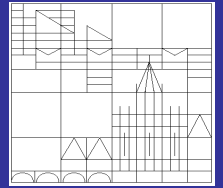




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Tranching and Pricing in CDO-Transactions***

Günter Franke* and Thomas Weber**

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Abstract

This paper empirically investigates the tranching and tranche pricing of European securitization transactions of corporate loans and bonds. Tranching allows the originator to issue bonds with strong quality differences and thereby attract heterogeneous investors. We find that the number of differently rated tranches in a transaction is inversely related to the quality of the underlying asset pool. Credit spreads on tranches in a transaction are inversely related to the number of tranches. The average price for transferring a unit of expected default risk, paid in a transaction, is inversely related to the default probability of the underlying asset pool. The average price, paid for a tranche, increases with the rating of the tranche, it is higher for the lowest rated tranche and very high for AAA-tranches in true sale-transactions. It varies little across butterfly spreads obtained from rated tranches except for the most senior spread.

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1 Introduction

The financial crisis starting in 2007 is intimately related to the securitization of mortgage backed securities. The crisis triggered a general discussion on the future of securitization including the role of originators and rating agencies. Currently, banks and regulators attempt to revive securitization because it is considered an important instrument for trade and allocation of default risks. The purpose of this paper is to analyse the tranching and pricing of bond tranches issued in a sample of European CDO (collateralized debt obligation)-transactions. Investors and originators can evaluate the costs and benefits of securitization only if they understand tranching and pricing. These properties are also important determinants of the social costs and benefits of securitizations. Mispricing of tranches, for example, might lead to misallocation of risks and necessitate regulation.

We analyse tranching and pricing because they are interdependent. In a perfect market tranching would be irrelevant. Market imperfections drive tranching and pricing. In most transactions, several differently rated tranches are issued to lower the average credit spread. In our sample of CDO-transactions corporate loans and bonds are securitized, as opposed to mortgage-backed securities transactions. The rating agencies have been criticised for overly optimistic ratings of mortgage-backed securities, but not for their ratings of CDO-transactions. The ratings of corporate loans and bonds have been quite stable until 2008. This also holds for the securitization of these instruments (Newman et al (2008)). Therefore insights from CDO-transactions launched before the crisis still appear useful for understanding securitizations.

CDO-transactions can be split in CLO- and CBO-transactions. In a collateralized loan obligation (CLO)-transaction a bank usually securitizes part of its corporate loans. In a collateralized bond (CBO)-transaction, a bank or an investment company buys corporate bonds, pools them and securitizes the asset pool. The transaction is either a true sale or a synthetic transaction. In a true sale transaction the originator sells the asset pool without recourse to a special purpose vehicle which funds itself through issuing an equity tranche and rated tranches. In a synthetic transaction the originator transfers the default risk of the underlying asset pool to a special purpose vehicle through a credit default swap. The special purpose vehicle also issues differently rated tranches, but usually only for a small portion of the par value of the asset pool.

The allocation of default losses to the issued tranches is governed by strict subordination. In a true sale transaction the equity tranche is usually not rated and called the First Loss Position (FLP). All default losses of the underlying asset pool are allocated exclusively to the FLP

until it is exhausted. Losses exceeding the FLP are allocated exclusively to the tranche with the lowest rating until it is exhausted, then exclusively to the tranche with the second lowest rating and so on. Therefore, the rated tranches exhibit strong quality differences. Strict subordination can be characterized also by the attachment and detachment point of tranches. These points are defined by special portfolio loss rates, i.e. ratios of default losses over the par value of the underlying asset pool. The attachment point of a tranche defines the portfolio loss rate such that the tranche incurs (no) losses whenever the portfolio loss rate is above (below) the attachment point. The detachment point of a tranche equals its attachment point plus its size, with the size of a tranche being its par value divided by the par value of the asset pool. Whenever the portfolio loss rate exceeds the detachment point of a tranche, then this tranche is fully exhausted by default losses. The detachment point of a tranche also defines the attachment point of the tranche with the adjacent better rating. In a true sale-transaction the sizes of the equity tranche, i.e. the First Loss Position, and the rated tranches add up to 1. The investors buying the rated tranches take the Second Loss Position.

In synthetic transactions loss allocation is somewhat different. The size of the FLP is a threshold of the portfolio loss rate such that the credit default swap only covers losses beyond the FLP. The credit default swap covers losses only up to its par value. This par value defines a Second Loss Position taken by the investors who buy the tranches from the special purpose vehicle. Losses which exceed the FLP and the par value of the credit default swap are born by the originator unless she insures against these losses. These non-securitized losses on the super-senior claims define a Third Loss Position. Such a position does not exist in true sale transactions.

Given the underlying asset pool, the originator, together with rating agencies and important investors, decides about the First Loss Position and the tranching of the rated bonds. In an imperfect market, these decisions may matter because of regulatory costs, management and transaction costs, costs related to asymmetric information, illiquidity premiums. To our best knowledge, this paper is the first to look at the interdependencies between tranching, pricing and asset pool quality. As the size of the FLP has been investigated in another paper (*Franke, Herrmann and Weber 2008*), this paper analyses the tranching and pricing of rated tranches.

The main findings of this paper can be summarized as follows. First, the number of differently rated tranches varies between 1 and 6. It tends to be higher for an asset pool of lower quality, i.e. a portfolio with a higher expected default loss or less diversification. For a lower asset pool quality a more differentiated tranching apparently pays for the originator. Also, a larger asset pool appears to raise the number of differently rated tranches, indicating

economies of scale effects. The tranche ratings are concentrated in the high rating classes. About 14 percent of the tranches are sub-investment grade. For lower quality-asset pools we often observe more tranches with lower ratings. Yet, within a transaction, tranches tend to be clustered more in the range of high than of low ratings.

In 88 percent of the transactions there exists a Aaa-tranche. In true sale-transactions, we observe very thick Aaa-tranches while in synthetic transactions the Aaa-tranche is usually very thin. Thickness or size of a tranche is defined by the par value of the tranche, divided by the par value of the underlying portfolio. In true sale-transactions the originator maximizes the size of the Aaa-tranche since the credit spread on this tranche is lower than that on any other tranche. In synthetic transactions the originator chooses a thin Aaa-tranche. This tranche may be an important quality signal for investors and regulators justifying its existence. But it is likely to be of little use in transferring default risk. Given high credit spreads of Aaa-tranches relative to corporate bonds and the restriction in synthetic transactions that the funds from issuing bond tranches need to be invested in top quality securities, presumably it does not pay for the originator to issue a higher volume of such a tranche than needed for signalling purposes.

Second, given the asset pool and the FLP, the originator tranches so as to minimize her transaction costs plus the weighted average credit spread paid on the rated tranches, besides of other costs such as the costs of required equity capital. Since weighted average credit spreads cannot be reasonably compared across transactions, we analyse annual risk premiums. The annual risk premium of the rated tranches in a transaction is defined as the weighted average credit spread minus the expected annual default loss borne by the rated tranches. To derive it, we approximate the probability distribution of the default loss rate of an asset pool by a lognormal distribution. This is clearly an approximation which could lead to biased results. We find for true sale-transactions that the annual risk premium of all rated tranches increases with the weighted average default probability of the underlying asset pool. This is not surprising since a higher weighted average default probability tends to raise the volume of transferred default risk which in turn should raise the risk premium. The risk premium declines in the number of rated tranches. More tranches apparently allow the originator to better tailor the tranches to differentiated investor needs so as to extract more investor rents. Also a higher number of tranches provides more information to investors and, thus, may mitigate information asymmetry problems and thereby reduce credit spreads.

Third, consider the relative risk premium of all rated tranches, i.e. the annual risk premium divided by the expected annual default loss of all rated tranches. The relative risk premium is

the average price for the transfer of a unit of expected default loss. It would be zero in a perfect, risk-neutral market. Our findings indicate that this price *declines* in the weighted average default probability of the underlying portfolio and *increases* in the size of the FLP. These price sensitivities are presumably driven by a pricing kernel effect. A lower asset pool quality tends to be associated with relatively more default losses in “cheap” macro states, i.e. in states with low stochastic discount factors. This property should also hold for all rated tranches together, lowering the average price for the transfer of a unit of expected default loss. Consistent with this, a higher share of expected default losses borne by the FLP raises the average price because it tends to take away default losses in the “cheap” macro states. A higher number of tranches lowers the average price, consistent with extracting more investor rents. The observed negative impact of asset pool diversification on the average price is consistent with an information asymmetry effect. More diversification tends to reduce information asymmetry which might reduce credit spreads.

Fourth, the empirical analysis of individual tranches mostly confirms the results for the risk premiums of all rated tranches. While the annual risk premium of a tranche *increases* with the weighted average default probability of the underlying asset pool, the relative risk premium *declines*. A higher number of subordinated tranches tends to lower the annual risk premium of a tranche. This finding is not surprising since more subordinated tranches indicate a higher attachment point of the tranche, reducing its expected default loss. Interestingly, the explanatory power of the number of subordinated tranches is stronger than that of the attachment point. The negative impact of the number of subordinated tranches is also consistent with an information asymmetry effect since more tranches mitigate this asymmetry. Fifth, in general, the relative risk premium of a tranche increases with its attachment point, also with its rating. This finding can be explained by a pricing kernel effect. Against the rule, the lowest rated tranche generates a higher relative risk premium than the mezzanine tranches. This suggests a complexity premium of the lowest rated tranche, perhaps for more expensive risk management of this tranche. Much more dramatic, however, is the very high relative risk premium paid on Aaa-tranches in true sale-transactions. This can be attributed to a very strong pricing kernel effect. Aaa-tranches tend to incur default losses only in states in which the aggregate default losses are very high indicating high stochastic discount factors. Since Aaa-tranches should be very information-insensitive, the high relative risk premium cannot be explained by information asymmetry. To check the pricing kernel effects more carefully, we also analyse butterfly spreads, similar to state-contingent claims. Surprisingly, we do not find a significant relation between the relative risk premium of a butterfly spread and its

attachment point although the relative premium of Aaa-tranches in true sale-transactions increases with the attachment point. Hence the finding that the relative risk premium of a tranche increases with its attachment point should not be taken as evidence of a monotonically increasing pricing kernel.

These findings are new, to our best knowledge, and improve our understanding of tranching and pricing in securitization transactions. The evidence is based on a set of European securitization transactions which may not be representative for other parts of the globe. Also the financial crisis has led to changes in regulation and behaviour of originators and investors. Therefore tranching and pricing might have changed. Further research is needed to better understand these issues.

The paper is organized as follows. The next section provides a literature review. Section 3 derives hypotheses about tranching and pricing. These hypotheses are tested and discussed in section 4. Section 5 concludes.

2 Literature Review

Various theoretical papers analyse the optimal design of financial contracts. Several papers advocate the benefits of tranching in the presence of information asymmetry between the seller and the buyer of a claim. Tranching allows to differentiate the degree of information-sensitivity of the issued 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 portfolio diversification which mitigates information asymmetries. *DeMarzo (2005)* considers a bank which may securitize a portfolio of debt claims by issuing a collateralized debt obligation (CDO). The bank can sell claims separately and, thereby, signal information about the quality of the different loans. Pooling the claims precludes this, but leads to a well-diversified portfolio mitigating information asymmetries. This allows the originator to issue low-risk, information-insensitive tranches. *DeMarzo* argues that for large portfolios the diversification benefit of pooling outweighs the information destruction cost.

To analyse the pricing of securitization tranches, it is necessary to model the distribution of the portfolio default losses. Many papers discuss this issue. *Duffie and Garleanu (2001)* suggest a default risk model using obligor default intensities. They discuss Moody's diversity

score and illustrate the sensitivity of the portfolio loss rate distribution to various parameters including the weighted average default probability, the default correlation and the diversity score. *Krahnert and Wilde (2008)* simulate the portfolio loss rate distribution and the tranche loss rate distributions for CDO-transactions. They also analyse the sensitivity of these loss rate distributions to changes in the simulation parameters. The differences between the loss rate distributions of standard bonds and CDO-tranches are nicely illustrated¹. *Duffie et al (2009)* argue that models underestimate the tail risks because they miss unobservable, non-stationary risk factors which raise default correlations. Also *Berndt, Ritchken and Sun (2010)* address default correlations in several ways; shocks to the economy can cause jumps in the credit spreads. *Tarashew (2010)* shows that parameter uncertainty also raises the tail risk. *Albrecher, Ladoucette and Schoutens (2007)* propose a generic one factor Lévy model for the portfolio loss rate distribution. *Burtschell, Gregory and Laurent (2009)* derive default intensities for CDOs using models with one latent factor and different copulas. *Krekel (2008)* proposes a Gaussian base correlation model with correlated recovery rates to improve the empirical model fit.

Several empirical papers investigate individual name corporate bond spreads and find high expected excess returns, e.g. *Driessen (2005)* and *Chen, Collin-Dufresne, Goldstein (2009)*. This is often referred to as the ‘credit spread puzzle’. *Elton et al (2001)* find that only a small fraction of credit spreads is explained by expected default losses, substantial fractions are explained by tax and liquidity effects. Other empirical papers study the tranching and pricing in securitizations. *Amato and Remolona (2003)* analyze the credit spread puzzle and, in particular, investigate collateralized bond obligations. They find very high average spread ratios of the tranches; the spread ratio of a bond is defined as its promised spread divided by its annualized expected default loss. They argue that, due to the strong skewness of the default loss distribution, idiosyncratic default risk cannot be fully diversified in typical bond portfolios, and therefore earns a significant premium.

Childs, Ott and Riddiough (1996) investigate the pricing of Commercial Mortgage-Backed securities (CMBS) and conclude that the correlation structure of the asset pool and the tranching are important determinants of the launch spreads of the tranches. *Maris and Segal (2002)* examine credit spreads in CMBS-transactions and document the empirical impact of several macro-variables, similar to *Duffee (1998)*. *Titman, Tompaidis and Tsyplakov (2005)* analyse determinants of credit spreads in MBS-transactions and find that spreads widen after poor performance of real estate markets. *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 initial spreads of tranches in securitizations and finds that ratings are very important determinants besides of general capital market conditions.

Longstaff and Rajan (2008) analyze the market prices of tranches on the CDX credit index. They find a three-modal loss rate distribution and attribute about two thirds of the CDX spread variations to firm specific risk, one fourth to market expectations about joint defaults of firms in an industry, the remaining small rest to systemic default risk. The paper which is closest to ours is *Weber* (2008). He uses launch spreads of tranches in synthetic CDO-transactions and information on the underlying portfolio quality to derive levels of relative risk aversion implied by the credit spreads of tranches. He finds significantly higher levels of relative risk aversion for better rated tranches indicating high risk premiums for defaults in states with high aggregate default losses. Deteriorating portfolio quality lowers relative risk aversion. *Weber* also finds that the lowest rated tranche of a transaction earns an additional risk premium and that deteriorating portfolio diversification increases risk premiums for the two lowest rated tranches. He interprets this as evidence for additional costs due to information asymmetries².

Finally, several recent papers address moral hazard issues in securitizations, for example *Purnanandam* (2008), *Loutskina and Strahan* (2009) and *Piskorski, Seru and Vig* (2010).

3 Derivation of Hypotheses

This section derives hypotheses about tranching and pricing in securitization transactions. Given the underlying asset pool in a transaction, tranching is defined by the size of the non-rated FLP, the number and the properties of the rated tranches. The offering circular shows for each tranche the attachment and the detachment point, the rating and the credit spread so that this is public information. The originator decides about the number, the ratings and credit spreads of rated tranches, in cooperation with rating agencies and major investors. Rating agencies play a very important role in this process. They determine the attachment and detachment points of the tranches and their ratings. The main tool for determining these tranche properties are simulation models, supplemented by stress tests and the analysis of various transaction characteristics. We derive hypotheses about tranching and pricing by analysing, first, effects of market imperfections, and, second, pricing kernel effects.

3.1 Market imperfections and tranching

Tranching and pricing are driven by market imperfections. They include transaction and management costs, incompleteness of capital markets, costs of regulatory equity capital, illiquidity and liquidity risks of securities, taxes and information asymmetries between the originator and investors. Investors buy rated tranches to optimize their expected net income and their risk. Net income is defined as the gross income (= interest income - funding costs - default losses) minus other costs including transaction costs and taxes. Investors demand credit spreads which compensate them for their costs and the tranche risks. The level of these costs and risks may depend on tranching. Hence the originator may use tranching to reduce these costs.

3.1.1 Market incompleteness, portfolio quality and information asymmetry

Market incompleteness is one reason for tranching. If markets are incomplete, then adding new securities which are not spanned by existing securities is mostly beneficial (*Marin/Rahi (2000)*). New securities enlarge the set of trading opportunities for investors and, thus, allow them to put together portfolios which better fit their needs. This should lower credit spreads and, thus, motivate the originator to issue many rated tranches (*Cuchra (2005)*)³.

Arguments for tranching can also be derived from information asymmetry. (1) A bank securitizing part of its loan portfolio is likely to know more about the quality of the underlying loans than investors. According to *Boot and Thakor (1993)*, the originator should split the bonds in a securitization transaction into information-insensitive senior and information-sensitive junior bonds (see also *DeMarzo and Duffie (1999)*). This idea can be extended to the subset of rated tranches. More differently rated tranches provide more differentiation of information sensitivity and, thus, may better fit investor needs. (2) A higher number of rated tranches provides more information to investors. For each rated tranche, the attachment and the detachment points together with the rating and the credit spread are published. This information helps investors to more reliably infer the parameters of the portfolio loss rate distribution. (3) Suppose that tranche-ratings are governed by tranche-default probabilities as is true of S&P and Fitch. Split one tranche with a given size and a given rating into two tranches which together have the same size. Hence the new senior tranche has a better rating. As ratings affect credit spreads in the presence of information asymmetries, tranche splitting should reduce the overall credit spread paid on both tranches (see also *Brennan/Hein/Poon 2009*). (4) A higher number of rated tranches may provide investors of senior tranches with more early warning signals. Each time a subordinated

tranche is hit by default losses for the first time, a signal is sent. The more rated tranches exist, the more signals are sent, the smaller information asymmetry may be, perhaps leading to smaller credit spreads. The preceding arguments motivate

Hypothesis 1: Given the underlying portfolio quality and the size of the equity tranche, a higher number of differently rated tranches reduces the weighted average credit spread of the rated tranches.

The optimal number of tranches chosen by the originator depends on marginal costs and benefits of tranches. The originator's management and transaction costs increase in the number of tranches. Hence there is a tradeoff between the benefits and costs of additional tranches. As the marginal benefit declines, an interior optimal number of tranches should exist. Due to economies of scale-effects, a higher transaction volume should raise the marginal tranche benefit, and, thus, the optimal number of tranches.

The marginal benefit of a tranche should be inversely related to the quality of the underlying asset pool for two reasons. First, given a very good quality, there is little to be gained by tranching. Hence we should observe only a few tranches. For a low asset pool quality, the loss rate distribution would have a high mean and be broad providing more room for differently rated tranches.

Second, the marginal benefit of a tranche should be higher, the stronger is the information asymmetry between the originator and investors. This asymmetry cannot be observed directly. We proxy it by the asset pool quality. We conjecture an inverse relation between asset pool quality and information asymmetry. Rating agencies publish information on the asset pool quality. It can be measured by the weighted average default probability of the asset pool (WADP) and its diversity score (DS). WADP is an average of the default probabilities of all assets, weighted by the par values of assets. Since the loss given default for each asset is often not available, assume that it is a constant being the same for all assets. Then the expected portfolio loss rate equals WADP, multiplied by this constant. The second measure of asset pool quality is asset pool diversification. The diversification of the loan portfolio can be summarized in a diversity measure as done in Moody's Diversity Score (DS) or, in a refined version, an adjusted diversity score (ADS). An increase in WADP lowers asset pool quality while an increase in DS improves it. Errors in estimating WADP are likely to be proportional to the true WADP, implying a positive relation between WADP and information asymmetry. But a high DS reduces information asymmetries because the idiosyncratic risks of the assets are diversified away (DeMarzo (2005)). This inverse relation between asset pool quality and

information asymmetries is also consistent with the empirical findings in *Franke, Herrmann/Weber* (2008) about asset pool quality and loss allocation in securitization transactions. They find that a better quality reduces the size of the FLP. The FLP is the most important credit enhancement in a securitization to mitigate problems of adverse selection and moral hazard. Hence we use asset pool quality as an inversely related proxy for information asymmetry. The preceding arguments support

Hypothesis 2:

- a) *The optimal number of differently rated tranches is inversely related to the quality of the asset pool.*
- b) *The optimal number of differently rated tranches grows with the transaction volume.*

3.1.2 Costs of Equity Capital and Funding Costs

Within a transaction the credit spread is lower for a tranche with a better rating. Hence every originator minimizes the attachment of the Aaa-tranche to minimize credit spreads. Also regulators require less equity capital for a better rated tranche under Basel II⁴. Therefore, the originator maximizes the size of the Aaa-tranche in a fully funded true sale-transaction.

In synthetic transactions the revenue from issuing tranches needs to be invested in top quality-securities so that the originator cannot use it for funding. As shown by *Franke, Herrmann and Weber* (2008), synthetic transactions are preferred to true sale transactions by banks with a strong rating. For them funding through standard bank bonds appears to be cheaper than funding through a Aaa-tranche. Also a Aaa-tranche does not allow a substantial default risk transfer so that we should not observe Aaa-tranches in synthetic transactions. Yet, most synthetic transactions include a Aaa-tranche. The purpose of this tranche may be to provide a quality signal to investors and regulators. Also the quality of the non-securitized super-senior tranche should be even better than that of the Aaa-tranche, implying very little regulatory capital and low cost of buying protection for default risk. For these purposes, a very small Aaa-tranche should suffice in synthetic transactions. This motivates

Hypothesis 3: In true sale-transactions the originator chooses a very large Aaa-tranche, in synthetic transactions a very small Aaa-tranche.

3.2 Absolute and Relative Risk Premiums of Rated Tranches

3.2.1 Loss Volume and Information Asymmetry

Credit spreads of bonds are driven by expected default losses, pricing kernel effects, tax, liquidity, maturity and other effects (*Driessen 2005*). This should also be true for initial credit spreads of tranches in securitization transactions. Since we analyse initial credit spreads, we need not care about seasoning effects. We do not have data on taxes, transaction costs and liquidity premiums for our set of European transactions. Therefore we refrain from modelling these determinants of credit spreads. To investigate the pricing of default losses in securitization transactions, we focus on the volume of expected default losses, on information asymmetry effects and on pricing kernel effects. We analyse the annual risk premiums of rated tranches,

$$\begin{aligned} \text{annual risk premium of tranche} &= \text{tranche credit spread} \\ &- \text{expected tranche loss per € invested / transaction maturity} \end{aligned}$$

Since the credit spread is the spread earned per € invested, we subtract the annualized expected tranche loss per € invested. It equals the expected default loss borne by the tranche divided by its par value and by the maturity of the transaction. Without loss of generality, we assume a par value of 1 € for the transaction volume. Then the default loss of the asset pool equals its loss rate and the par value of a tranche equals its size. For simplicity, the tranche loss per € invested is denoted the tranche loss.

The annual risk premium is the credit spread of the tranche minus its expected annual default loss. If investors are risk averse, then a higher expected tranche loss should imply a higher annual risk premium.

Hypothesis 4 (loss volume effect):

- a) *An increase in the annualized expected tranche loss raises its annual risk premium.*
- b) *Given the loss share of the First Loss Position, the annual risk premium of the rated tranches increases with the weighted average default probability of the asset pool.*

Hypothesis 4a) relates the annual risk premium of an individual tranche to its expected loss volume. Hypothesis 4b) addresses the annual risk premium of all rated tranches in a transaction. The annual risk premium of the rated tranches in a transaction is defined as the weighted average credit spread minus the annualized expected default loss borne by the rated tranches. Assuming the same loss given default across transactions, the expected default loss rate of the asset pool is determined by its weighted average default probability. By Hypothesis 4b), a higher expected loss rate of the asset pool should raise the annual risk premium of the rated tranches, given the loss share of the First Loss Position. This share is defined as the

expected default loss borne by the First Loss Position, divided by the expected loss of the asset pool. Given the loss share, the expected loss of the rated tranches increases with the weighted average default probability of the asset pool so that the risk premium should increase (Hypothesis 4b). This is not precisely true for synthetic transactions because the loss share of the non-securitized Third Loss Position might change. But this share is very small anyway so that we ignore it here.

To address information asymmetry effects, we analyse the annual risk premium and the relative risk premium.

relative risk premium of tranche = annual risk premium of tranche/ annualized expected tranche loss

The relative risk premium of a tranche can be interpreted as the average risk price per unit of expected default loss for this tranche. It would be zero in a perfect, risk-neutral market; then the credit spread would cover the expected loss only. *Amato/Remolona (2003)* and *Chen et al (2009)* use the risk-neutral over the physical probability of default losses to analyse the credit spread puzzle. This measure is closely related to ours.

Since investors are averse to information asymmetry, this asymmetry should raise the annual and the relative tranche-risk premiums.

Hypothesis 5 (information asymmetry effect): The annual and relative risk premiums of rated tranches increase with information asymmetry. Hence they are inversely related to asset pool quality, to the loss share of the First Loss Position and the number of rated tranches.

The impact of asset pool quality and the number of rated tranches on information asymmetry has been discussed before. A higher First Loss Position discourages the originator from adverse selection and moral hazard so that a higher loss share should reduce information asymmetry, and, thus, risk premiums.

3.2.2 Pricing Kernel Effects

More complicated are the pricing kernel effects on tranche pricing. Several studies find that the relative risk premium is lower for bonds and loans with a lower rating. For European Aaa, Aa, A and Baa rated bonds *Amato/Remolona (2003)* find average ratios of credit spreads over annualised expected losses of 210, 35, 6.7 and 1.6, respectively. For the US, they report 625 for Aaa-bonds and 2.2 for Baa-bonds. *Berndt et al (2005)* find that the ratio of risk neutral over actual default intensities is higher for safer firms. Similarly, *Chen et al (2009)* find much

higher values for Aaa- than for Baa-firms. Similar effects should also be observed for securitizations with different WADPs of the asset pools. *Weber* (2008) looked into synthetic transactions and derived the portfolio loss rate distribution by a simulation model. Using a pricing kernel with constant relative risk aversion, he finds that the estimated relative risk aversion is highest for the Aaa-tranche and lower for lower rated tranches except for the lowest rated tranche. Since the Aaa-tranche only bears the tail risk which is likely to materialize in states of high aggregate default losses, the tail risk should command a high risk premium. But it should be kept in mind that the estimation of the tail risk is particularly sensitive to estimation errors. Therefore the estimates of the Aaa-tranche risk premiums should be interpreted with caution. The intuition for all these findings is that the losses of the better rated bonds are more heavily concentrated in bad macro-states with high stochastic discount factors.

To model the pricing kernel effect, we assume that the stochastic discount factor depends on a macro-factor and, perhaps, orthogonal industry-factors. The macro-factor might be the aggregate default loss rate in the economy. This would be true in a world in which investors only bear default risk. But even if investors also invest in stocks, it is likely that stock prices are depressed when default losses in the economy are high and vice versa. Therefore the pricing kernel is likely to be an increasing function of the aggregate default loss rate. It might also increase in industry default rates. Given a rather well-diversified asset pool it is likely that the asset pool-loss rate is strongly positively correlated with the aggregate default rate.

For illustration, consider a standard linear *Gordy*-type model (2003) and combine it with the KMV-approach (see also *Tarashew* (2010)). We use this simple model to illustrate the basic idea which also holds in more sophisticated models. In this model, the at t - total market value of an obligor firm in industry i , $V(t)$, divided by the current market value $V(0)$, is driven by the aggregate default rate m , an orthogonal industry-factor n_i and an idiosyncratic risk factor ϵ , all standardized to zero expectation and unit variance,

$$V(t)/V(0) = a + \sigma[-m\sqrt{\rho} - n_i\sqrt{\rho} + \epsilon\sqrt{(1-\rho-\rho)}]$$

$-\sqrt{\rho}$ is the correlation coefficient between the firm value and the macro-factor, $-\sqrt{\rho}$ the correlation coefficient between the firm value and the orthogonal industry-factor. $V(t)/V(0)$ has an expectation of a and a standard deviation of σ . Suppose that the firm defaults when $V(t)$ falls below a given trigger D . Then, assuming that the industry-factor and the idiosyncratic factor are normally distributed, the physical *PD* of the obligor, conditional on m , is given by

$$PD(m) = Prob(V(t) \leq D | m) = N((- \Delta + m\sqrt{\rho})/\sqrt{1-\rho})$$

with $\Delta = (a-D/V(0))/\sigma$ being the distance to default and $N(\cdot)$ the cumulative standard normal distribution. Clearly, the conditional PD increases with the aggregate default rate if $\rho > 0$.

To see the impact of the macro-factor on tranche pricing, first consider a standard corporate bond. Then a lower obligor quality, measured by a smaller distance to default, should raise the annualized risk premium, because the volume of expected default losses increases. But, given a negative correlation between firm value and macro-factor, the relative risk premium should decline because default losses should be concentrated relatively more in the “cheap” macro-states where the macro-factor, say the aggregate default rate, is low⁵. If the orthogonal industry-factor is also priced, this might reinforce the decline in the relative risk premium. Hence the relative risk premium should decline if the distance to default does. This is in line with the empirical findings for corporate bonds. Similarly, the relative risk premium for the asset pool underlying a securitization should decline with the pool-distance to default.

For a rated tranche, the distance to default-effect is complicated by the feedback-effect on its attachment point. A higher WADP of the asset pool tends to raise the FLP and also the attachment points of the rated tranches, given their ratings. An increase in the attachment point, ceteris paribus, should raise the relative risk premium of the tranche because a higher attachment point tends to concentrate tranche losses in the range of “expensive” macro-states with high aggregate default rates. This motivates Hypothesis 6a).

Hypothesis 6 (pricing kernel and attachment point effects):

- a) *The relative risk premium of a rated tranche increases with its attachment point.*
- b) *An increase in the weighted average default probability of the asset pool lowers the relative risk premiums of the rated tranches with a low rating and raises those of highly rated tranches.*
- c) *An increase in the diversity score of the asset pool lowers the relative risk premiums of all rated tranches.*

To motivate Hypothesis 6b), we analyse two opposing effects of an increase in the WADP of the asset pool. While the relative risk premium of the asset pool tends to decline with increasing WADP, the likely increase in the attachment point of a tranche should raise its relative risk premium. If the pricing kernel is relatively flat for a wide range of macro-states

and increases strongly in the bad macro-states, then the attachment point effect should be relatively small for tranches with low attachment points. Therefore the relative risk premium of the lower rated tranches should decline with increasing WADP. For tranches with high attachment points, we might see the opposite result because the default losses are concentrated in the very bad macro states. Then the attachment point effect might dominate the WADP-effect.

Hypothesis 6c) relates to asset pool diversification. A higher diversity score concentrates asset pool default losses around the expected loss rate. Assuming value additivity, this should have no effect on the relative risk premium of the asset pool. Hence the effect of the DS on the relative risk premium of a tranche should be driven by the attachment point effect. Suppose that the attachment point is larger than the expected portfolio loss rate⁶. Then a higher DS should lower the attachment point of a rated tranche to preserve its PD or its expected loss. As a consequence, according to Hypothesis 6a), the relative tranche-risk premium should decline.

A final hypothesis concerns the importance of ratings for risk premiums. Rating agencies claim to have very good information so that their ratings depend little on information asymmetries. Also, ratings appear to be very important for investors. This suggests that investors rely more on tranche rating than on asset pool quality and observable tranche properties. This motivates

Hypothesis 7: The annual and the relative risk premium of a tranche are better explained by the tranche rating than by the underlying portfolio quality, the size and the attachment point of the tranche.

These hypotheses will be tested in the following.

4 Empirical Findings

4.1 Summary Statistics

Our empirical analysis is based on 167 European CDO-transactions. Except for two poorly documented transactions, these transactions include all European CDO-transactions between the end of 1997 and the end of 2005, for which we know Moody's diversity score and for which we can derive WADP. These transactions represent about half of the European CDO-transactions over this time period. The data are collected from offering circulars, Moody's presale reports on CDO-transactions and from the Deutsche Bank Almanac.

Moody's diversity score DS was criticized as a diversification measure because it ignores correlations between obligors of different industries. The adjusted diversity score is a more sophisticated diversification measure; it assumes an asset correlation ρ_{ex} between all obligors in the underlying asset pool and an additional correlation ($\rho_{int} - \rho_{ex}$) for obligors within the same industry. Rating agencies use these correlations in their simulation models to derive the loss rate distributions of asset pools. We use additional information on the industry structure of asset pools from securitization documents to derive the adjusted diversity score ADS. This is possible only for 92 transactions. We assume an intra-industry correlation $\rho_{int} = 20$ percent and an inter-industry correlation of $\rho_{ex} = 0, 2$ or 4 percent. There is no agreement on the "correct" asset correlations. As illustrated in *Fender/Kiff* (2004) and confirmed in informal discussions with the rating agencies, the assumed correlations appear to be roughly in line with those used by the agencies.

First, we present some summary statistics (Table 1). About 48 % are true sale-transactions, about 52 % are synthetic. About 44 (56) % are CLO (CBO)-transactions. Most of the transactions were set up between 2000 and 2004.

- Table 1 -

As shown in Table 2, the weighted average default probability (WADP) is, on average, much smaller for synthetic than for true sale-transactions. As expected, the FLP shows a similar pattern. CLO-transactions tend to be much better diversified than CBO-transactions.

- Table 2 -

Table 3 provides an overview of the tranching. In many transactions, there are some rated tranches which are not subordinated to each other. For example, two equally ranking tranches are denominated in different currencies or one tranche pays a fixed coupon while the other tranche pays a floating rate. We count tranches of equal ranking as one tranche because we focus on quality differentiation in tranching. As the upper and the lower panel in Table 3 show, the number of tranches with different ratings varies between 1 and 6. Most transactions have 3 to 5 differently rated tranches. 14 transactions have only one rated tranche (single-tranche deals⁷) while 6 transactions have 6 tranches. In 9 transactions with 4 or 5 tranches there are two strictly subordinated Aaa-tranches which we count as two differently rated tranches. The total number of tranches within a rating class is, by far, the highest for Aaa. 88

% of all transactions have at least one Aaa-tranche. Also, there is a concentration of tranches in Aa2, A2, Baa2 and Ba2 which correspond to the “even” S&P-ratings AA, A, BBB and BB. The tranches in the few-tranche-deals are mostly concentrated in the good rating classes. The more tranches are issued, the more likely low rated tranches are issued, too. About 14% of the tranches are subinvestment-grade. They exist mostly in 4, 5- and 6-tranche deals. B-rated tranches are issued only in synthetic deals with at least 4 tranches.

- Table 3 -

Additional evidence on tranche rating can be obtained by looking at the rating range and the average rating gap for transactions with at least two rated tranches. The rating range of a transaction, i.e. the range between the lowest and the highest rating within a transaction, is defined as (1 + the difference between the lowest and the highest rated tranche measured in rating notches). We assign 1 to the rating Aaa, 2 to Aa1, 3 to Aa2 and so forth until 16 to B3. Given at least two rated tranches, the minimum rating range is 2 while the maximum rating range is 16 (for a transaction with a Aaa- and a B3-tranche). In addition, define for each transaction

average rating gap = (rating range - number of rated tranches) / (number of rated tranches - 1).
It indicates how many notches between two adjacent tranche ratings are missing on average within a transaction. Table 4 gives the results.

- Table 4 -

This table supports the visual impression of Table 3 that a higher number of tranches is associated with a wider rating range. Since most transactions have a Aaa-tranche, a higher number of tranches tends to add tranches with lower ratings. While the median rating gap is 4 given 2 rated tranches, it declines to 2, given 4 or more rated tranches. Hence even though a higher number of tranches includes tranches with lower ratings, the median rating gap declines, indicating a stronger clustering of ratings.

If there are more than two rated tranches, then the question arises whether these tranches are clustered more in the higher or the lower rating range. Define for each transaction

$$\text{rating asymmetry measure} = \sum_i (\text{rating gap } i / \text{average rating gap of transaction}) (i / \sum_i) - 1$$

The rating gap between two adjacent tranches is the difference between their numerical ratings minus 1, i.e. the number of missing notches between the two tranches. The rating gap between the two highest rated tranches is indexed by $i = 1$, the rating gap between the second and third best rated tranches is indexed $i = 2$ and so on. Rating gaps are attached a higher weight ($i/\sum i$), the lower are the ratings of the adjacent tranches. The rating asymmetry measure is 0 when the rating gaps are the same for tranches with high and low ratings. The measure is positive when the rating gaps are larger between tranches with low ratings. In our sample the rating asymmetry measure has a mean of 0.087, a standard deviation of 0.20, a minimum of $-1/3$ and a maximum of 1.17. This indicates that rating gaps tend to be stronger between tranches with lower ratings, i.e. ratings are clustered more in the higher rating range. Possibly a more differentiated tranching does not pay in the range of lower ratings because investors buying these tranches are more sophisticated and do not rely much on ratings. Another potential explanation might be that tranche sizes tend to be smaller in the range of low ratings so that it does not pay to split a small tranche. Therefore we next look at the tranche sizes (Table 5).

- Table 5 -

In true sale transactions the average size of the Aaa-tranche is large. It declines from 81% for single-tranche deals to 68% for deals with 6 rated tranches, with an average of about 76 %. In synthetic deals the average size of the Aaa-tranche varies between 3 % for single-tranche deals and 5 % for deals with 3 or 4 tranches, with an average of about 4.5 %. Thus, Hypothesis 3 is clearly supported. The small average size of Aaa-tranches in synthetic deals can be understood better in relation to the non-securitized super-senior tranche (Third Loss Position) which is on average about 87 % (excluding 3 atypical fully funded synthetic transactions). Adding this and the average size of the Aaa-tranche yields 91.5 % for synthetic deals. Hence the attachment point of Aaa-tranches is about 15 % higher in synthetic than in true sale transactions. This is due to the better quality of the asset pools in synthetic deals. The quality difference materializes also in the sizes of the FLPs. The average size of the FLP is about 8.7 % in true sale and 3.3 % in synthetic transactions. The aggregate size of all rated non-Aaa-tranches is $100 - 8.7 - 76 = 15.3$ % in true sale transactions, but only $100 - 3.3 - 87 - 4.5 = 5.2$ % in synthetic transactions. This explains why the average sizes of the non-AAa-tranches tend to be much smaller in synthetic deals. For true sale transactions, Table 5 shows several examples of average tranche sizes above 10 % in the A-range, but for synthetic transactions there is only one example for single tranche-deals.

The average size of tranches below A3 is small. In most transactions, the size of a tranche tends to decline with its rating. But the originator cannot choose the tranche sizes arbitrarily because they are constrained through the default probabilities resp. the expected losses as defined by the rating agencies. As an example⁸ demonstrates, the tranche size does not decline monotonically with the tranche rating. Also, if two tranches with adjacent ratings are merged, then the merged tranche is rather thick. In our transaction sample, within a transaction the size of a tranche is larger than that of the adjacent lower rated tranche in about 75 % and smaller in about 25 % of the cases. Surprisingly, in synthetic transactions we observe rather thin tranches with a rating below Ba3, which are absent in true sale-transactions. Possibly there is more investor demand for low rated tranches in high quality synthetic transactions.

A puzzling finding relates to the initial credit spreads of rated tranches. Within a transaction, the credit spread always increases from one tranche to the adjacent tranche with a lower rating. Fig. 1 plots the credit spreads of all rated tranches for all transactions on a logarithmic scale, differentiated with respect to the issuance quarter. For tractability, Fig. 1 differentiates only among the rating classes Aaa, Aa, A, Baa, Ba and B. Although the black dots for the A-related ratings are mostly below those for the B-related ratings, there is surprisingly much overlap in several issuance quarters. These overlaps neither can be explained by variations over time nor by different transaction maturities. *Berndt et al* (2005) also find a rather strong overlap of credit spreads for corporate bonds.

- Figure 1 -

4.2 Regression results

Next we run regressions to test the hypotheses stated before. In all regressions we control for originator characteristics which may affect credit spreads and tranching decisions. 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. In the regressions we include as controls

- the tier 1-capital ratio and the total capital ratio,
- capital structure: equity/total assets,
- asset structure: loans/total assets,
- profitability: return on average equity capital in the transaction year, 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,
- the bank's rating. Rating is captured by an integer variable which equals 1 for a Aaa-rating and increases by 1 for every notch, with 16 for a rating of B3. A higher integer indicates a lower rating.

These bank data are obtained from the Bank Scope Database. As these data are not available for investment firms, we subtract from each bank control variable its average to eliminate effects of averages. The standardized bank control variable then is multiplied by a dummy which is 1 for a bank being the originator and 0 otherwise. In the regressions, reported in the following sections, insignificant regressors are mostly excluded and, thus, not shown.

4.2.1 The Number of Tranches

The first regression is a probit regression explaining the number of tranches in a transaction by several characteristics of the transaction and of the originator. For banks, the average return on equity and the loans/assets ratio have some explanatory power and therefore are included. We find

Number of tranches =

$$.19 \text{ WADP} + 9.6 \text{ } 1/\ln \text{ ADS} - .19 \text{ FLP} + .58 \text{ } \ln \text{ vol} - .70 \text{ CBO} - .04 \text{ } \text{return on equity} + .02 \text{ } \text{loans/assets}$$

(0.0000) (0.0377) (0.0002) (0.0004) (0.0101) (0.0353) (0.0068)

$$\text{Pseudo-R}^2 = 0.238$$

The regression coefficients are shown together with their p-values (in parentheses). The regression is based on the 92 transactions for which we can derive the adjusted diversity score (*ADS*), based on asset correlations $\rho_{\text{int}} = 20$ and $\rho_{\text{ex}} = 2$ percent. *FLP* is the size of the FLP, defined as a fraction of the transaction volume. *Vol* is the €-volume of the transaction. *CBO* is a dummy which is 1 for a CBO-transaction and 0 otherwise. The regression indicates that the number of tranches is inversely related to the portfolio quality as stated in Hypothesis 2a. Not surprisingly, the FLP-size has a negative impact on the number of tranches because a larger FLP reduces the space for rated tranches. The positive impact of the transaction volume on the number of tranches clearly supports Hypothesis 2b. The negative sign of the CBO-dummy indicates that the number of tranches tends to be smaller in CBO-transactions. This is not surprising since 13 out of 14 single tranche-deals are CBO-transactions.

While the regression coefficient of *WADP* is stable in various regressions, the regression coefficient of $1/\ln \text{ ADS}$ depends on the regressors included. The regression coefficient for $1/\ln \text{ ADS}$ is positive even though the correlation coefficient between the number of tranches and $\ln \text{ ADS}$ is 0.31. This sign reversal is intuitive since well diversified asset pools tend to have a

high transaction volume and a small FLP, both suggesting a high number of tranches. Controlling for transaction volume and *FLP* reveals a negative impact of asset pool diversification on the number of tranches.

Only two originator characteristics have a significant impact on the number of tranches. For banks as originators, a lower return of equity and a higher loan to assets ratio tend to raise the number of tranches. The positive impact of the loans to assets-ratio might indicate more securitization activity of the originating bank and, thus, a need for a broader investor base; this might be easier to attract through more differentiated tranches. A lower return on equity might also intensify a bank's securitization activities to raise bank profits quickly as found by *Titman/Tsyplakov* (2010). The impact of these originator characteristics on the explanatory power of the regression is quite limited, however. If we exclude them, the pseudo-R² decreases to 0.201.

4.2.2 Annual Risk Premium of Transactions

Next, we analyse the risk premiums on all rated tranches in a transaction. The originator of a transaction is interested in minimizing her transaction cost and the credit spreads on the rated tranches, given the asset pool quality and the FLP. The weighted average spread of all tranches should be inversely related to the number of differently rated tranches (Hypothesis 1). Given the loss rate distribution of the asset pool, the FLP, and, in a synthetic transaction, the Third Loss Position, minimizing the weighted average credit spread is equivalent to minimizing the annual risk premium paid on all rated tranches (ARP).

As Moody's does not publish expected tranche losses, we need to estimate them. The rating agencies use multi-period simulation models to derive the loss rate distribution of the asset pool. These models produce uni-modal loss rate distributions. Given the strong impact of rating agencies in securitization, we also use a uni-modal distribution. This may be dangerous. *Longstaff/Rajan* (2008) analysed the loss rate distribution of CDX-tranches and find a three-modal loss rate distribution where the second (third) mode has a much smaller density than the first (second). The modes might be attributable to different default clustering factors.

From Moody's we know for each transaction the weighted average default probability (WADP) of the asset pool and its diversity score (DS) and, for a restricted sample, the more refined adjusted diversity score (ADS). This allows us to use a two-parameter distribution. As in *Franke, Herrmann and Weber* (2008), we assume that the loss rate distribution can be reasonably approximated by a lognormal distribution⁹. Also Moody's (2000) used this

distribution. The two parameters of this distribution are inferred from WADP and ADS as explained in Appendix 1. The lognormal distribution approximates the distribution, obtained from the simulation models of the rating agencies, reasonably well. This approximation allows us to use the Black-Scholes framework, and hence, to use analytic expressions for the expected tranche losses and the share of expected default losses of the asset pool borne by the FLP. This share is called the FLP-loss share.

Table 6 shows the regression results. Regressions are based on 37 true sale- and 45 synthetic observations. We have assigned the atypical 3 fully funded synthetic Geldilux-transactions to the true sale-sample. We distinguish true sale and synthetic transactions because the average ARP for true sale transactions is 39 basis points while it is 102 bp for synthetic transactions. This difference is due to the large non-sold super-senior portion in synthetic transactions which is not included in ARP. In true sale-transactions the large Aaa-tranches earn an average credit spread of 35 basis points, but they bear an annual expected loss per € invested of only 2.5 basis points. Hence the annual risk premium on the Aaa-tranches is 32 bp. The large Aaa-tranche strongly pulls down the ARP in true sale-transactions.

- Table 6 -

The first regression shows that in *true sale-transactions* the annual weighted average risk premium ARP increases with WADP. This supports the loss volume effect stated in Hypothesis 4a. A higher WADP imposes more default losses on investors (see also *Krahnert and Wilde (2008)*) and, hence, they charge a higher risk premium. A higher WADP is also associated with stronger information asymmetry which should also raise ARP, consistent with Hypothesis 5. According to this hypothesis, a lower diversity score should also raise ARP. But this is not supported by the regressions.

To account for different conditions in credit markets, we include the IBOXX-spread at the issuance date as a regressor. This spread is the difference between the BBB- and the government credit spreads for a maturity between 3 and 5 years. Not surprisingly, a higher IBOXX-spread raises ARP. More importantly, a higher number of rated tranches lowers ARP, supporting Hypothesis 1. Issuing more tranches allows the originator to better signal the asset pool quality and to better exploit heterogeneous investor preferences. One might expect also a negative influence of the FLP-loss share. But this variable has no significant impact. This may be due to the observation that the loss share varies only little across transactions (*Franke/Herrmann/Weber (2008)*).

The second regression indicates that a higher rating asymmetry measure tends to lower ARP. This measure is higher in a transaction where the tranche ratings are clustered more in the high rating range. This tends to reduce the weighted average credit. This finding supports the conjecture that tranche ratings clustered in the low rating range have less impact on ARP because investors buying these tranches are more sophisticated and, therefore, rely less on ratings and more on their own analysis. Originator characteristics do not play a significant role.

Regressions (3) and (4) in Table 6 analyse ARP for *synthetic* transactions. Again, a higher number of rated tranches and a higher rating asymmetry measure lower ARP, supporting Hypothesis 1. Surprisingly, regression (3) shows a negative regression coefficient of WADP, significant at the 5%-level. When we include in regression (4) the number of tranches and the rating asymmetry measure, the coefficient of WADP is no longer significant. Hence the puzzling sign of the WADP-coefficient in regression (3) may be driven by tranching effects. Also in synthetic transactions WADPs are, on average, quite small and have small standard deviations (Table 2). Therefore, WADPs may convey little information to investors in synthetic transactions. Adjusted diversity scores, however, are significant in synthetic transactions. The negative coefficient indicates that investors may prefer highly diversified transactions because of smaller information asymmetry (Hypothesis 5).

4.2.3 *Relative Risk premiums of Transactions*

To analyse pricing kernel effects, we first study the relative risk premium of all rated tranches in a transaction, RRP. It is defined as ARP, divided by the annualised expected loss borne by all rated tranches. Since the RRP is 7.8 for synthetic transactions and 27.5 for true sale-transactions, due to the expensive Aaa-tranche in true sale transactions, we run regressions on RRP first separately for true sale and synthetic transactions, then jointly for all transactions. The results are shown in regressions (5) to (8) in Table 6.

In all these regressions WADP and ADS have a clearly negative impact on the RRP as suggested by the pricing kernel effect. As stated in Hypothesis 6 b), an increase in WADP should reduce the relative risk premiums of most tranches, and hence RRP. Similarly, Hypothesis 6 c) predicts a negative effect of the diversity score. Hence, these regressions support Hypothesis 6.

The FLP-loss share has a significant positive impact on RRP in all four regressions. A higher loss share suggests a higher attachment point for the lowest rated tranche which, by a pricing kernel effect, should raise RRP (Hypothesis 6 a). But a higher loss share also supports

investor confidence and thus should *lower* RRP (Hypothesis 5). Apparently, the pricing kernel effect dominates. As expected, the IBOXX-spread has a positive impact on RRP. A higher number of rated tranches has a clearly negative impact on RRP only in regressions (6) and (7), as claimed in Hypothesis 1.

Including the synthetic dummy in the last regression renders the number of tranches insignificant. The synthetic dummy has a strongly negative impact on RRP. By the pricing kernel effect, the better quality of asset pools in synthetic transactions suggests a higher RRP, but the exclusion of the non-securitized super-senior tranche suggests a lower RRP. Also, the better quality of the asset pool suggests a lower RRP due to less information asymmetry. Apparently, the latter two effects dominate. Regressions (5) - (8) suggest that a higher number of tranches has a significant impact on RRP only in synthetic transactions. Finally, originator characteristics are mostly irrelevant. But a bank with a higher total capital ratio and lower return variability pays a smaller RRP. Investors may have more confidence in an originator with better capitalization and less profitability risk.

It is worth noting that the adjusted R²s are much higher for the RRP- than for the ARP-regressions. This indicates that the pricing of risk transfer in securitizations follows a common logic making it difficult to earn arbitrage profits by trading securitization tranches against each other.

4.2.4 Risk Premiums of Individual Tranches

So far, we analysed risk premiums on all rated tranches of a transaction. Next, we analyse the annual and the relative risk premiums of individual rated tranches. There are 4 tranches with an annual risk premium below -1 %. We exclude these tranches because of potential data errors. Since most transactions have more than one tranche, the residuals of tranches belonging to one transaction might be clustered. Therefore the p-values are estimated using a clustered residual robust variance matrix¹⁰. Originator characteristics play a small role in risk premiums of all rated tranches as shown above. Their effect on individual tranche risk premiums is even smaller because tranche characteristics play a more important role. Therefore originator characteristics do not show up as regressors in the following regressions.

First, we run OLS-regressions to explain the annual tranche risk premium (ATRP). In the first regression of Table 7, WADP/maturity, a proxy for the annual expected portfolio loss, has a significant, positive impact on ATRP, supporting a loss volume effect (Hypothesis 4). This is also consistent with an information asymmetry effect (Hypothesis 5). But asset pool

diversification measured by the adjusted diversity score has no impact. The loss volume effect is supported by the FLP-impact. Since an increase in WADP/maturity raises the FLP in a linear regression with the coefficient 2.72, we use $(FLP - 2.72 \text{ WADP/maturity})$ as a regressor. Its negative coefficient indicates that a higher FLP takes away more default losses from the rated tranches and therefore reduces ATRP. Also, a higher number of subordinated rated tranches reduces ATRP. More subordinated tranches signal a higher attachment point and, thus, a smaller expected tranche loss which should reduce the annual tranche risk premium (Hypothesis 4 a). Also more subordinated tranches may provide more information about the tranche risk which should reduce risk premiums. Consistent with this finding is the strong additional risk premium for the lowest rated tranche as shown by the positive regression coefficient for the lowest rated tranche-dummy. This tranche is particularly risky, it is the most information-sensitive rated tranche, also managing its risk is most complex (see also Weber 2008). Surprisingly, the number of subordinated tranches adds more to the explanatory power of the regression than the attachment point. As expected, the IBOXX-spread has a positive impact on the tranche risk premium.

- Table 7 -

Next we ask whether the annual tranche risk premium can be better explained by the tranche rating than by the observable economic properties used in regression (1). As shown in regression (2), substituting tranche rating for economic tranche properties slightly increases the explanatory power of the regression from 39.1 to 42.6 %. This supports the strong impact of ratings and, thus, Hypothesis 7. Yet, the R^2 of only 42.6 % indicates that investors do not blindly trust ratings, but also evaluate other tranche properties. Tranche size and originator characteristics do not help explaining ATRP.

While the annual tranche risk premium appears to be driven primarily by volume and pricing kernel effects, the *relative risk premium of a tranche (RTRP)* should be driven primarily by pricing kernel effects. To check for this, consider first the average RTRP for different ratings classes. Senior tranches generate losses primarily in the “expensive” macro-states and therefore should pay a high risk premium per unit of expected loss. This should be particularly true for the thick Aaa-tranches in true sale transactions, not so much for the thin Aaa-tranches in synthetic transactions. This conjecture is strongly supported by the following table which shows the average relative risk premia for different rating classes in our sample. Since the estimation of the very small expected loss of the Aaa-tranche is subject to strong

estimation error implying a very strong effect on the relative risk premium, we winsorize the risk premiums of Aaa-Tranches assigning a cap of 200 to all tranches with a higher value.

rating class	TS Aaa	SYN Aaa	Aa and A	Baa	Ba and B
Average rel RP	47.7	20.39	7.97	5.22	3.31

The relative risk premiums shown in the table are in line with the spread ratios for corporate bonds derived by *Amato/Remolona* (2003). The pricing kernel effect clearly dominates the potential information asymmetry effect. The senior tranches are less information-sensitive which should reduce their relative risk premiums.

Regressions (3) to (6) in Table 7 display our findings on the relative risk premiums of individual tranches. Since WADP and the attachment point are strongly correlated, we regress on *WADP* and on $(WADP - 0.424 \text{ attachment point})$ with 0.424 being the coefficient of the attachment point on WADP in a linear regression. As a primer, the R^2 of regression (3) is 77% which is surprisingly high. This indicates that the pricing of securitization tranches is more homogeneous than suggested by Fig. 1. The attachment point has a clearly positive impact on *RTRP*, supporting Hypothesis 6 a). The regression coefficient of *WADP* is negative, in line with Hypothesis 6 b) for lower rated tranches. We will see, however, that this result needs to be differentiated for rating classes. The IBOXX spread has a positive impact as usual.

The dummy “TS-Aaa”, being 1 for the Aaa-tranche in true sale transactions and 0 otherwise, has a very strong impact on the RTRP. The Aaa-tranche carries a very high RTRP. This is not surprising, given the very high relative risk premium of 47.7 shown in the previous table. The dummy “lowest” also has a strong positive regression coefficient indicating a complexity premium for the lowest rated tranche. Regression (4) in Table 7 excludes true sale-Aaa-tranches, otherwise being the same. The R^2 strongly goes down from 77 to 48.6%. This illustrates the strong effect of the true sale-Aaa-tranches on regression results.

Again, we check the explanatory power of ratings by substituting the tranche rating for WADP and attachment point. Since rating agencies do not care about pricing kernel effects, ratings should do a poor job in explaining relative risk premiums of tranches. Regression (5), which includes true sale Aaa-tranches, shows that the substitution clearly reduces the explanatory power from 77 to 57.9 %. The regression coefficient of the tranche rating is

negative as expected. The dummies for the true sale-Aaa-tranche and the lowest rated tranche remain significant. In regression (6), we exclude the true sale Aaa-tranches. The decline of R^2 from 48.6 to 10.1 % is dramatic. This confirms that ratings ignore pricing kernel effects. Yet, the rating coefficient remains strongly significant. This is in line with Hypothesis 6 a), since a better rating indicates a higher attachment point.

The minor importance of ratings in explaining relative risk premiums of tranches is also supported by another regression excluding true sale-Aaa-tranches (not shown). If we add the tranche rating as a regressor in regression (4), the R^2 increases only from 48.6 to 52.3%. These findings indicate that investors rely less on ratings and more on economic tranche properties. The observed tranche pricing is consistent with pricing kernel effects predicted by theory.

4.2.5 *Relative Risk Premia of Butterfly Spreads*

The previous findings for the relative risk premiums of tranches document a positive attachment point effect as well as a positive impact of the tranche rating. This suggests that the stochastic discount factor increases with the aggregate default rate. It is, however, also possible that the pricing kernel is flat over a large range of aggregate default rates and only increases in the range of high rates. The findings for the relative risk premiums of tranches would be similar because the tranche losses occur not only between the attachment and the detachment point of the tranche, but more so in the range of very high loss rates of the asset pool, i.e. in the range of very “expensive” macro-states.

To obtain a more precise picture of the pricing kernel, we check the relative risk premiums of butterfly spreads. Consider two adjacent tranches i and $(i+1)$ in a transaction with sizes s_i and s_{i+1} and tranche i having the better rating. A butterfly spread is a portfolio of investing 1 € in tranche $(i+1)$ and selling short s_{i+1}/s_i € of the better rated tranche i . The butterfly spread generates triangular default losses for a portfolio loss rate between the attachment point of tranche $(i+1)$ and the detachment point of tranche i . Otherwise the payoff of the spread is zero. The loss of the butterfly spread is highest at the attachment point of tranche i . Hence a butterfly spread is similar to a state-contingent default loss if both tranches have a small size. Thus, butterfly spreads should reveal pricing kernel effects more clearly than tranches with default losses in a wide range of states.

15 (14) out of 78 (90) butterfly spreads in true sale- (synthetic) transactions have a negative relative risk premium. This is to be expected whenever the (forward) stochastic discount factor is mostly below 1 in the range between the attachment and the detachment point of the

butterfly spread. We would expect that for butterfly spreads with low attachment points. An exception might be the butterfly spreads including the lowest rated tranche because this tranche is expensive as shown before. But negative relative risk premiums might also indicate a puzzle similar to that in option pricing discovered by *Jackwerth* (2000) and later confirmed by *Rosenberg/Engle* (2002) as well as *Barone-Adesi et al* (2008). The puzzle is that the aggregate relative risk aversion implicit in option prices appears to be negative in some moneyness-range. A similar phenomenon might explain negative relative risk premiums of some butterfly spreads in securitizations.

Plotting the residual from a regression of the relative risk premiums of butterfly spreads (*RRPBS*) against the attachment points of the butterfly spreads reveals no systematic pattern, with the exception of the most senior butterfly spreads in true sale-transactions which includes the large Aaa-tranche. For these the relative risk premium tends to be higher. This is also confirmed in the regressions reported in Table 8.

- Table 8 -

Regression (1) in Table 8 shows the determinants of the relative risk premiums for butterfly spreads in *synthetic transactions*. The attachment point of the butterfly spread has *no* significant effect. The dummy lowest equals 1 for the butterfly spread with the lowest attachment point within a transaction and 0 otherwise. Its regression coefficient of 1.508 indicates a complexity premium for this butterfly spread, but it is insignificant, in contrast to the findings for the lowest rated tranche. Besides of the IBOXX-spread, *WADP* and *ADS* have strong negative effects, supporting Hypothesis 6 b) and c). The ADS-effect may be driven by information asymmetry as stated in Hypothesis 5 rather than an attachment point effect. This is likely since the attachment point effect is insignificant even in the absence of the ADS-regressor.

For *true sale-transactions*, log ADS turns out to be insignificant (regression (2)). But the attachment point effect is positive and strongly significant, as expected. This finding disappears, however, if we exclude the most senior butterfly spread of each transaction. In regression (3) the attachment point effect is clearly insignificant. This indicates that the pricing kernel is flat in the range of asset pool loss rates below the attachment points of Aaa-tranches and strongly increases above these points. A much higher R² can be obtained by substituting log ADS for the negatively correlated attachment point (regression (4)). The stronger effect of ADS on R² may be due to an information asymmetry effect, related to ADS.

These findings correspond to those in regression (1) for synthetic transactions. Overall, these results indicate that the attachment point effect disappears if we exclude the most senior butterfly spreads. The pricing kernel appears to be rather flat in a wide range of asset pool loss rates.

4.3 Checks and Robustness Tests

4.3.1 Relative Risk Premia and Ratings of Tranches

In the following, we check our findings by additional regressions and by robustness tests. First, since a better rating tends to be associated with a higher attachment point, we also check for the attachment point effect by analysing the impact of WADP and ADS on the relative risk premiums of tranches separately for each rating class. Besides of the Aaa-tranches in true sale- and synthetic transactions, we do not differentiate within the rating classes Aa, A, Baa, Ba and B. We use a dummy variable which is 1 if the tranche has a specific rating and 0 otherwise. In an OLS–regression we find for 301 observations (p-values in parentheses)

Rel RP =	82.1	(0.0000)
349 D(TS Aaa)	WADP	(0.0050)
375 D(SYN Aaa)	WADP	(0.0652)
-21.5 D(Aa and A)	WADP	(0.3534)
-32.0 D(Baa)	WADP	(0.0002)
-24.9 D(Ba and B)	WADP	(0.0000)
22.8 D(TS Aaa) ln ADS		(0.0000)
-5.01 D(SYN Aaa) ln ADS		(0.0603)
-3.86 D(Aa and A) ln ADS		(0.0477)
-4.74 D(Baa) ln ADS		(0.0112)
-5.40 D(Ba and B) ln ADS		(0.0002)

$$\text{Adj } R^2 = .58$$

These results corroborate our finding that Aaa-tranches are special. A higher WADP tends to raise the relative risk premium of a Aaa-tranche, but to lower that of a lower rated tranche. This supports Hypothesis 6b). While a higher WADP appears to lower the relative risk premium of the asset pool, it raises the attachment point of a tranche concentrating default losses in the more expensive macro-states. If the pricing kernel increases weakly with the

aggregate default rate in the range of low aggregate default rates, but strongly in the range of high rates, then the relative risk premium of a tranche with a weak (strong) rating should decline (increase) with WADP. These findings are consistent with those derived from butterfly-spreads.

A stronger asset pool diversification should lower the relative risk premium of all tranches because it may reduce information asymmetry (Hypothesis 5) and lower the attachment point of a tranche (Hypothesis 6c). This ADS-effect is supported by the regression, with the exception of Aaa-tranches in true sale-transactions. A possible explanation for this exception might be that a higher diversity score concentrates default losses of the Aaa-tranches in the very expensive macro-states.

4.3.2 *Different Measures of Diversification*

One controversial issue is the correlation between debtor defaults in an asset pool. Therefore we check our findings by using different diversity scores. So far, we used the adjusted diversity score based on an asset correlation of debtors within the same industry of 20 percent and of debtors in different industries of 2 percent. First, we replace the adjusted diversity score by Moody's traditional diversity score which ignores correlations of debtors in different industries. But this should be viewed with caution because the allocation of default losses to individual tranches reacts quite sensitively to the input parameters (*Duffie/ Garleanu (2001)*). The difference between the adjusted diversity score and the diversity score can be quite large. While the diversity score has a mean of 63.6 in all 167 transactions, the mean adjusted diversity score in the subset of 92 transactions is 25.3. This suggests that the adjusted diversity score is less than half the diversity score. For the 92 transactions, the average of the difference (0.5 diversity score - adjusted diversity score) is 12.3, the difference is above 40 for 8 transactions. Therefore it would be surprising if regressions based on 0.5 diversity score would provide answers similar to those obtained with the adjusted diversity score. This conjecture is verified. Even though the number of observations almost doubles when we use 0.5 diversity score instead of the adjusted diversity score, the adjusted R² almost invariably goes down, sometimes dramatically. Also in many cases the coefficients of regressors which are significant in our previous regressions, show higher p-values or lose significance.

In addition, we run the regressions with the adjusted diversity score based on asset correlations of $\rho_{ex} = 0$ or 4 percent for debtors in different industries. The significance of the regressors changes little when we replace $\rho_{ex} = 2$ by $\rho_{ex} = 0$ or 4. But the adjusted R² s are clearly smaller for $\rho_{ex} = 0$ than for $\rho_{ex} = 2$. Replacing $\rho_{ex} = 2$ by $\rho_{ex} = 4$ sometimes raises and

sometimes lowers the adjusted R^2 . This suggests that a range between 2 and 4 percent was considered realistic by market participants.

4.3.3 *The Impact of Diversification Across Industries*

Our findings on the pricing of tranches depend on the underlying assumptions, in particular on approximating the asset pool loss rate distribution by a lognormal distribution. Many papers use more sophisticated distributions like Levy-distributions, based on more complicated default factor structures. But we cannot obtain the information required for more sophisticated distributions from the offering circulars and other available documents. Also, the simulation models used by the rating agencies generate loss rate distributions which are reasonably approximated by a lognormal distribution. To check for default clustering effects found by *Longstaff/Rajan* (2008), we include the regressor $(1/ADS_4 - 1/ADS_0)$ with ADS_4 based on $\rho_{ex} = 4$ and ADS_0 based on $\rho_{ex} = 0$ percent. Given an asset pool with equally sized loans, m industries and the same number of loans in each industry, $(1/ADS_4 - 1/ADS_0) = 0.04(1 - 1/m)$ (see *Fender/Kiff* (2004)). Hence it would monotonically increase in the diversification of the asset pool across industries. This regressor turns out to have no significant impact on risk premiums in our sample. Hence, interindustry diversification does not seem to have an impact on tranche pricing beyond what is captured in the adjusted diversity score. In that sense, we do not find evidence of priced industry factors.

In all loss rate models, however, the upper tail reacts very sensitively to the parameter input. It is difficult to reliably estimate the loss rate distribution for loss rates much beyond the expected portfolio loss rate because the density approaches zero in this range. This casts doubt, in particular, on the expected losses and, hence, the relative risk premiums derived for Aaa-tranches. *Duffie et al* (2009) argue that most models miss unobservable default risk factors which imply a much higher tail risk.

4.3.4 *CBO-versus CLO-Transactions*

Another issue might be our joint analysis of CLO- and CBO-transactions. *Franke/Herrmann/Weber* (2008) found that the FLP-loss shares tend to be higher in CBO- than in CLO-transactions. In our regressions, we check for potential differences between CLO- and CBO-transactions by including a dummy which is 1 for CBO-transactions and 0 otherwise. This dummy always turns out to be insignificant; therefore we do not report it in our regressions. The difference between true sale and synthetic transactions, however, is important as shown before.

4.3.5 Originator Characteristics and Endogeneity Issues

The impact of originator characteristics on our findings is very limited. These characteristics are apparently of little concern to investors and rating agencies. This suggests that tranching and pricing depend mainly on transaction characteristics. We cannot rule out that the originator chooses these characteristics taking into consideration their impact on tranching and pricing. But this potential endogeneity is of little concern because we try to find out the effects of transaction characteristics on tranching and pricing. Thus, we take the transaction characteristics as exogenous. We account for interdependencies between them by avoiding strongly correlated regressors or by using regressors adjusted for linear dependencies.

5 Conclusion

This paper analyses the tranching and pricing of securitized pools of corporate bonds and loans, using a sample of European securitizations. The number of issued bond tranches with different ratings varies between 1 and 6. 88 percent of the transactions have at least one Aaa-tranche, about 14 percent of the tranches are subinvestment grade. Given a transaction with at least three differently rated tranches, tranche ratings tend to be clustered more in the good rating classes. Since credit spreads of Aaa-tranches are lower than those of lower rated tranches, the originator issues very large Aaa-tranches in true sale-transactions. In synthetic transactions the originator cannot use the funds from issuing bond tranches. As the transfer of default losses through Aaa-tranches is expensive, we observe very small Aaa-tranches and large non-securitized super-senior tranches in synthetic transactions.

The number of tranches tends to be higher for larger asset pools and for those with lower quality. More tranches provide more signals about asset pool quality and permit the originator to extract more investor rents. In line with this, the annual risk premium paid on all rated tranches tends to decline if the number of tranches increases. This is also true of the relative risk premium on all rated tranches, i.e. the average price for transferring one unit of expected default loss.

The annual risk premium, paid on all rated tranches in a transaction, increases with the expected default loss of the asset pool in true sale-transactions, presumably because a larger volume of losses is transferred. For synthetic transactions, the expected default loss has no systematic effect when we include the positively correlated number of tranches. The relative risk premium, paid on all rated tranches in a transaction, *declines* with a higher expected loss of the asset pool, in line with a pricing kernel effect. Apparently this effect dominates the opposite information asymmetry effect. A higher FLP-loss share raises the relative risk

premium on all rated tranches, again indicating the dominance of the pricing kernel over the information asymmetry effect.

Our findings for the annual and the relative risk premiums of individual tranches mostly confirm the results obtained for all rated tranches in a transaction. A decline in asset pool quality should reinforce information asymmetry and, thus, raise the risk premium, while the pricing kernel effect should lower it. The relative strength of these effects appears to vary across tranches. The lowest rated tranche earns a higher risk premium indicating a complexity premium, perhaps because this tranche is very information-sensitive and very risky. The relative risk premium tends to increase with a better tranche rating. It is very high for Aaa-tranches in true sale-transactions, consistent with a pricing kernel effect even though this tranche is very information-insensitive. Therefore it seems to be very expensive to transfer losses through a Aaa-tranche. This may explain the large number of synthetic transactions with a small Aaa-tranche.

The analysis of individual tranches is complicated by the fact that their attachment and detachment points depend on the quality of the asset pool. The relative risk premiums of butterfly-spreads which are obtained from two adjacent tranches, provide a more precise picture of the pricing kernel. We find that the attachment point of a butterfly spread has almost no effect on the relative risk premium except for the most senior butterfly spread. This suggests that the pricing kernel may be rather flat below the attachment points of the Aaa-tranches, but increases strongly with the loss rates of asset pools beyond these points.

The finding that tranche ratings have very little power explaining the relative risk premiums of non-Aaa-tranches, confirms that ratings ignore pricing kernel effects. Yet the economic properties of tranches explain their relative risk premiums reasonably well. This indicates that investors do not blindly rely on ratings, but adjust required credit spreads for pricing kernel and information asymmetry considerations.

This paper is a first step to better understand tranching and pricing in securitizations. More research is needed. The paper uses particular measures of expected losses and diversification of asset pools and postulates a lognormal loss rate distribution. It is necessary to check the sensitivity of findings to the model setup in further studies. Also, the findings are based on a European sample of securitization transactions and might differ for US-transactions. Moreover, we need to better understand the interdependence between the pricing kernels in credit and in stock markets. Since tranching is often considered a driver of the subprime crisis, new insights on tranching may also be helpful in improving regulation of securitization transactions.

Appendix

1. The Parameters of the Lognormal Loss Rate Distribution

We estimate the portfolio loss rate distribution assuming a lognormal distribution. We simplify the analysis by a two date-analysis so that all default losses occur at date 1. Hence we ignore that in these transactions payments are usually made on a quarterly basis.

The expected portfolio loss rate equals $E(l) = \lambda\pi$ with

$$\pi = WADP,$$

λ = loss given default, assumed to be non-random.

Hence we need to know the standard deviation of the loss rate of the asset pool to obtain the parameters of the lognormal distribution. Let denote

S = standard deviation of the loan loss rate ,

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

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

P_i = par value of loan i , divided by the par value of all loans; $i = 1, \dots, n$,

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

Assuming identical default properties of all loans, the variance of the loan loss rate is

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

Then the variance of the asset pool loss rate is

$$S_p^2 = \sum_{i=1}^n \sum_{j=1}^n S^2 \rho_{ij} P_i P_j = S^2 \sum_{i=1}^{DS} \left(\frac{1}{ADS} \right)^2 = S^2 / ADS .$$

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

For a lognormally distributed asset pool loss rate,

$$S_p^2 = [E(l)]^2 \left[\exp \sigma^2 - 1 \right]$$

so that

$$\sigma^2 = \ln \left[1 + \left(\frac{S_p}{E(l)} \right)^2 \right] = \ln \left[1 + \frac{1/\pi - 1}{DS} \right] .$$

For μ we obtain

$$\mu = \ln E(l) - \frac{\sigma^2}{2} = \ln(\lambda\pi) - \frac{1}{2} \ln \left[1 + \frac{1/\pi - 1}{DS} \right].$$

2. Expected Default Losses of Tranches

Given strict subordination of tranches, the expected default loss of a tranche with attachment point a and detachment point d equals

$$\int_a^d (l-a) dF(l) + (d-a) (1 - F(d)).$$

$F(l)$ is the cumulative lognormal distribution function of the portfolio loss rate l . Since the expected tranche loss equals the expected loss of a call with strike price a minus the expected loss of a call with strike price d , we derive the expected loss of the tranche analytically, as in the Black-Scholes world. The expected tranche loss per € invested is the expected tranche loss, divided by $(d-a)$, the par value of the tranche which equals its market value at the issuance date.

References

- Albrecher, H., S. Ladoucette, W. Schoutens (2007). A Generic One-Factor Lévy Model for Pricing Synthetic CDOs. In: Elliott, R. et al (eds), *Advances in Mathematical Finance*, Birkhaeuser, 1-20.
- Amato, J. D., E. M. Remolona (2003). The Credit Spread Puzzle. *BIS Quarterly Review*, December 2003, 51-63.
- Barone-Adesi G., R. Engle, L. Mancini (2008). A GARCH Option Pricing Model with Filtered Historical Simulation. *Review of Financial Studies* 21, 1223-1258.
- Berndt, A., R. Douglas, D. Duffie, M. Ferguson, D. Schranz (2005). Measuring default risk premiums from default swap rates and EDFs. BIS working paper No 173.
- Berndt, A., P. Ritchken, Z. Sun (2010). On Correlation and Default Clustering in Credit Markets. *Review of Financial Studies* 23, 2680-2729.
- Boot, A., A. Thakor (1993). Security Design. *Journal of Finance* 48, 1349-1378.
- Brennan, M., J. Hein, J., S. Poon (2009). Tranching and Rating. *European Financial Management* 15, 891-922.
- Burtschell, X., J. Gregory, J.-R. Laurent (2009). A Comparative Analysis of CDO Pricing Models under the Factor Copula Framework. *Journal of Derivatives* 16, No.4, 9-37.
- Cebenoyan, A. S., P. E. Strahan (2004). Risk management, capital structure and lending at banks. *Journal of Banking and Finance* 28, 19-43.
- Chen, L., P. Collin-Dufresne, R. Goldstein (2009). On the Relation Between the Credit Spread Puzzle and the Equity Premium Puzzle. *Review of Financial Studies* 22, 3367-3409.
- Childs, P. D., Ott, S. H., T.J. Riddiough (1996). The pricing of multi-class commercial mortgage-backed securities. *Journal of Financial and Quantitative Analysis* 31, 581-603.
- Cuchra, M. (2005). Explaining Launch Spreads on Structured Bonds. Discussion paper, Oxford University.

- Cuchra, M., T. Jenkinson (2005). Security Design in the Real World: Why are Securitization Issues Tranched? Discussion paper, Oxford University.
- David, A. (1997). Controlling Information Premia by Repackaging Asset-Backed Securities. *Journal of Risk and Insurance* 64, 619-648.
- DeMarzo, P. (2005). The Pooling and Tranching of Securities: A Model of Informed Intermediation. *Review of Financial Studies* 18, 1-35.
- DeMarzo, P., D. Duffie (1999). A liquidity-based model of security design. *Econometrica* 67, 65-99.
- Driessen, J. (2005). Is Default Event Risk Priced in Corporate Bonds? *Review of Financial Studies* 18, 165-195.
- Duffee, G. (1998). The Relation Between Treasury Yields and Corporate Bond Yield Spreads. *Journal of Finance* 23, 2225-2241.
- Duffie, D., N. Garleanu (2001). Risk and the Valuation of Collateralized Debt Obligations. *Financial Analysts Journal* 57, 41-59.
- Duffie, D., A. Eckner, G. Horel, L. Saita (2009), Frailty Correlated Default, *Journal of Finance* 64 , 2089-2123.
- Elton, E., M. Gruber, D. Agrawal, C. Mann (2001). Explaining the Rate Spread on Corporate Bonds. *Journal of Finance* 56, 247-277.
- Fender, I., J. Kiff (2004). CDO rating methodology: Some thoughts on model risk and its implications. BIS working paper # 163.
- Franke, G., Herrmann, M., T. Weber (2008). Information Asymmetries and Securitization Design, working paper, University of Konstanz
- Gordy, M. (2003). A risk-factor model foundation for ratings-based bank capital rules. *Journal of Financial Intermediation* 12, 199-232.
- Hein, J. (2007). Optimization of Credit Enhancements in Collateralized Loan Obligations - The Role of Loss Allocation and Reserve Account. Discussion Paper, University of Konstanz.

- Higgins, E. J., J. R. Mason (2004). What is the value of recourse to asset-backed securities? A clinical study of credit card banks. *Journal of Banking and Finance* 28, 875-899.
- Krahen, J. and C. Wilde (2008). Risk Transfer with CDOs. Discussion paper, University of Frankfurt.
- Jackwerth, J. (2000). Recovering Risk Aversion from Option Prices and Realized Returns. *Review of Financial Studies* 13, 433-451.
- Krekel, M. (2008). Pricing distressed CDOs with Base Correlation and Stochastic Recovery. Working paper, Uni Credit Markets & Investment Banking.
- Longstaff, F.A., A. Rajan (2008). An Empirical Analysis of the Pricing of Collateralized Debt Obligations. *Journal of Finance* 63, 529-563.
- Loutschina, E., P. Strahan (2009). Securitization and the Declining Impact of Bank Finance on Loan Supply: Evidence from Mortgage Originations. *Journal of Finance* 64, 861-889.
- Marin, J., R. Rahi (2000). Information Revelation and Market Incompleteness. *Review of Economic Studies* 67, 563-579.
- Maris B., Segal W. (2002). Analysis of Yield Spreads on Commercial Mortgage-Backed Securities. *Journal of Real Estate Research*, vol. 23.
- Moody's Investor Service (2000), The Lognormal Method Applied to ABS Analysis. International Structured Finance, special report.
- Newman, D., F. Fabozzi, D. Lucas, S. Goodman (2008). Empirical Evidence on CDO Performance. *Journal of Fixed Income*, Fall 2008, 32-40.
- Piskorski, T., A. Seru, V. Vig (2010). Securitization and distressed loan renegotiation: Evidence from the subprime crisis. *Journal of Financial Economics* 97, 369-397.
- Purnanandam, A. (2008). Originate-to-distribute model and the sub-prime mortgage crisis. Discussion paper, University of Michigan.
- Riddiough, T. J. (1997). Optimal Design and Governance of Asset-Backed Securities. *Journal of Financial Intermediation* 6, 121-152.

- Rosenberg, J., R. Engle (2002). Empirical pricing kernels. *Journal of Financial Economics* 64, 341-372.
- Tarashew, N. (2010). Measuring portfolio credit risk correctly: Why parameter uncertainty matters. *Journal of Banking and Finance* 34, 2065-2076.
- Sheridan Titman, S., S. Tsyplakov (2010). Originator Performance, CMBS Structures, and the Risk of Commercial Mortgages. *Review of Financial Studies* 23, 3558-3594.
- Titman S., Tompaidis S., Tszplakov S. (2005). Determinants of Credit Spreads in Commercial Mortgages. *Real Estate Economics* 33, 711-738.
- Weber, T. (2008). Default Risk premiums in Synthetic European CDOs. Working Paper, University of Konstanz.

Tables and Figures

	True sale	Synthetic	Σ
CLO	35	38	73
CBO	45	49	94
Σ	80	87	167

Table 1: The table shows the number of transactions in the sample differentiating CLO- and CBO-transactions as well as true sale- and synthetic transactions.

	CLO – ts	CLO – synth	CBO – ts	CBO – synth
WADP – mean	7.2 %	3.5 %	14.0 %	1.9 %
WADP – std.	7.3 %	2.3 %	9.6 %	3.1 %
DS – mean	89	88	32	56
DS – std.	45	29	10	26
FLP – mean	5.6 %	2.9 %	11.2 %	3.6 %
FLP std.	4.7 %	1.4 %	5.7 %	2.5 %

Table 2: The table presents averages 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) and FLP (the initial size of the first loss position as a percentage of the volume of the asset pool). The data are presented separately for the four subsets of CLO-true sale, CLO-synthetic, CBO-true sale and CBO-synthetic transactions.

Absolute frequencies of tranches. Total number of tranches is 594

# tr. per transact.	# transact.	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3
1	14	6	2	2		1	1			1		1					
2	17	14	2	1	2	2	6	1		3	3						
3	47	37	8	17	8	11	10	7	5	20	6	4	6	2			
4	46	46	8	16	5	9	19	11	10	29	6	5	13	6	1		
5	37	44	10	23	3	5	23	7	7	19	12	8	16	7		1	
6	6	5	4	4	1	1	5			4	1		5	1		2	3
Σ	167	152	34	63	19	29	64	26	22	76	28	18	40	16	1	3	3

Relative frequencies of tranches.

# tr. per transact.	# transact.	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3
1	14	43 %	14%	14%	-	7%	7%			7%		7%					
2	17	82%	12%	6%	12%	12%	35%	6%		18%	18%						
3	47	79%	17%	36%	17%	23%	21%	15%	11%	43%	13%	9%	13%	4%			
4	46	100%	17%	35%	11%	20%	41%	24%	22%	63%	13%	11%	28%	13%	2%		
5	37	119%	27%	62%	8%	14%	62%	19%	19%	51%	32%	22%	43%	19%		3%	
6	6	83%	67%	67%	17%	17%	83%			67%	17%		83%	17%		33%	50%

Table 3: In both panels, transactions in the first column are classified by the number of differently rated tranches. The second column shows the observed number of transactions for each class. In the upper panel the following columns show the total number of tranches in the class issued with the rating shown in the top line. The last line displays the total number of transactions and of tranches with a given rating; bold figures indicate local maxima in a line.

The lower part of the table shows the relative frequencies of tranche ratings (= number of tranches/ number of transactions, in percent) for transactions with a given number of differently rated tranches. All figures greater or equal to 50 % are bold.

Number of tranches	2	3	4	5	6
Median of rating range	6	9	10	12	15
Median of average rating gap	4	3	2	2	2

Table 4: It shows the median of the rating range (= 1+ difference between highest and lowest rating) and the median of the average rating gap for transactions, given the number of differently rated tranches.

Table 5: The table displays the average tranche size separately for true sale (upper panel) and synthetic transactions (lower panel). The first column classifies transactions by the number of differently rated tranches, the second column shows the total number of rated tranches in this class in parentheses, the following columns display for each rating the average tranche size (= tranche volume/transaction volume, in percent), below in parentheses the number of tranches with the indicated rating. The last column gives the average size of the FLP, below the number of transactions in parentheses. Average tranche sizes of at least 10% are in bold numbers. The last line in each panel displays the number of rated tranches in parentheses as the sum of the numbers in parentheses in the respective column. In the FLP-column the number of true sale transactions is 80 as shown in the last line in parentheses.

The lower panel displays the same for synthetic transactions, with the third loss position TLP (non-securitized super senior tranche) in the third column, below the number of transactions in parenthesis. The number of synthetic transactions is 87.

True Sale

Transactions:

average tranche size

# tr. per transact.	Total # rated tranches	average tranche size																
		Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3	FLP
1		81%		88%														18%
	(6)	(4)		(1)														(6)
2		79%			14%	15%	10%			11%								10%
	(14)	(7)			(1)	(1)	(4)			(1)								(7)
3		78%	31%	38%	6%	5%	8%	5%	3%	6%	5%	3%	2%	8%				8%
	(65)	(18)	(6)	(5)	(3)	(6)	(6)	(3)	(1)	(9)	(4)	(2)	(2)	(1)				(22)
4		77%	14%	13%	10%	3%	5%	10%	4%	4%	7%	1%	2%	3%				8%
	(104)	(28)	(2)	(9)	(1)	(4)	(12)	(6)	(5)	(18)	(3)	(2)	(8)	(6)				(26)
5		71%	6%	9%	2%		7%	8%	3%	5%	5%	1%	3%	2%				9%
	(90)	(22)	(4)	(12)	(1)		(12)	(5)	(1)	(9)	(8)	(2)	(8)	(6)				(18)
6		68%	1%	7%			7%				4%			4%				9%
	(6)	(1)	(1)	(1)			(1)				(1)			(1)				(1)
Σ	(286)	(80)	(13)	(28)	(6)	(11)	(36)	(14)	(7)	(37)	(16)	(6)	(18)	(14)				(80)

**Synthetic
Transactions**

average tranche size

# tr. per transact.	Total # rated tranches	average tranche size																	
		TLP	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3	FLP
1		89%	3%	5%	17%		3%						6%		3%				
	(8)	(8)	(2)	(2)	(1)		(1)						(1)		(1)				
2		89%	4%	6%	4%	4%	3%	10%	1%				5%	5%					
	(20)	(10)	(7)	(2)	(1)	(1)	(1)	(2)	(1)				(2)	(3)					
3		88%	5%	1%	3%	3%	3%	3%	2%	3%	2%	2%	2%	1%	1%				
	(75)	(25)	(19)	(2)	(12)	(5)	(5)	(4)	(4)	(4)	(11)	(2)	(2)	(4)	(1)				
4		87%	5%	2%	3%	3%	1%	2%	2%	1%	1%	2%	1%	2%		1%			
	(80)	(20)	(18)	(6)	(7)	(4)	(5)	(7)	(5)	(5)	(11)	(3)	(3)	(5)		(1)			
5		86%	4%	2%	3%	1%	1%	1%	1%	2%	1%	1%	1%	1%	1%		0.5%		
	(95)	(19)	(22)	(6)	(11)	(2)	(5)	(11)	(2)	(6)	(10)	(4)	(6)	(8)	(1)		(1)		
6		82%	4%	2%	3%	0.5%	3%	2%					2%				0.5%	2%	
	(30)	(5)	(4)	(3)	(3)	(1)	(1)	(4)					(4)			(5)		(2)	(3)
Σ	(308)	(87)	(72)	(21)	(35)	(13)	(18)	(28)	(12)	(15)	(39)	(12)	(12)	(22)	(2)	(1)	(3)	(3)	(87)

Explained variable	ARP True sale (1)	ARP True sale (2)	ARP Syn (3)	ARP Syn (4)	RRP True Sale (5)	RRP Syn (6)	RRP All (7)	RRP All (8)
Constant	0.442 (0.0335)	0.484 (0.0235)	4.986 (0.0186)	4.669 (0.0209)	-21.90 (0.2047)	52.34 (0.0076)	54.96 (0.0007)	26.04 (0.0927)
WADP (%)	0.0233 (0.0000)	0.0228 (0.0000)	-0.074 (0.0337)	-	-0.67 (0.0002)	-1.18 (0.0000)	-0.35 (0.0021)	-0.57 (0.0000)
ln ADS	-	-	-1.50 (0.0319)	-1.20 (0.0707)	-16.42 (0.0000)	-19.3 (0.0003)	-27.12 (0.0000)	-20.58 (0.0000)
Rating asymmetry	-	-0.350 (0.0245)	-	-1.339 (0.0746)	-	-	-	-
FLP- loss share (%)	-	-	-	-	84.5 (0.0000)	24.5 (0.0646)	45.4 (0.0028)	50.88 (0.0029)
Spread35	0.137 (0.0290)	0.120 (0.0622)	0.656 (0.0319)	0.647 (0.0139)	14.83 (0.0000)	2.88 (0.2788)	7.25 (0.0004)	9.60 (0.0000)
No. of tranches	-0.115 (0.0145)	-0.0115 (0.0135)	-	-0.195 (0.0655)	-	-0.89 (0.0696)	-1.53 (0.0440)	-
SYN-dummy	-	-	-	-	-	-	-	-9.34 (0.0001)
Total capital ratio	-	-	-	-	-	-	-	-1.34 (0.0271)
Var of return on equity	-	-	-	-	-	.0332 (0.0001)	-	-
Adj. R ²	0.538	0.586	0.248	0.356	0.833	0.573	0.633	0.729
Observations	37	37	45	45	37	45	82	82

Table 6: The table shows the regression coefficients from OLS-regressions with Newey-West heteroscedasticity adjusted p-values (in parentheses), explaining the annual risk premiums ARP and the relative risk premiums RRP of all rated tranches in a transaction. Rating asymmetry is the rating asymmetry measure explained above. FLP-loss share is the share of expected losses of the asset pool borne by the FLP. Spread 35 is the IBOXX-spread difference between BBB- and government bonds for a maturity of 3-5 years at the issue date. No. of tranches is the number of differently rated tranches. SYN is a dummy variable which is 1 for a synthetic transaction and 0 otherwise. Total capital ratio and var of return on equity are the originating banks' total capital ratio and variance of its return on equity.

explained variable	ATRP (%) (1)	ATRP (%) (2)	RTRP +1 (3)	RTRP +1 w/o TS-Aaa (4)	RTRP +1 (5)	RTRP +1 w/o TS-Aaa (6)
constant	.0867 (0.742)	-1.008 (0.001)	-33.04 (0.000)	-16.51 0.000)	2.378 (0.756)	13.70 (0.016)
WADP/ maturity	0.253 (0.023)	-	-	-	-	-
FLP – 2.72 WADP/mat.	- 0.072 (0.003)	-	-		-	-
WADP -0.424 attachment point	-	-	-1.43 (0.000)	-1.68 (0.000)	-	-
attachment point	-	-	3.18 (0.000)	2.73 (0.000)	-	-
no of sub tranches	-0.262 (0.000)	-	-	-	-	-
spread 35	0.754 (0.000)	0.714 (0.000)	13.03 (0.000)	5.22 (0.016)	10.53 (0.013)	4.05 (0.114)
dummy TS-Aaa	-	-	60.39 (0.000)	-	101.26 (0.000)	-
dummy lowest	1.067 (0.000)	0.881 (0.000)	7.26 (0.001)	6.47 (0.000)	3.99 (0.021)	5.50 (0.000)
Tranche rating	-	0.117 (0.000)	-	--	-1.59 (0.000)	-1.80 (0.000)
Adj R ²	.391	0.426	.770	.486	.579	0.101
Observations	298	298	298	261	298	261

Table 7: The table shows the regression coefficients from OLS-regressions with heteroscedasticity, clustered residual adjusted p-values (in parentheses) explaining the annual risk premiums ATRP and the relative risk premiums RTRP of individual tranches. RTRP + 1 equals the credit spread of the tranche, divided by its annualized expected loss. Attachment point is the attachment point of the tranche. No of sub tranches is the number of subordinated rated tranches. Spread 35 is the IBOXX-spread difference between BBB- and government bonds for a maturity of 3-5 years at the issue date. Dummy TS-Aaa is 1 for a Aaa-tranche in a true sale transaction and 0 otherwise. Dummy lowest is 1 if the tranche is the tranche with the lowest rating in a transaction, and 0 otherwise. Tranche rating is captured by an integer variable which is 1 for Aaa and 16 for B3.

explained variable	<i>RRPBS</i> synthetic tr. (1)	<i>RRPBS</i> true sale-tr. (2)	<i>RRPBS</i> w/o top BS true sale-tr. (3)	<i>RRPBS</i> w/o top BS true sale-tr (4)
constant	63.07 (0.001)	-19.29 (0.000)	-6.393 (0.010)	58.23 (0.003)
Attachment point		2.16 (0.0000)	0.67 (0.2149)	-
Dummy lowest	1.508 (0.1189)	-	-	-
WADP (-0.54 attachment point for regr. (2) and (3))	-0.820 (0.0000)	-1.38 (0.0000)	-0.71 (0.0779)	-0.175 (0.0306)
Log ADS	-19.43 (0.0000)	-	-	-19.50 (0.0006)
Spread 35	4.52 (0.0002)	9.55 (0.0108)	5.92 (0.0087)	5.95 (0.0193)
Adj R ²	0.467	0.578	0.353	0.506
Observations	90	78	48	48

Table 8: The table shows OLS-regressions explaining the relative risk premiums of butterfly spreads in synthetic and true sale-transactions, with heteroscedasticity, clustered residual adjusted p-values (in parentheses). In regressions (1) and (4) *WADP* is a regressor. In regressions (2) and (3) (*WADP – 0.54 attachment point*) is used to neutralize the dependence between the attachment point and *WADP* as given by a linear regression. Dummy lowest is 1 for the butterfly spread with the lowest attachment point in a transaction and 0 otherwise. In regressions (3) and (4) the top butterfly spread of a transaction including the large Aaa-tranche is excluded.

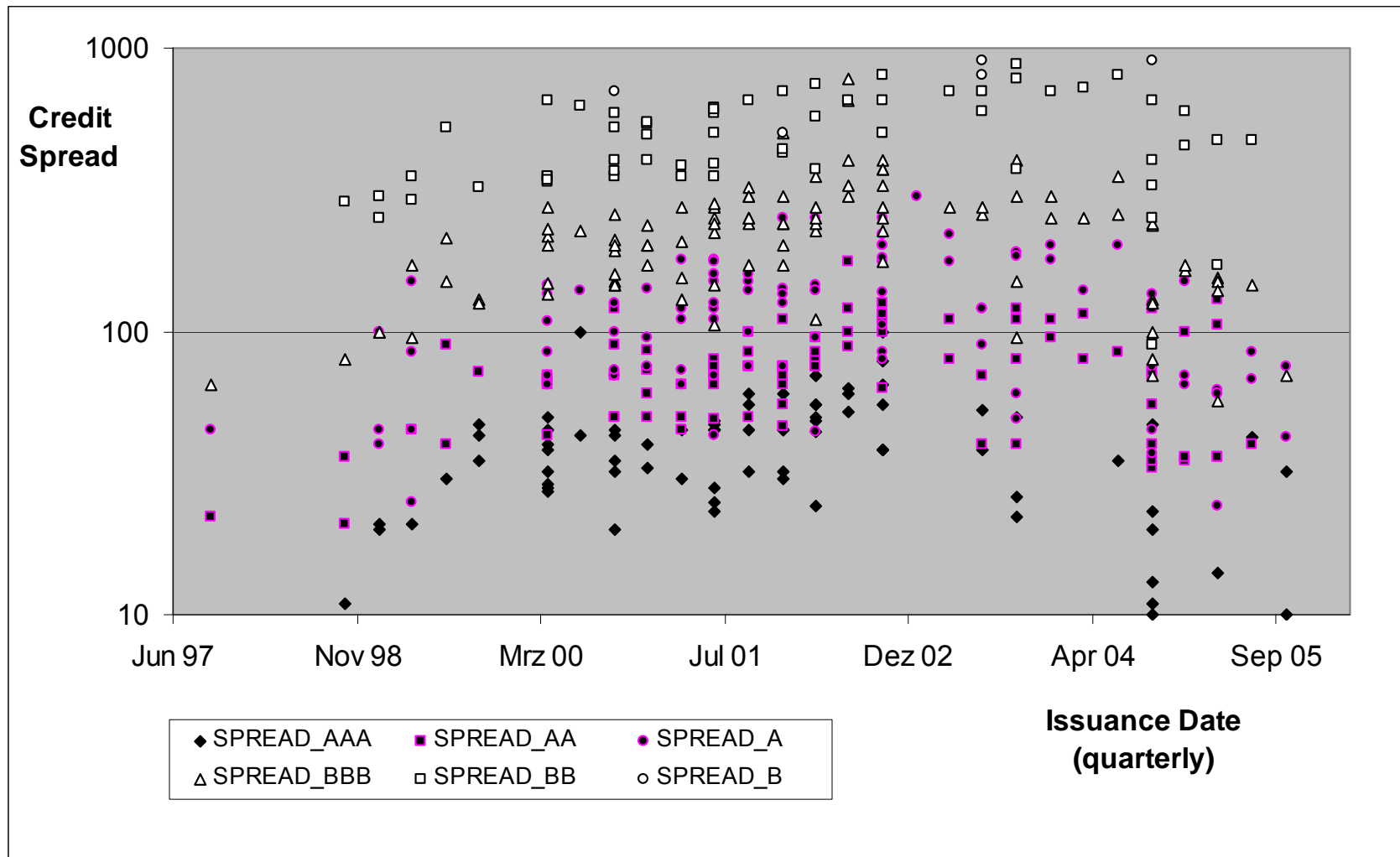


Figure 1: It displays the credit spreads (logarithmic scale) of rated tranches across issuance quarters differentiated for the main rating classes.

Footnotes

- ¹ *David* (1997) asks how many tranches should be issued in a securitization transaction. 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.
- ² *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 have less capital than other banks and more risky assets relative to total assets.
- ³ The benefits of quality differences between tranches derive from investor heterogeneity. Institutional investors may have statutes which allow them to invest in Aaa-tranches only. Regarding the capacity of analysing und managing default risks, investors with low capacity may prefer tranches with low default risk. Sophisticated investors like hedge funds may prefer high risk tranches.
- ⁴ Under Basel I, the standard risk weight of 100 percent applied to all rated tranches, so that tranching had little impact on regulatory equity capital. But originators and investors anticipated capital requirements differentiated to tranche ratings according to Basel II. Regulators in some countries required little equity capital for the most senior tranche if it was insured against default risk.
- ⁵ $\frac{\partial^2 \ln(\text{PD}(m) \text{ LGD})}{\partial(-\Delta) \partial(-m\sqrt{\rho})} = [N(y_m)y_m + n(y_m)] n(y_m) / [(1-\rho)N^2(y_m)]$, with $y_m = (-\Delta + m\sqrt{\rho})/\sqrt{1-\rho}$. This derivative is positive whenever the first term in brackets on the right hand side is positive. This is true whenever $y_m \geq -4$. Hence default losses tend to grow faster in “cheap” macro-states if $-\sqrt{\rho} < 0$.
- ⁶ *Franke, Herrmann* and *Weber* (2008) find in their European sample that the FLP always exceeds the expected portfolio loss rate.
- ⁷ Single-tranche deals are often initiated by investors looking for an investment in a diversified asset pool with a prespecified tranche rating.
- ⁸ To provide an intuition, consider a lognormal distribution of the portfolio loss rate and derive the attachment points for a B, BB, BBB, A, AA and AAA tranche in a true sale transaction according to the idealized probabilities of default according to S&P. Assume a transaction with 6 years maturity, WADP = 6 %, loss given default $\lambda = 50\%$ and an adjusted diversity score of 40. Then the tranche sizes are depicted in the following Table.

Tranche rating	Tranche -PD S&P	Tranche size
AAA	0.19%	83.88%
AA	0.51%	2.77%
A	1.01%	1.75%
BBB	3.61%	3.02%
BB	13.31%	2.80%
B	29.73%	1.64%
FLP	100 %	3.45%

- ⁹ Theoretically, a lognormal distribution allows for portfolio loss rates above 1. But for all realistic parameter values, the cumulative probability of these loss rates is negligible.
- ¹⁰ The differences in p-values between the Newey-West and the cluster robust estimates are very small.