2. It appears that this share with a mean of 86 percent and a low standard deviation of 8.4 percent represents the strong guideline for choosing the FLP. In contrast, the support-probability of the FLP reacts inversely to the weighted average default probability and to the diversity score invalidating Hypothesis 3. This inhomogeneous impact of the two quality measures is not surprising in view of Lemma 3.

These findings also shed some light on the relevance of adverse selection and moral hazard effects. Given our model, Proposition 2 indicates that in the absence of reputation costs the support-probability of the FLP should be independent of the asset pool quality. In the presence of substantial reputation costs, the share of expected losses borne by the FLP may

decline with portfolio quality. For moderate reputation costs, the share of expected losses could be invariant to portfolio quality. Since this invariance is found in the data, this finding is consistent with a market in which both, adverse selection and reputation costs, exist. This is in line with intuition.

The FLP is lower in synthetic transactions, controlling for asset pool quality. Strong asset pool quality makes a synthetic transaction more attractive relative to a true sale transaction supporting Hypothesis 11. Hence a synthetic transaction may signal strong asset pool quality so that investors demand a smaller FLP, given the published asset pool quality. In synthetic transactions, the originator usually takes a TLP which appears to *grow* with asset pool quality supporting Hypothesis 12. This is in strong contrast to the FLP which *inversely reacts* to asset pool quality. This indicates that the purposes of the FLP and the TLP are quite different. While the FLP serves to mitigate information asymmetry problems, the TLP appears to be driven by the originator motive to avoid high default risks.

Loss sharing through the FLP is not higher in CLO- than in CBO-transactions, invalidating Hypothesis 4. Our conjecture that information asymmetries are stronger in CLO-transactions may be wrong. The generally higher diversity score in CLO-transactions renders idiosyncratic default risks rather unimportant supporting Hypothesis 5. Also, loss sharing through the FLP is not higher in managed than in static transactions despite of stronger moral hazard concerns invalidating Hypothesis 6. This may be due to the stringent conditions for management resp. replenishment. Hypothesis 7 claiming lower loss sharing through FLPs for originators with higher Tobin´s Q is also not supported by the data.

The properties of the lowest rated tranche reflect asset pool quality and the size of the subordinated FLP. It turns out that the rating of this tranche can be explained to a large extent by the asset pool quality, the FLP and the tranche size supporting Hypothesis 8. Including the share of expected losses improves the explanatory power of the regression. The DS negatively affects the rating in line with Lemma 3. The credit spread of the lowest rated tranche is explained best by WADP, the share of expected losses, the tranche size and the issue date, if rating is excluded. Thus, Hypothesis 8 is partly supported. The issue date is quite important for this spread reflecting changing market sentiment and risk aversion.
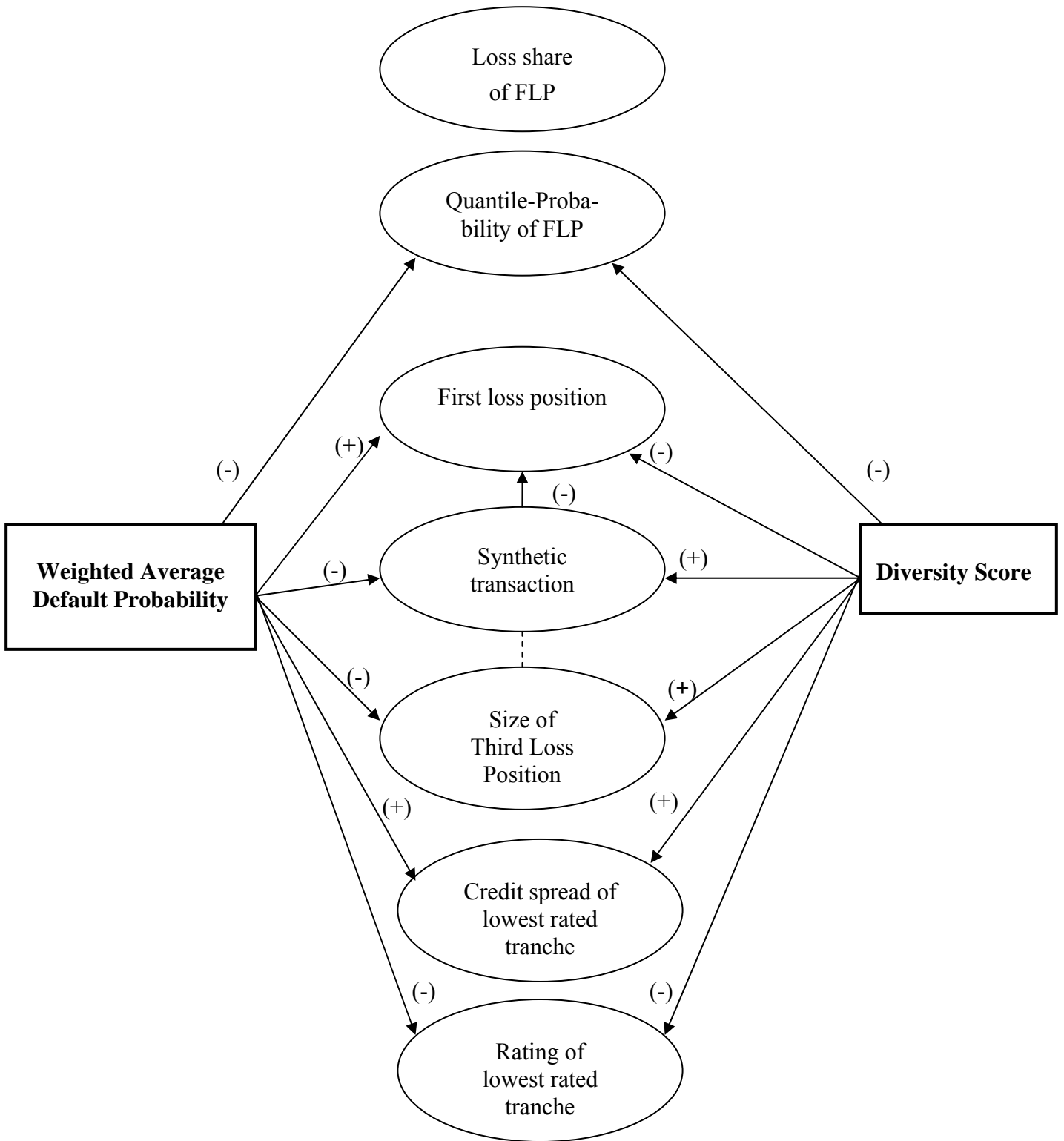
Fig. 2   It summarizes the empirical impact of the asset pool quality on other transaction characteristics. (+), (-) denotes a positive resp. negative regression coefficient.

But the credit spread of the lowest rated tranche is much better explained by its squared rating, the maturity of the transaction and the issue date, supporting Hypothesis 9. Adding other regressors does not improve the explanatory power of the regression. Investors may believe that rating agencies have much better information for valuing this very information-sensitive tranche and, hence, attach a high significance to the rating. Hypothesis 10, claiming a liquidity premium effect of the tranche volume on the credit spread, is not supported.

Finally, we discuss the impact of bank characteristics. Regarding asset pool quality, Tobin´s Q has no effect. Banks with a high total capital ratio appear to prefer asset pools with high WADP *and* high DS. It may be that banks with a high total capital ratio can afford to grant loans with high default probabilities and mitigate the high default risk of the loan portfolio through strong diversification. A high Tobin´s Q appears to render synthetic transactions less attractive relative to true sale transactions. It might be that an originator with a high Q is not interested in retaining the senior tranche with low credit risk since she has attractive real options. A high total capital ratio makes synthetic transactions more attractive, perhaps because the originators, not being plagued by capital regulation, may not worry about the default risk of the TLP.

A better originator rating renders synthetic transactions more attractive due to the funding motive. Otherwise this rating appears irrelevant. The funding motive helps to explain the puzzle that the least information-sensitive tranche is not sold to investors in a synthetic transaction. Fig. 3 displays two histograms, the left one shows credit spreads over EURIBOR/LIBOR of European bank bonds with a maturity of at least 5 years, rated AA- and better, issued between 2000 and 2005. The right histogram shows the credit spreads of only AAA-rated CDO-tranches of our sample. The mean credit spread of the bank bonds is 9.9 basis points, while it is 40.6 basis points for the AAA-tranches. The minimum (maximum) spread of the bank bonds is -27 (+25) basis points, while it is +1 (+100) basis points for the AAA-tranches. These figures clearly show that the credit spreads of highly rated bank bonds are often lower than those on AAA-tranches. Thus, funding through a true sale transaction likely implies a higher funding cost for highly rated banks than issuing standard bonds combined with a synthetic transaction. Possibly highly rated banks have a very good reputation which is not adequately reflected in their rating. This argument is also supported by the recent discussion of a proposal of Moody´s to upgrade the big banks because they might be too big to fail. Conversely, a AAA-tranche in a securitization transaction may face some investor scepticism because securitization transactions are relatively new instruments and there is no reliable history on their performance. Therefore a standard bond of a highly rated bank may be subject to fewer problems of information asymmetries than a AAA-tranche of a securitization transaction.
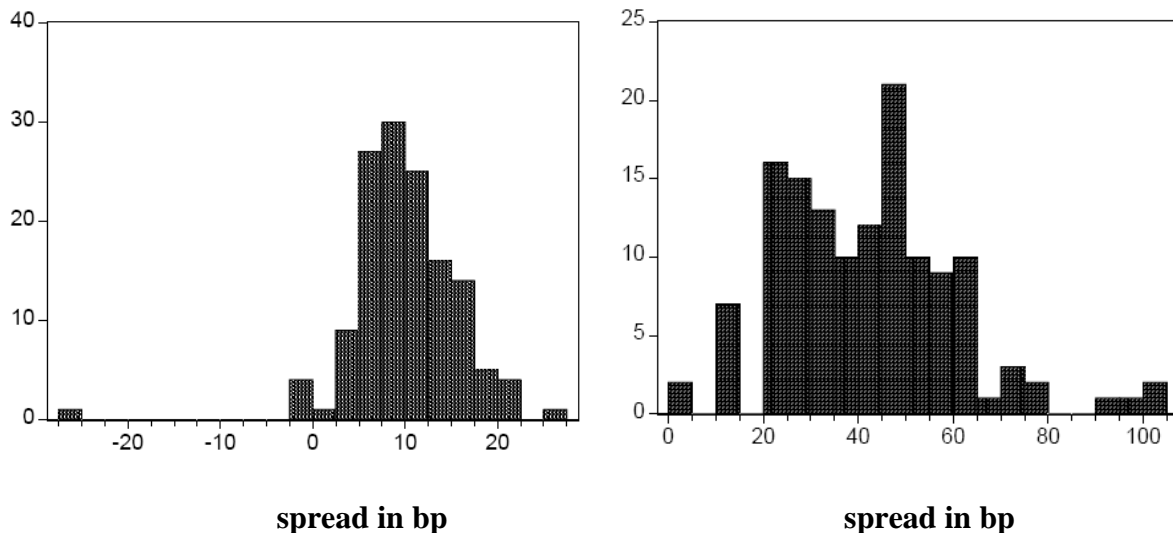
spread in bp   **spread in bp**

Fig. 3: The left histogram shows the credit spreads over EURIBOR/LIBOR of 137 European bank bonds with a maturity of at least 5 years, rated AA- or better, issued between 2000 and 2005. Data are obtained frorm DEALSCAN. The right histogram shows the credit spreads over EURIBOR/LIBOR of the 135 AAA-rated CDO-tranches of our securitization sample.

6. Conclusion

This paper investigates how problems of information asymmetries are dealt with in collateralised debt obligations through loss sharing arrangements. Market imperfections such as information asymmetries, regulatory costs, funding costs, transaction and management costs are likely to play a role in the transfer of default risks. The originator optimises the design of the securitization transaction so as to maximize her benefit. This paper analyses, in particular, the relation of the First Loss Position and, in synthetic transactions, the Third Loss Position to the quality of the underlying asset pool and the originator characteristics.

Using a sample of European transactions, asset pool quality is measured by its weighted average default probability and its diversity score. A higher default probability lowers the quality, while a higher diversity score improves it. Asset pool quality should be inversely related to information asymmetry and have a strong impact on the transaction design. It turns out that the First Loss Position is strongly inversely related to asset pool quality. Hence this position serves to mitigate information asymmetry problems. This position also is the most information-sensitive tranche which should not be sold to investors. The general guideline for the market appears to be that the First Loss Position should cover a high share of the expected default losses, independent of the asset pool quality. 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 *and* the diversity score of the asset pool.

Asset pool quality positively affects the originator´s preference for a synthetic transaction. More than half of the transactions are synthetic in which the originator does not sell the large information-insensitive super-senior tranche. This tranche represents a Third Loss Position of the originator unless she covers its default risk through a senior credit default swap. The size of the Third Loss Position increases with the quality of the asset pool, in strong contrast to the First Loss Position. Hence the Third Loss Position dos not serve to mitigate information asymmetry problems. Retaining this position is in strong contrast to the literature which argues that the originator should sell the least information-sensitive tranche. Selling this tranche does not achieve a substantial risk transfer, but may involve transaction costs and relatively high credit spreads so that the originator may consider this funding mechanism as too expensive. This appears to be true in particular for originators with a good rating.

The rating of the lowest rated tranche which is protected through the subordinated First Loss Position, is inversely related to the weighted average default probability *and* the diversity score of the asset pool and improves with loss sharing of the First Loss Position. Not surprisingly, the same variables affect the credit spread of the lowest rated tranche, but with opposite signs. Credit spreads are, however, better explained by the tranche ratings indicating that investors believe in superior information of rating agencies.

Bank characteristics have a surprisingly small impact on these choices. This indicates that choices are largely driven by attitudes of investors and rating agencies and much less by originator motives. The findings of this paper should be considered a first step. Clearly more empirical research is needed to better understand the design of CDO-transactions.

Appendix 1: Proof of Lemma 1a) and b)

a) A mean preserving spread is a second order stochastic dominance shift in the probability distribution of the loss rate, holding the mean constant. Let $F_1(l)$ and $F_2(l)$ denote the cumulative probability distribution before resp. after the mean preserving spread. A necessary and sufficient condition for a second order stochastic dominance shift is that $F_2(l)$ intersects $F_1(l)$ once from above. Let $\bar{l}$ denote the loss rate at the intersection. This is illustrated in Fig. 4.
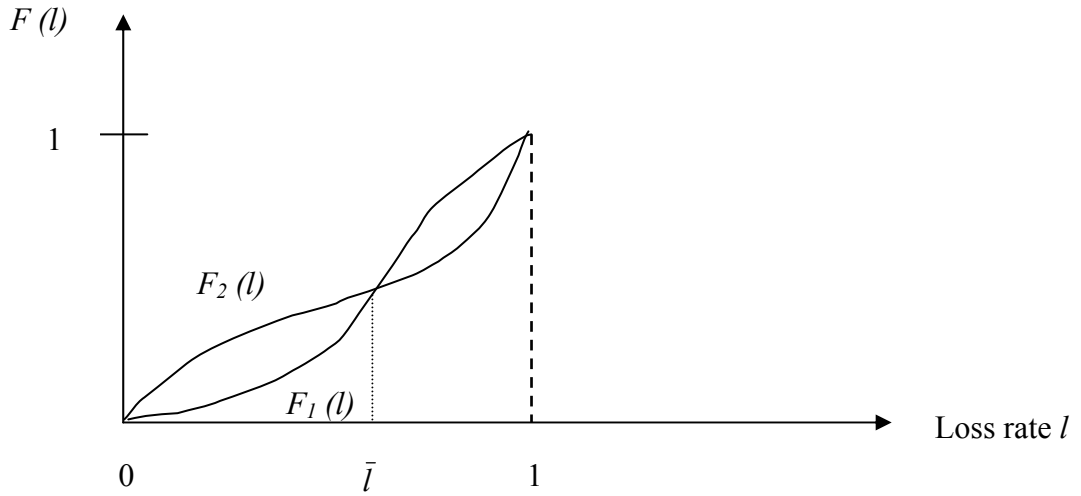
Fig. 4: The cumulative probability distribution of the loss rate $F_2(l)$, obtained from $F_1(l)$ by a mean preserving second order stochastic dominance shift, intersects $F_1(l)$ once from above at $l = \bar{l}$.

First, we show that the expected loss of the FLP is smaller under $F_2(l)$ than under $F_1(l)$. Suppose that the size of the FLP is smaller than $\bar{l}$. For $l \geq \bar{l}$, the loss of the FLP always equals FLP. For $l \leq \bar{l}$, $F_1(l)$ first order stochastically dominates $F_2(l)$. Hence the expected loss of the FLP is smaller under $F_2(l)$. Therefore the expected loss of the sold tranches must be higher, holding the mean constant.

Now suppose that the size of the FLP is higher than $\bar{l}$. Then, for $l \leq \bar{l}$, investors do not bear any losses. For $l \geq \bar{l}$, $F_2(l)$ first order stochastically dominates $F_1(l)$. Hence the sold tranches incur a higher expected loss under $F_2(l)$ so that the FLP bears a smaller expected loss.

b) A first order stochastic dominance deterioration in the loss rate distribution is characterized by $F_1(l) \geq F_2(l), \forall l$. This implies a higher probability of a complete loss of the FLP. Since a first order stochastic dominance deterioration is equivalently

characterized by replacing l through $l + \varepsilon(l)$ with $\varepsilon(l) \geq 0$ for every l, it follows that the FLP and the sold tranches incur higher expected losses.

Appendix 2

2.1 The parameters of the lognormal loss rate distribution

Let denote

λ = average loss given default across loans,

π = WADP = average probability of default,

S = average standard deviation of the loss rate across loans,

σ = standard deviation of the lognormally distributed portfolio loss rate, $\sigma = \sigma(\ln l)$,

μ = expectation of the lognormally distributed portfolio loss rate, $\mu = E(\ln l)$,

F_i = par value of loan i, divided by the par value of all loans; $i = 1, ..., n,$

ρ_{ij} = asset correlation between loan i and loan j.

Then the expectation of the portfolio loss rate equals

$E(l) = \lambda \pi$,

the average standard deviation of the loan loss rate across loans, S, is given by

$$S^2 = (0 - \lambda\pi)^2 (1 - \pi) + (\lambda - \lambda\pi)^2 \pi$$

$$= \pi(1 - \pi)\lambda^2 \tag{A.1}$$

Then the variance of the portfolio loss rate is obtained by dividing through the DS,

$$S_P^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} S^2 \ \rho_{ij} \ F_i F_j = S^2 \ \sum_{i=1}^{DS} \left(\frac{1}{DS} \right)^2 = S^2 / DS. \tag{A.2}$$

The latter part of the equation follows from the definition of the diversity score. It is the number of equally sized loans whose defaults are uncorrelated which generates the same variance of the portfolio loss rate.

Now assume that the portfolio loss rate is lognormally distributed. Then

$$S_P^2 = [E(l)]^2 \left[\exp \sigma^2 - 1 \right] \tag{A.3}$$

so that

$$\sigma^2 = ln \left[1 + \left(\frac{S_P}{E(l)} \right)^2 \right]$$

$$= ln \left[1 + \frac{1/\pi - 1}{DS} \right]. \tag{A.4}$$

For μ we obtain

$$\mu = ln E(l) - \sigma^2 / 2$$

$$= ln(\lambda \pi) - \frac{1}{2} ln \left[1 + \frac{1/\pi - 1}{DS} \right] \tag{A.5}$$

From these equations we obtain the sensitivities

$$\frac{\partial \mu}{\partial ln \pi} = 1 + \frac{1}{2} \frac{1}{1 + \pi(DS - 1)} > 0 \tag{A.6}$$

$$\frac{\partial \mu}{\partial ln DS} = \frac{1}{2} \frac{1 - \pi}{1 + \pi(DS - 1)} > 0 \tag{A.7}$$

$$\frac{\partial \sigma}{\partial ln \pi} = -\frac{1}{2\sigma} \frac{1}{1 + \pi(DS - 1)} < 0 \tag{A.8}$$

$$\frac{\partial \sigma}{\partial ln DS} = -\frac{1}{2\sigma} \frac{1 - \pi}{1 + \pi(DS - 1)} < 0 \tag{A.9}$$

2.2 Proof of Lemma 1c)

We show that given a lognormal loss rate distribution, the share of the expected loss borne by the FLP declines with a first order stochastic dominance deterioration. The expected loss of the FLP equals (*FLP – EP)* with *E(P)* being the expected loss of a put on the loss rate with strike price FLP. Applying the Black-Scholes model, the expected loss of the put equals

EP = - λ WADP N(h) + FLP N(h+σ)

with $h = \ln$ *(FLP/λ WADP)/σ –σ/2*. Hence the share of the expected loss borne by the FLP is

$s = $ *FLP / λ WADP - EP / λ WADP = N(h) +(FLP / λ WADP) (1 – N(h+σ)).*   (A.10)

Differentiating s with respect to ln *WADP* yields

$$\frac{\partial s}{\partial \ln WADP} = \frac{FLP}{\lambda\, WADP}\left(-\left[1 - N(h+\sigma) \right] - n(h+\sigma)\frac{\partial \sigma}{\partial \ln WADP}\right)$$

$$= -\frac{FLP}{\lambda\, WADP}\left(1 - N(h+\sigma) - n(h+\sigma)\frac{1}{2\sigma}\frac{1}{1+WADP(DS-1)}\right).$$

Hence $\partial s/\partial \ln WADP < 0$ if the term in the second bracket is positive.

Next we show that the second bracket is positive whenever $FLP \geq \lambda\, WADP$ and $\sigma(1+WADP(DS-1)) > 0.1$.

$$1 - N(h+\sigma) - n(h+\sigma)\frac{1}{2\sigma}\frac{1}{1+WADP(DS-1)} > 0 \text{ if}$$

$$\sigma(1+WADP(DS-1)) > \frac{1}{2}\frac{n(h+\sigma)}{1-N(h+\sigma)}.$$

$FLP \geq \lambda\, WADP$ implies $h + \sigma > 0$. For $h + \sigma \geq 0$ the right hand side of the previous inequality attains its maximum at $h + \sigma = 0$ which then yields about 0.1 for the right hand side.   Hence $FLP \geq \lambda\, WADP$ and $\sigma(1+WADP(DS-1)) > 0.1$ are sufficient for $\partial s / \partial \ln WADP < 0$.

It remains to be shown that $\sigma(1+WADP(DS-1)) > 0.1$. This is always true. Taking the square of this inequality and substituting for σ yields

$$\ln\left(1+\frac{\frac{1}{WADP}-1}{DS}\right) > \left(\frac{0.1}{1+WADP(DS-1)}\right)^2.$$

Taking exponentials yields approximately

$$1+\frac{\frac{1}{WADP}-1}{DS} > 1+\left(\frac{0.1}{1+WADP(DS-1)}\right)^2 \quad \text{or}$$

$$100\left(\frac{1}{WADP}-1\right) > \frac{DS}{(1+WADP(DS-1))^2}.$$

The right hand side attains its maximum at $DS = (1/WADP - 1)$. Therefore the last inequality holds if

$$100 > \frac{1}{(1+WADP(DS-1))^2}.$$

This is always true.   q.e.d.

2.3   Proof of Lemma 2a)

We need to show that, given a lognormal loss rate distribution, a mean preserving spread of this distribution implies a lower (higher) support-probability of the *FLP* if and only if the condition in Lemma 2a) holds.

Consider the probability distribution $N\left(\frac{lnl-\mu}{\sigma}\right)$. Differentiate with respect to *ln DS*.

$$\frac{\partial N(.)}{\partial lnDS} = n\left(\frac{lnl-\mu}{\sigma}\right)\left(-\frac{lnl-\mu}{\sigma^2}\frac{\partial\sigma}{\partial lnDS} - \frac{1}{\sigma}\frac{\partial\mu}{\partial lnDS}\right).$$

$\partial N(.)/\partial lnDS = 0$ at $l = \hat{l}$ if

$$-\frac{ln\hat{l}-\mu}{\sigma}\frac{\partial\sigma}{\partial lnDS} = \frac{\partial\mu}{\partial lnDS}.$$

Substituting from (1.10) and (1.12) yields $ln\hat{l} = \mu + \sigma^2$. Hence $\partial N(.)/\partial lnDS = 0$ at $l=FLP$ if $ln\ FLP = \mu + \sigma^2$. $\partial N(.)/\partial lnDS > 0$ at $l = FLP$ if $ln\ FLP > \mu + \sigma^2$ for a mean preserving contraction. Since $\mu = lnE(l) - \sigma^2/2$, $FLP \geq E(l)\exp(\sigma^2/2)$ is necessary and sufficient for $\partial N((lnFLP - \mu)/\sigma)/\partial lnDS > 0$. Substituting for σ yields the condition in Lemma 2a).

Appendix 3: Proof of Lemma 3

We need to show for a lognormal loss rate distribution that an adjustment of the FLP to a change in portfolio quality which preserves the loss share leads to a specific adjustment of the support-probability of the FLP if and only if $h<n\ (h+\sigma)/(1 - N(h+\sigma))$. The loss share is given by equation (A.10). Differentiating with respect to $ln\ \pi$ yields

$$\frac{\partial s}{\partial ln\pi} = \frac{\partial FLP}{\partial ln\pi}\frac{1 - N(h+\sigma)}{\lambda\pi} - \frac{FLP}{\lambda\pi}(1 - N(h+\sigma)) - \frac{FLP}{\lambda\pi}n(h+\sigma)\frac{\partial\sigma}{\partial\ln\pi} \qquad (A.11)$$

Hence $\partial s/\partial ln\pi = 0$ implies

$$\frac{\partial lnFLP}{\partial ln\pi} = 1 + \frac{n(h+\sigma)}{1 - N(h+\sigma)}\frac{\partial\sigma}{\partial\ln\pi} \qquad (A.12)$$

The support-probability of the FLP is $\gamma(FLP) = N(h+\sigma)$. Hence

$$\frac{\partial\gamma}{\partial ln\pi} = n(h+\sigma)\left[\frac{1}{\sigma}\left(\frac{\partial lnFLP}{\partial ln\pi} - 1\right) - \left(\frac{ln\dfrac{FLP}{\lambda\pi}}{\sigma^2} - \frac{1}{2}\right)\frac{\partial\sigma}{\partial ln\pi}\right]$$

$$= \frac{n(h+\sigma)}{\sigma}\left[\frac{\partial lnFLP}{\partial ln\pi} - 1 - h\frac{\partial\sigma}{\partial ln\pi}\right]$$

Hence $\partial\gamma/\partial ln\pi < 0$ if the bracketed term is negative. Substitute $\partial lnFLP/\partial ln\pi$ from (A.12). Then the bracketed term yields

$$\frac{\partial\sigma}{\partial ln\pi}\left[\frac{n(h+\sigma)}{1 - N(h+\sigma)} - h\right]. \qquad (A.13)$$

Since $\partial\sigma/\partial ln\pi < 0$ by (A.8), the term in (A.13) is negative if $h < n(h+\sigma)/(1 - N(h+\sigma))$. This proves Lemma 3 with respect to WADP $= \pi$. The proof for DS is analogous.

To prove the last statement in Lemma 3, note that $\partial\sigma/\partial ln\pi < 0$ and (A.12) imply $\partial lnFLP/\partial ln\pi < 1$. Hence $\partial FLP/\partial\pi < 1$ if $FLP \le \pi$.

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