



No. 2005/06

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Default Risk Sharing Between Banks and Markets: The Contribution of Collateralized Debt Obligations*

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February 15, 2005

Abstract:

This paper contributes to the economics of financial institutions risk management by exploring how loan securitization affects their default risk, their systematic risk, and their stock prices. In a typical CDO transaction a bank retains through a first loss piece a very high proportion of the expected default losses, and transfers only the extreme losses to other market participants. The size of the first loss piece is largely driven by the average default probability of the securitized assets. If the bank sells loans in a true sale transaction, it may use the proceeds to expand its loan business, thereby incurring more systematic risk. We find an increase of the banks' betas, but no significant stock price effect around the announcement of a CDO issue. Our results suggest a role for supervisory requirements in stabilizing the financial system, related to transparency of tranche allocation, and to regulatory treatment of senior tranches.

JEL Classification: D82, G21, D74

* We are very indebted to Dennis Hänsel, Thomas Weber and Christian Wilde for their excellent computational assistance and their comments which greatly helped us to improve the paper. We also thank Andreas Jobst in helping to set up the data base and to discuss the intricacies of ABS markets, and Ralf Elsas for helpful comments. We are also indebted to market experts from major banks and agencies for their support and comments, in particular M. Hermann (HSBC), T. Weinelt (Commerzbank), S. Nicolaus and R. Froitzheim (Deutsche Bank), T. Althaus (S&P), S. Bund (Fitch), C. Benkert (JPMorgan), T. Klotz (Moody's), J. Wasmund (DWS), C.-R. Wagenknecht and B. Specht (DrKW). Furthermore, we have received numerous helpful suggestions during the 2004 NBER-conference on Risks in Financial Institutions in Woodstock, Vermont. We are indebted to Mark Carey and Rene Stulz, the organizers, and to Gary Gorton, Phillippe Jorion, Hashem Pesaran and Til Schuermann. Finally, we are grateful for financial network support by Deutsche Forschungsgemeinschaft and by the Center for Financial Studies at Frankfurt's Goethe University.

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1 Introduction

Consider a bank which securitizes part of its loan portfolio by issuing collateralized debt obligations: What does this transaction imply for the default risk exposure of the issuing institution? This study will look at financial institutions that securitize part of their loan book, analyzing the impact of securitization on risk and market value of the issuing bank. Our focus is on tranching as the financial innovation characterizing collateralized debt obligations (henceforth CDOs). Tranching matters because it determines the eventual sharing of default risks between a bank as the issuer and investors as the buyers of these bonds.

First, and contrary to what many observers believe, the expected default loss of the securitized portfolio largely remains on the books of the issuing institution. Second, in a fully funded transaction the risk of extreme unexpected losses, i.e. tail risk, is transferred from banks to investors, mostly other financial institutions, or institutional investors. We argue that the combined effect of retaining the first-loss piece and selling senior tranches will reduce the bank's exposure to extreme, or systemic risk.

But this potentially enables the bank to expand its loan business so that in the end its systematic risk will be affected. The direct consequences of loan securitization on the bank's default risk are derived from simulations of the portfolio's default rates. The default rate distribution and the first loss position of the bank jointly determine the eventual risk transfer to investors in a fully funded transaction.

Additional insights are obtained from analyzing the effect of default rate correlations on the bank's aggregate position. Usually a bank securitizes only part of its loan book. Hence the risk effect of securitization also depends on the correlation between the securitized and the non-securitized loans. Higher correlations are generated by a stronger exposure of the loans to a macrofactor of default risks. The strength of this factor determines the shape of the portfolio's loss distribution and the extent of risk reduction achieved by securitization. It also affects the joint risk effect of securitization and the ensuing expansion of the loan business. In the end, the diversification effect of attracting more loans of different obligors in different industries will be smaller the smaller are idiosyncratic risks relative to macro risks.

Expanding the loan business through loan securitization will normally expose the bank relatively more to macroeconomic risks than to idiosyncratic risks. Given the strong correlation between credit spreads and the market return, as documented by [5], we hypothesize that the bank's beta increases with securitization and expansion. The empirical findings support this conjecture (section 3). We use a new data set of European securitizations to ana-

lyze this beta effect and the announcement effect on the banks' share prices. While we find no abnormal stock returns around the announcement date, there is a significant rise in the bank's systematic risk. The cross sectional analysis reveals some differences between static and dynamic transactions.

In the concluding section 4 we summarize our findings and discuss implications for banking supervision.

2 Tranching and the allocation of risk

2.1 Contract design

Information asymmetries are a major obstacle to trading debt claims, in particular claims against small obligors about whom little is known publicly [11]. Adverse selection and moral hazard of the bank create problems similar to those in the insurance business. Therefore, suitable mechanisms of protection are also applied in CDO transactions. The main instruments are first loss positions (deductibles in the case of insurance contracts) and risk sharing arrangements (coinsurance in the case of insurance contracts). First loss positions have been shown to be optimal arrangements in a number of papers, including [1], [23], [8].

There are basically two types of CDO transactions, fully funded asset backed securities (ABS) and synthetic transactions (CLN). In an ABS transaction the bank sells part of its loan portfolio to a special purpose vehicle (SPV) which refinances itself through the issue of bonds. Usually the bank has to take a first loss position, i.e. the bank agrees to absorb default losses up to a specified limit. To achieve this, the bank can buy the non-rated tranche (equity tranche) which absorbs all default losses up to its par value, before other tranches have to bear any further losses. In addition or alternatively, the bank can set up a reserve account which absorbs default losses in a similar way. In these transactions, the bank can use the proceeds from the sale of its loans to generate new business.

In a CLN (credit linked note) transaction the bank retains the loans, but buys protection through a credit default swap with an SPV as the counterparty: the SPV issues bonds and invests the proceeds in high quality debt claims. The bank has no access to the proceeds. Quite often these proceeds are only a small fraction of the value of the loan portfolio for which the bank buys protection. Again, the bank usually takes a first loss position by establishing a threshold such that the SPV has to compensate the bank for

default losses of the underlying portfolio only for losses exceeding the threshold. Moreover, the SPV never pays the bank a compensation in excess of the value of the issued bonds. Hence, if this value is only a small fraction of the initial value of the underlying loan portfolio, then the investors cover default losses only up to this fraction. The bank thus retains the risk of default losses exceeding those covered by the SPV. The bank may buy protection for these risks through a senior credit default swap with a different counterparty.

The importance of default risk for the size of the first loss position can be seen from a sample of 43 European CLO transactions, for which we could get a standardized measure of portfolio default risk.

This is done by converting Moody's weighted average rating factor or, if it is not available, the weighted average quality of the underlying loans into a weighted average default probability (*wadp*). We then regress the nominal size of the first loss piece on the weighted average default probability, the issue date, and Moody's diversity score (*ds*). The latter statistic captures the diversification of the underlying asset portfolio. Its score is increasing if portfolio loans are spread more evenly within and across industries.

$$flp = c + \beta \cdot wadp + \gamma \cdot ds + \delta \cdot date + \varepsilon$$

The regression result finds β to be positive and highly significant ($p = 0.00$), while γ is negative and weakly significant ($p = .07$); the adjusted R-squared is 0.73. The issue date is insignificant. Thus, the weighted average default probability is a strong determinant of the size of the FLP, confirming our conjecture that the first loss position increases with the expected default loss of the underlying portfolio. As will be shown, the FLP thus yields significant investor protection against adverse selection and moral hazard. The protective role of the FLP will become more apparent when, in the next section, we simulate the loss distribution of the underlying portfolio, and estimate the share of expected default losses covered by the first loss position.

The shape of the loss distribution is essential for understanding the relevance of the diversity score for the size of the first loss position. A large diversity score is indicative of a steep loss distribution, with loss observations being more heavily concentrated around the mode.

A common feature of asset securitizations is the allocation of portfolio risk to several layers of claims. These layered claims, or tranches, obey the principle of strict subordination. Losses up to the par value of the lowest tranche are completely absorbed by the holders of this tranche. If accumulated losses of the underlying asset portfolio exceed the par value of the lowest tranche, which is the detachment point of the tranche and the attachment point of the next senior tranche, the latter will absorb the remaining losses, up to its detachment point, and so on for the remaining tranches. In this way,

tranches which are more senior will only be affected if the waterfall of losses reaches their attachment point, after having wiped out all junior tranches.

According to the model in [7], optimal securitization design aims at a structure that facilitates funding of relationship specific assets by uninformed, remote investors. Senior tranches are suited for these investors since, by construction, they are largely free of default risk. Therefore, holders of senior tranches are rarely exposed to the moral hazard component of the underlying lending relationships. Investors need not spend resources on monitoring the underlying lending relationships, thus lowering the required tranche rate of return in equilibrium¹. Issuing mezzanine tranches to sophisticated investors supports the reduction in delegation costs even further. These investors have an expertise in risk assessment and monitoring, providing a buffer between the first loss piece held by the issuer and the senior piece held by remote investors.

The number of distinct mezzanine tranches will therefore depend on the shape of the loss rate distribution. How does the number of tranches of a given transaction relate to the degree of diversification and the default probability of the underlying loan portfolio? An empirical estimate follows from regressing the number of tranches on Moody's diversity score and on the weighted average default probability:

$$\#tranches = c + \beta \cdot wadp + \gamma \cdot ds + u$$

In a simple OLS regression using the same 43 European CLO transactions as before, we find that the diversity score has a positive and significant coefficient ($p = 0.00$), while $wadp$ is insignificant. The adjusted R-squared is 0.2. Thus, after controlling for the default probability, a steeper loss rate distribution is associated with a higher number of mezzanine layers. Inclusion of the first loss piece and the issue date does not change the regression results.

The implications of [7] relate to the risk allocation achieved by tranching the underlying collateral portfolio. By acquiring the senior tranche, remote investors essentially take on macroeconomic risk. To be more precise, the payoff from holding a senior tranche is effectively indexed to system wide macroeconomic shocks. Define the macrofactor of default risks as the average default rate on the aggregate portfolio of debt claims. This factor is random and, by definition, ranges in the (0,1) interval. Then a well-diversified loan portfolio of average initial quality will only incur average default rates beyond, say, ten percent if the macrofactor is in the same range. Hence the senior tranches will only incur default losses if the macrofactor turns out to

¹See [18] and [4] for a review of relationship lending and its role in a bank-oriented financial system.

be very bad.

This is not to say that in a like situation there is no moral hazard of the bank. It may well be that in a severe downturn situation banks do not care much about their loans anymore. Moral hazard behavior may then be difficult to detect, so that reputational costs are low. Yet, the senior tranches are only impaired if the macrofactor turns out to be bad. If the macrofactor turns out to be good, then even strong moral hazard behavior is very unlikely to affect the senior tranches at all.

Thus, the structural aspects characterizing collateralized debt obligations are devised to solve the inherent tension that exists between the originator who has private information, and a diversified investor base without this information, a problem much discussed in the corporate finance literature, see [10] and [20].

In the next sections we will characterize the properties of junior and senior tranches, building on the information provided in the offering circulars of a large number of European CDOs.

2.2 Estimating the loss distribution

To estimate the loss distribution of the underlying portfolio and the implied loss allocation to the various tranches, we proceed as follows. First, we use the information in the offering circular² on the quality of the underlying loans and their initial portfolio weights, as indicated by a rating agency. If this information is not available, we use the average initial loan quality as indicated by a rating agency. Then we use Moody's transition matrix for different loan qualities to estimate the default probabilities for particular loans over the lifetime of the transaction: we use Monte Carlo simulation to generate a distribution of rating migration paths assuming a 47.5% recovery rate throughout. Absent better data on loss given default, these assumptions are standard in the literature.

Multi-year asset value migration tables are derived from the one-year table through repeated multiplication. The migration matrix is then mapped into a matrix of standard normal threshold values. For each asset, a random draw from the standard normal distribution yields a migration from the beginning of the year to the end of the year rating notch. To arrive at a

²Offering Circulars (OC) are official documents describing the issue's collateral composition, among many other contractual and legal details of the arrangement. OCs are public information to be posted at issue date. In addition, most issues are accompanied by pre-sale reports published by rating agencies

portfolio return, the correlations between loan migrations need to be taken into account. This is done by a Cholesky transformation.

For assets in the same industry (in different industries), the correlation coefficient is initially set at 0.3 (0.0), following common practice[21]. Alterations of the assumptions on asset correlations will later on be used to analyze the impact of systematic risk on loss correlations between tranches.

The generation of final portfolio cash flows and their allocation to the tranches that constitute the issue is achieved in a last step. The cash flows of each period t are transformed in a realized final (compound) value, RFV_t , using a flat term structure of interest rates (4%). If a credit event is recorded (default), then the assumed recovery is accounted for, and all further cash flows from this asset are set equal to zero. All final cash flows are allocated to tranches according to the principle of subordination, as defined in the offering circular. Finally, for each tranche, the nominal claims of each period, NV_t , are transformed into a final value as well, NFV_t . The sum of these final values over all tranches defines the final value of all claims. The ratio of these two final values defines the portfolio loss rate, $PLR_T = 1 - \frac{\sum_t RFV_t}{\sum_t NFV_t}$. Using 50,000 observations, a loss distribution is generated that reflects the loss cascading inherent in the tranche structure³.

Figure 1 about here

Figure 1 shows the loss rate distribution of the London Wall 2002-2 transaction, issued by Deutsche Bank in 2002, which appears to be a typical example of a CDO transaction. Here we assume an intra-industry correlation of 0.3, and a zero interindustry correlation. The graph shows a pronounced skewness. The expected loss is 150 bp (1.5%) with a first loss position of 246 bp. By retaining the FLP, the originator bears losses within the 91%-quantile of the loss rate distribution. Hence, a large fraction of losses is not transferred to investors, which serves as a strong barrier to adverse selection and moral hazard.

2.3 Loss allocation in CDO transactions

How is the risk of an underlying portfolio allocated to tranches? In particular, to what extent are expected losses, given the estimated probability distribution of loss rates, absorbed by the various tranches? In a typical issue, the

³There are a few simplifying assumptions: (i) there is no rating upgrade once an asset has reached default status; (ii) a defaulted asset returns the recovery rate multiplied by the nominal amount immediately; (iii) every asset has a bullet structure, there is no prepayment.

first loss piece comprises between 2% and 10 % of the issue volume, while the senior AAA-rated tranche comprises as much as 80-95%. Further evidence is derived from looking at a sample of 40 European CDO-transactions with close to 200 tranches, see the list in Table 7. This sample has some overlap with the CLO-sample used for the regressions in section 2.1.

In calculating the loss distributions for this European CDO sample, we rely on our own loss estimator, introduced in the last section. We then determine the tranching by defining the tranches such that their default probabilities correspond to Moody's multi-year default rate tables, starting with the most senior tranche, and ending with the lowest rated tranche. The unrated first loss piece is then determined by the attachment point of the lowest rating tranche. Table 1 summarizes the results of this exercise. The table presents average values by type of asset. We consider three asset classes, collateralized loan obligations (CLO) with large loans and bonds, CLOs with small corporate loans (CLO/SME), and the rest (other, including CBOs and portfolios of CDO tranches). These asset classes differ with respect to diversification and relationship intensity. First, the degree of diversification is low for CBOs and high for CLO/SME issues, while CLOs are somewhat in between, as evidenced by the average diversity scores. Second, the relationship character of the underlying lending relationship is probably highest in the case of the SME loans, and lowest in the case of CBOs, which typically comprise bonds issued by large caps.

Table 1 about here

Table 1 uses a broad classification of 40 European transactions issued between January 1999 and July 2002⁴. It is instructive to compare the second and the fourth column, SME CLOs and CBOs, because the underlying assets differ. The former consists of bank loans extended to small and mid sized industry, while the latter refers to bonds issued by large corporates. Not only is the average issue size of SME portfolios about 80% higher than that of the average CBO portfolio, but also the number of loans by far exceeds the number of bonds, suggesting that SME CLOs are more granular, i.e. more diversified than CBOs. The table also shows that while the average size of the first loss piece is similar for both issue types⁵, it covers a much wider portion of the loss rate distribution in case of CBOs. The size of their FLPs is on average 3.36 times the expected loss of the underlying portfolio, and it is 1.34 times in case of SME-CLOs, although the difference in rating quality of the underlying portfolios is small. Due to the difference in first loss positions, the median rating of the most junior rated tranche of the CBO transactions

⁴All issues were selected for which we could get the offering circular.

⁵The size of the first loss piece is measured in percent of the underlying portfolio volume.

is several notches higher than its counterpart among SME-CLO transactions, see Table 1. CBO first loss pieces cover 0.96 of the cumulative density of the underlying portfolio’s loss rate distribution, on average. The remaining risk to be allocated to investors is relatively small, allowing for only 2.85 additional tranches to be issued for CBOs. This number is significantly lower than in case of SME CLOs where it reaches 4.57.

In all asset classes, the first loss piece covers more than 100% of the mean expected loss. Variations are sizeable, but there is no clear picture across asset classes. The average size of the first loss piece is 7.1%, with a significant variation between Non-SME CLOs and CCBOs. As a consequence, FLPs take over most of the expected losses, and the losses allocated to the senior tranche are restricted to extreme, systematic events. Their expected value is very low, 0.01% of the tranche volume on average, as is their default probability (0.5%).

2.3.1 Effects on the bank’s overall default risk

Assuming a true sale with all tranches being sold to outside investors, except the first loss piece, what are the consequences for the risk exposure of the bank? The answer depends on several aspects: first, what other assets does the bank have on its book and how are their cash flows and default risks correlated with those of the securitized loans? Second, what would be the effect of securitizing all default risks? Third, how does securitization change the bank’s loan policy? In order to improve our understanding, we consider a bank with a portfolio of 50 identical loans extended to obligors in 5 different industries, one year to maturity, and the same quality. The latter is set equal to a B rating, implying a 8.5 % default rate[17]. The bank can either keep the loans in its books, or securitize them. For the securitized portfolio, the bank retains a non-rated tranche of 10.11 percent, i.e. a first loss position. The bank then reinvests the proceeds amounting to $(100 - 10.11)$ percent in new loans to obligors with the same properties as those in the initial loan book. Hence the on-balance sheet loan book of the bank, including the retained first loss piece, has the same size as before securitization.

Table 2 shows the first four moments of the distribution of loss rates (1) for the original loan portfolio without securitization and (2) for the new portfolio whose default losses are composed of those from the FLP of the securitized portfolio plus all default losses from the newly granted loans. The moments depend on the assumed intra- and interindustry correlations, therefore we report different correlations scenarios. In the first, the base case, intra-industry dependence is set a 0.3, while inter-industry correlation is zero. The other scenarios assume a stronger dependency, suggesting the existence of a com-

mon systematic factor. Higher correlations reflect a stronger macrofactor of default risks.

Table 2 about here

First, consider the effect of securitization and reinvestment in the correlation base case. Figure 2 plots the difference between the default rate distribution of the new and that of the original portfolio. The graph indicates that securitization and reinvestment lower the default probabilities in the range 0 to 18 %, and raise them in the range 18 to 46 %. Therefore, the mean loss rate of the new portfolio is higher than the respective rate of the original portfolio. The ratio of the mean of the new portfolio over that of the original portfolio is not just $(1 + (1 - 0.1011)) = 1.8989$, but clearly lower. The reason is that in the new portfolio the loss of the securitized portfolio is restricted to the FLP.

More difficult to grasp are the effects on the second, third and fourth moments of the loss rate distribution. First, consider the standard deviation. In Table 2 the standard deviation of the new portfolio exceeds that of the original portfolio. Intuitively, this is explained by scaling up losses through securitization and reinvestment. But this is not true in general. Let the par value of the original portfolio be 1 \$. If the bank securitizes this portfolio taking a FLP of 0.1 \$, it grants new loans for 0.9 \$. Let σ_{op} denote the standard deviation of the loss of the original portfolio, σ_{flp} the standard deviation of the loss on the FLP, and ρ the correlation coefficient between losses. Then the variance of the new portfolio equals

$$\sigma_{flp}^2 + 2 \cdot 1 \cdot 0.9 \cdot \rho \cdot \sigma_{op} \cdot \sigma_{flp} + 0.9^2 \cdot \sigma_{op}^2$$

while the variance of the original portfolio equals σ_{op}^2 . Obviously, the variance of the new portfolio is *smaller* than that of the original portfolio if the FLP is small relative to expected loss so that it will be exhausted by losses with high probability. In the limit, σ_{flp} tends to zero, implying the variance of the new portfolio roughly to equal 81% of the variance of the original portfolio. Therefore it is not obvious whether the bank's standard deviation of default losses will increase or decline through securitization and reinvestment. From Table 2 one can see that skewness and kurtosis of the new portfolio decrease relative to the original portfolio. From Figure 2, this is not surprising given a shift of the probability mass from the lower tail to the center. This effect is more dramatic for the kurtosis than for the skewness which raises the differences to the mean to the fourth instead of the third power.

This latter effect can be seen more clearly from Table 3, which compares the exceedance probabilities before and after securitization, for various levels of loss rates. The exceedance probability is defined as the cumulative probability of exceeding the benchmark loss rate. While the exceedance probabilities are identical for a 0 % benchmark loss rate, they quickly diverge for all positive rates. The exceedance probability is always higher after securitization, with reaching a maximum difference at a benchmark loss rate of 20 %, where the probabilities are 15.91 % and 62.34 %, respectively. At the 40 % benchmark, the exceedance probability is almost zero before securitization (0.02 %), while it is still 0.59 % after securitization. These figures show that the change in the loss rate distribution caused by securitization is not merely a shift of the distribution, but also a spreading out of the distribution.

Second, we look at the effects of correlations on these results. Of course, correlations have no effect on the average default rate of the original portfolio. This is always the same (around 5,67%) even though the simulation produces slight differences. Figure 3 displays the difference between two frequency distributions of default losses of the original portfolio, the first being determined by correlations(0.7; 0.3) , the second by (0.3; 0.0) with the first number being the intraindustry correlation and the second the interindustry correlation. Raising the correlations shifts probability mass from the range (6 – 24 %) to both tails. Therefore, the standard deviation, the skewness and the kurtosis of the default rate of the original portfolio increase with correlations.

More complex is the effect of correlations on the default rate distribution of the new portfolio. Figure 3 indicates that a FLP of about 10 percent has to bear small losses (1 – 5 %) with higher probabilities, and high losses (6-10 %) with lower probabilities. Hence, in this example, higher correlations imply a lower average loss for the FLP. This also explains in Table 2 why the ratio of average losses of the new over the original portfolio declines with higher correlations.

Table 2 also indicates for our example that standard deviation and skewness of the new portfolio increase with correlations, while this is not always true of the kurtosis. The relative increase in standard deviation (new over original portfolio) tends to slightly decline with higher correlations. The relative changes in skewness and kurtosis do not display such regular patterns. The simulation exercise begs the question whether securitization and

reinvestment will have an impact on the systematic risk of a financial intermediary. We have assumed that first loss pieces will be retained, while all other tranches are not. Under these assumptions, tranching and reinvestment may change the granularity of the underlying loan book, which in turn affects

systematic cash flow risk. As a result, the bank's beta might be affected as well. We will look into this matter next.

3 Share price reactions to the issue of Collateralized Debt Obligations

In this section we want to analyze how the securitization of loan assets affects the equity valuation of the bank. In accordance with the last section, emphasis will be on effects that are due to tranching and reinvestment. Earlier studies, including the event studies by [14] and [22], have neglected the important risk repackaging aspect of loan securitization.

3.1 Hypotheses and test design

Our main hypothesis relates the effects of tranching and reinvestment to the systematic risk of the bank. As described in the preceding section, optimal tranching tailors the equity piece to the expected default rate of the loan portfolio. When the equity piece is retained by the originator, while other tranches are sold or swapped to external investors, securitization and reinvestment will systematically alter the risk exposure of the bank. Note that reinvestment is limited to the funded portion of the issue, up to 100% in true-sale transactions. In particular, reinvestment in loans of comparable quality to the existing loan portfolio will raise the granularity of the bank's loan book, reducing the importance of idiosyncratic default risks. Therefore the correlation between the bank's default losses and a macrofactor of corporate default risk should increase.

Moreover, our simulation results indicate that the standard deviation of the bank's default losses increases if the first loss position is sufficiently high so that the standard deviation of the default losses due to this first loss position is sufficiently high. Then securitization and reinvestment raise the standard deviation of the bank's default losses and its correlation with the macro factor of default risks.

The question then is how this translates into changes of the bank's stock return beta. Elton/Gruber/Agrawal [5] found a correlation of 0.6 to 0.8 between the credit spread changes of a corporate bond and the stock returns of the corporation. This suggests a high correlation between the macrofactor of default risks and the stock market return. We hypothesize that a higher correlation between a bank's default losses and the macrofactor of default

risks translates into a higher correlation between the bank's equity return and the market index.

We also hypothesize that a higher standard deviation of the bank's default losses raises the standard deviation of the bank's stock return. Both effects would imply a higher beta. Furthermore, these risk effects are expected to be stronger for banks that engage repeatedly in securitizations and that, over time, increase the share of equity tranches among its assets. This is our first hypothesis:

Hypothesis 1 *Issuance of collateralized debt obligations and reinvestment of proceeds in new loans will raise the bank's beta. This effect will be stronger for repeated transactions.*

We investigate the securitization impact on the bank's stock beta since we are interested in the impact on the shareholder position. Alternatively, one might look at the securitization impact on the bank's shareholders and bondholders. Then the bank's beta defined by the joint stock and bond return and the joint market index of stock and bond returns, would be relevant. This would require daily returns on the bank's debt a large part of which is not securitized. Thus, the necessary data are not available. Therefore, we use the conventional beta approach.

The first hypothesis relates to beta changes after securitizations, rather than expected securitizations. Otherwise one would expect to observe the compound risk shifting effect at the time of the first issue, t_0 . Announcement effects of new CDO issues on beta would then be indeterminate, because their impact on the bank's risk exposure would have been anticipated, though possibly with noise.

We now turn to the stock price reaction triggered by the announcement of the securitization, as captured by the abnormal return in a typical event study. The abnormal return is determined by the expectation of investors, given the information contained in the issue announcement⁶. If stockholders interpret the securitization as a pure change in the bank's financing strategy, then in a perfect market there should be no stock price effect unless the change in the financing strategy redistributes wealth from the stockholders to the bondholders, or vice versa. Since the stockholders hold the equity piece and the bondholders hold the senior tranche of the bank's assets, securitization should typically reduce the expected default losses of the bank's

⁶From conversation with practitioners we know that the valuation of CDO mezzanine tranches is typically preceded by a bookbuilding period resembling an English auction, as modeled in [19].

bondholders and, thus, enrich them at the expense of the stockholders. This would argue in favor of a negative stock price reaction.

Similarly, if the bank uses an ABS transaction to obtain new funding, then stockholders may interpret the transaction as unfavorable information about the bank's funding needs and react by a stock price decline. This, however, would not be true for a synthetic transaction because then the bank does not receive funding. Finally, the transaction cost of securitization is nonnegligible adding to a negative stock price impact.

On the other side, the securitization enables the bank to expand its loan business. This may be considered by the stockholders as a valuable real option of the bank so that the stock price should increase. Similarly, the securitization protects the bank against major default losses, and thereby reduces the costs of financial distress. This would also be good news for the stockholders.

Summarizing, the net impact of securitization on the bank's stock price is hard to predict. Across the entire sample we do not expect significant stock price reactions to the announcement of securitizations.

Hypothesis 2 *The announcement of a CDO-transaction by a bank does not lead to a significant reaction of its stock price.*

We shall test this hypothesis, first, by looking at all transactions, and second, by looking at different subsets of transactions to find out whether the hypothesis holds equally well for all these subsets.

There are a number of characteristics that may be relevant cross-sectionally. Among these characteristics is the synthetic nature of a deal, because synthetic deals eliminate the funding component in an issue and, therefore, synthetic issues have a smaller impact on the bank's asset composition, relative to a fully funded transaction.

A second characteristic of securitization transactions that may be relevant for cross sectional differences is the nature of the issue as static or dynamic. Static issues maintain the original asset composition of the collateral portfolio throughout the life of the transaction. This typically implies a gradual redemption of the outstanding issue, in accordance with repayment of the underlying loans. Dynamic issues, in contrast, tend to maintain their original volume throughout the entire term of the issue. If loans in the collateral portfolio are redeemed, the issuer replaces them by new loans, safeguarding certain quality standards. While replenishment standards vary between issues, a general implication is that banks are required to assign new loans to the collateral portfolio in a systematic, non-random way.

Since both properties - synthetic/true-sale and static/dynamic- exert an influence on the asset composition of the bank, we expect both characteristics to be consequential for the value effect of the issue announcement.

We use an event study methodology. Since there are many event data in a relatively short period of time with a lot of overlap, and since there are several banks with repeated issues, the abnormal return regressions are run as a system. To account for contemporaneous correlations between the regressors, we employ the Seemingly Unrelated Regression (SUR) methodology. Contemporaneous correlation between regressors is to be expected, since we observe some clustering of the event dates (see Figure 4). The regression system is run in calendar time rather than in event time, so that contemporaneous correlations are properly accounted for⁷.

Figure 4 about here

3.2 Data and results of the event study

In compiling our data set we initially looked at all transactions in Moody's European Securitization list of June 2003. The number of issues is 254, of which 185 have a Moody's "New Issue Report". It is this *New Issue Report* that contains the information required for conducting the study, including a description of the underlying assets as well as the covenants relevant for the issue. Among the many other features of the issue, the Report also contains the pricing of the tranches at the issue date and the name of the originator. Not every issue has a single originator⁸.

For 112 transactions we were able to identify the originator. We imposed the additional restriction that the originator is a listed company (else no stock price is available), and arrive at a sample of 92 transactions from 31 banks. We excluded the non-European banks and finally have 75 transactions issued by 27 banks. These issues are used for the event study and, later on, for the cross sectional analysis.

Table 4 presents the descriptives for our final data set. In the upper panel of Table 4 one can see that the average size of transactions is small relative to the entire balance sheet, up to 2 % of total assets. The average number of tranches over all transactions is about 6. The lower panel refers to a

⁷With 75 x 240 observations, there are enough degrees of freedom to estimate all coefficients in the SUR system.

⁸Several ABS products are managed arbitrage deals that pass through the cash flows of several originators at once.

subsample of the 75 issues, comprising 51 issues. It excludes all transactions whose issue date is less than 5 months (100 days) after another issue by the same bank. This subsample will later be used in the regression analysis. For repeat issuers this share of balance sheet assets adds up to 5-10 % of total assets, and in some cases an even larger share of the total loan book. The basic model is an augmented event study estimation.

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \gamma_{1,i} D_i^{event} + \gamma_{2,i} D_i^{other\ event} + \beta_i^\Delta D_i^{after} R_{m,t} + \varepsilon_i \quad ; \\ t = -20, \dots, +20.$$

The dependent variable $R_{i,t}$ as well as the independent variable $R_{m,t}$ are excess returns, defined as the log return minus log German interbank-one month lending rate, FIBOR (EURIBOR since 1999). The explanatory variables include the log of market excess return, defined as the DJ EuroSTOXX index, the dummy D^{event} whose coefficient captures the abnormal return over the event window. The window extends from day -20 to day +20 around the announcement date. Announcement dates were assumed to be the first public notification that could be identified in Lexis-Nexis, or in pre-sale reports of the three major agencies.

The estimation uses a 200-days window, symmetrically around the event window. Thus, for each event the time series extends over 240 trading days, approximately one year. Since we are interested in a possible change of systematic risk, the regression has a second variable capturing systematic risk, delta-beta (β^Δ), which is multiplied by a dummy, D^{after} , which equals one for the 100 days following the event window, again (-20, +20). The coefficient β^Δ measures the extent to which the after-event beta diverges from its pre-event value. The null hypothesis sets delta after-event beta at zero.

The estimation is complicated by the fact that for many cases in our sample, there are repeat issuers, and the interval between two consecutive announcement dates by the same issuer frequently is less than 100 days. Since a separate regression is run for every transaction, there is overlap among the estimation windows. In order to disentangle the effect of the original event on beta from the effect of a later event, we include a dummy "other event", $D^{other\ event}$, whose coefficient captures abnormal returns in a -20/+20 days window around the later event.

However, in some cases there is more than one "other event", up to a maximum of three. To deal with these frequent issue-cases, we set the dummy D^{after} equal to two (three) for the second (third) overlapping event. Thus, we force β^Δ to be of the same order of magnitude for all successive and overlapping events. Due to the overlap of events, and the relatively short period for which data are available (1999-2002), we estimate the equations as a system of seemingly unrelated regressions (SUR). The SUR methodology

increases the efficiency of the estimation in that correlations between the error terms are accounted for. Note that within the SUR framework, the daily returns are aligned in calendar time, so that the contemporaneous correlation is duly taken care of.

A second set of regressions explores the cross-sectional determinants of two key variables in our analysis, the abnormal return ($\gamma_{1,i}$) and the change in systematic risk (β_i^Δ). The estimated model is, where $X_j : \{\gamma_{1,i}, \beta_i^\Delta\}$,

$$X_j = \alpha_j + \lambda_{1,j}D^{dynamic} + \lambda_{2,j}D^{synthetic} + \lambda_{3,j}D^{CLO} + \lambda_{4,j}D^{CBO} + \lambda_{5,j}D^{other} + \lambda_{6-8,j}D^{year} + \varepsilon_j$$

The explanatory variables generate partitions of the sample. In particular, $D^{dynamic}$ is a dummy variable that equals one for managed issues, i.e. collateral portfolios that are being replenished over the life of the issue. $D^{synthetic}$ separates between synthetic and fully funded true sale issues, where the dummy equals one for synthetic issues. D^{CLO} , D^{CBO} , and D^{other} subdivides the sample into four categories according to the type of the underlying asset portfolio, as loans, bonds, mortgages (the reference group), and all others (e.g. credit card or leasing claims). The D^{year} -dummy stands for the issue years, with 2002 as the reference year.

Tables 5 and 6 report the result of the regressions. We will discuss the findings starting with Table 5. The augmented event study produces two important results. First, looking at regression A.1 with overlap, the average cumulative abnormal return around the announcement date (-20, +20) is very small and statistically insignificant. This holds true for the event window (γ_1), as well for any overlapping other event window (γ_2). This finding supports Hypothesis 2 and is consistent with the result in [22]. The regression in Table 6 analyzes the determinants of γ_1 and reveals that the average cumulative return in 1998 differs significantly from that in 1999 (λ_{6-8}). Returning to the time series regression A.1 in Table 5, we observe that the coefficient measuring a change of systematic risk after the event, β^Δ , is positive and significantly different from zero. Its positive sign suggests that banks engaged in securitizations are increasing their exposure vis-a-vis the market return. Since the coefficient captures the average increase in systematic risk per overlapping event, the risk increasing effect of asset securitizations is higher for repeat issuers than it is for one-time issuers. Thus, hypothesis 1 is confirmed.

In regression A.2 of Table 5 we reran the regression suppressing all observations with overlapping events. By construction, the subsample has fewer observations (51 instead of 75), and it underrepresents repeat issuers, i.e.

large issuers. While the γ_1 -coefficient is similar in size and significance, β^Δ is now much smaller and only marginally significant ($p = .09$). Thus, the beta-increasing effect of securitizations is more relevant and more visible for institutions that engage repeatedly in securitizations, and that are more likely to systematically alter their loan portfolio as a consequence of their access to the capital market.

The cross section analysis of β^Δ reported in Table 6 offers additional insight in what drives the increase in beta after securitizations. Among the structural characteristics, the dummy for managed issues, λ_1 , is the only one that turns out significant. Since its sign is negative, it signifies that managed issues have a lower increase in systematic risk, i.e. the bank may be less motivated to increase granularity in the aftermath of a securitization, or the bank may be more concerned to restrict the new risks to avoid early termination of the transaction, relative to static deals. The variables representing the type of underlying asset, like CLOs, CBOs remain insignificant altogether.

Clearly, these findings are explorative in nature, and they will have to be followed up by an integration of structural data concerning the collateral assets as well as balance sheet details of the bank.

3.3 Conclusions

An evaluation of the economic implications of securitizations for financial institutions risk management and for financial stability on the macro level necessitates first and foremost an understanding of the effective risk transfer. In this paper we have analyzed the design of CDO transactions and its impact on the default risk exposure of the originating bank. Adverse selection and moral hazard problems, which are considered strong barriers to trading default risks, are largely eliminated by a substantial first loss position of the originator. The size of the first loss position has been shown to increase with the average default probability of the underlying portfolio. The tranching typically leads to a large senior tranche which in the case of a fully funded transaction may be sold to remote investors. Securitization then protects the originator against high default losses that otherwise would lead to financial distress. The impact of securitization and reinvestment on the bank's default risk is illustrated by a simulation exercise which also illustrates the impact of correlations on the bank's risk exposure. If the bank uses the securitization proceeds to expand its loan business, then its systematic default risk tends to increase. This tends to translate also into an increase in its stock

beta, as confirmed by the empirical findings. We do not find a significant securitization announcement effect on the bank's stock price.

The economic consequences of securitization are depending as much on the way the issue is tranced as on the way these tranches are allocated to investors. First, the tranching technique allows to largely separate idiosyncratic from systemic risks. Assuming that the default risk of corporate loans depends on the relationship between the bank and its customers, tranching allows to allocate information-sensitive risks predominantly to the first loss piece, and to a lesser extent to the mezzanine pieces, while the senior tranches are largely free of these risks. In turn, extreme or systemic risks are borne predominantly by the holders of the senior tranches. The return of these senior tranches is effectively indexed to systemwide economic shocks. To the extent that loan securitizations replace the traditional financing of banks through deposits, one may conclude that bank funding is indexed to macro risks⁹.

Second, the economic consequences of loan securitization on financial stability also depend upon the allocation of tranches to different types of investors. To realize an optimal sharing of risk, the first loss piece of the issues should be retained by the originator of the loans, because then his incentives as a lender are kept intact. In contrast, senior tranches have to be allocated to remote investors in order to improve financial system stability. Remote investors, like pension funds, are defined as being located outside the financial system. The reason is that it is them who are in a better position to withstand a systemic shock to financial markets that otherwise endanger the stability of the financial system at large.

The advantages emanating from risk sharing between originating banks and remote investors require that first loss pieces are retained by the originator, and that senior tranches are effectively held by investors operating outside the core financial system. The latter condition implies that banks and insurance companies are neither investing in CDO senior tranches, nor retaining the senior tranches. Both conditions are likely to be violated in many markets today. The actual allocation of these tranches to investors in the economy is of particular relevance for bank supervisors. Furthermore, the treatment of asset securitizations in the new Basle II framework, in particular concerning the allocation of systemic risks, will play an important role in achieving a desirable allocation of tranches. It may well be that the low risk weight for senior tranches, proposed under the new Basle II rules, is not high

⁹Tranching and securitization can overcome the obstacles that have prevented the introduction of indexed deposits to date, see [12] and [13] for a discussion of macro risk indexation for bank deposits.

enough to motivate banks to sell senior tranches. One may therefore speculate that transparency concerning tranche allocation vis-a-vis the supervisory authorities will one day become an important instrument of financial stability assessment and management.

This suggests a demand for more research along the lines we have presented in this paper. On the modeling side, the correlation structure between tranches of different seniority is relevant for CDO bond portfolio management and for assessing financial system stability. For example, a change in the correlation between asset classes not only alters the default probabilities of tranches, but it also alters the joint default probabilities of different tranches, as suggested by Table 3. This latter statistic is relevant for an analysis of contagion effects, as pointed out by [15] and [2]. On the empirical side, the effective allocation of tranches to investor groups is of importance, as is the expanded role of commercial banks as intermediaries between capital markets and the corporate sector, as discussed in [16].

It appears that the securitization of bank loans provides an efficient new tool to combine the advantages of bank- and market-based financial systems.

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Figure 1: Loss distribution of London Wall 2002-2, 50'000 iterations

This table displays the loss distribution of London Wall, as it was simulated using the information contained in the Offering Circular. A loss rate distribution for the entire portfolio is generated that takes into account the correlation within and between industries and the credit migration risks referencing Moody's tables. The chart shows on the vertical axis the frequency of observations, and on the horizontal axis the associated loss rate, truncated at 13 %. There was no observation surpassing this threshold.

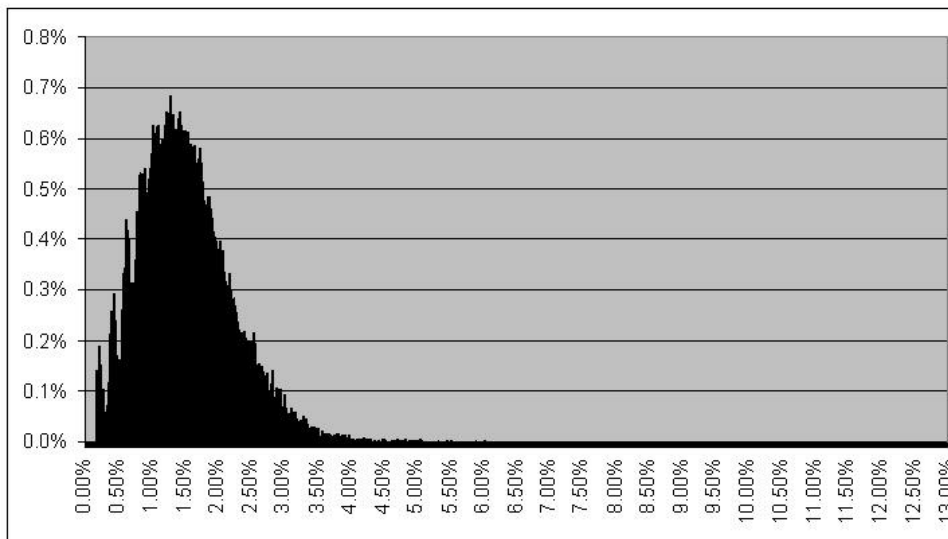


Figure 2: Securitization and reinvestment: Impact on marginal loss distribution, 10'000 iterations

This table displays the differential loss rate distribution of a simulated loan portfolio with and without securitization, followed by reinvestment. The original portfolio consists of 50 B-rated loans of equal par value with one year to maturity, split evenly across five industries. The new portfolio is obtained by securitizing the original portfolio retaining a first loss piece of 10.11 percent and reinvesting the par value of the original position minus the first loss piece in another portfolio which has the same characteristics. The loss given default is assumed to be 52.5 percent. The pairwise within-industry correlations are 0.3, while pairwise between-industry correlations are assumed to equal 0.0. The resulting differential loss rate distribution is displayed in the figure.

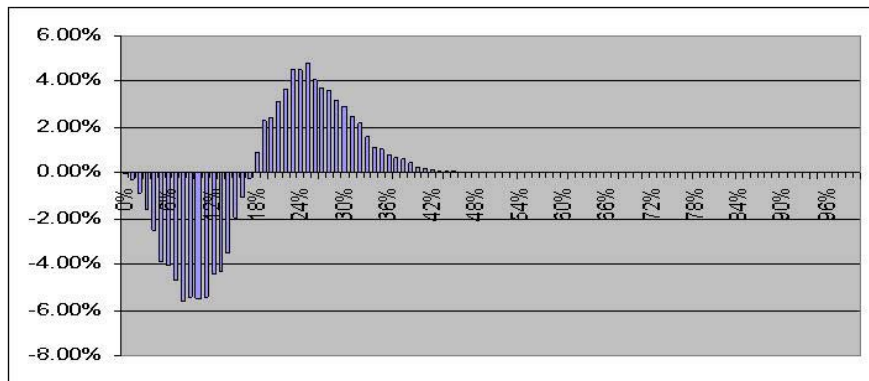


Figure 3: Impact on marginal loss distribution of an increase in correlation, 10'000 iterations

This table displays the differential loss rate distribution of a simulated loan portfolio with a low and a higher level of correlation. The original portfolio consists of 50 B-rated loans of equal par value with one year to maturity, split evenly across five industries. The loss given default is assumed to be 52.5 percent for each defaulting loan. The pairwise within-industry correlations are 0.3, while pairwise between-industry correlations are assumed to equal 0.0. These values increase to 0.7 and 0.3, respectively. The resulting differential loss rate distribution is displayed in the figure.

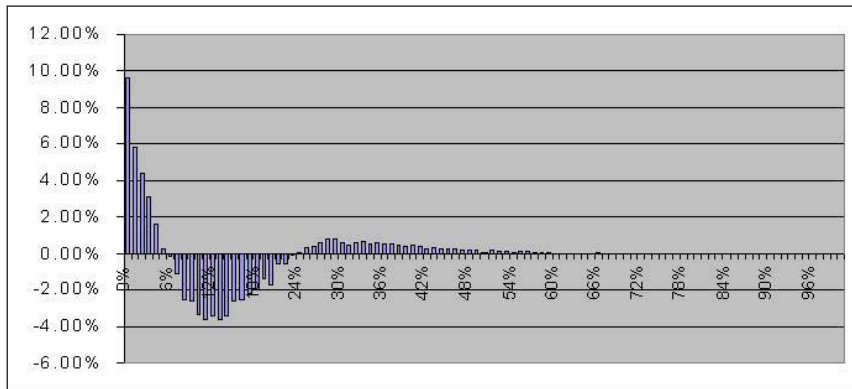


Figure 4: Time series of announcement dates

This figure plots the announcement of all 75 announcement dates between January 1999 and September 2002.

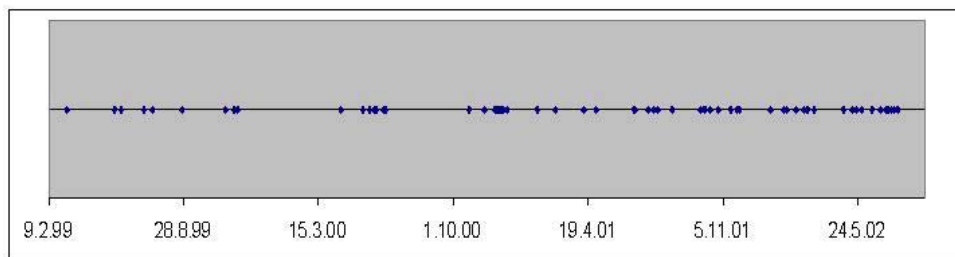


Table 1: Loss rate distribution of European CDOs: Descriptive Statistics

This table summarizes basic characteristics of the CDO sample used in the estimation of expected and unexpected loss. SME CLOs are collateralized loan obligations where underlyings comprise loans to small and medium size firms, CBOs are collateralized bond obligations, with large firm corporate bonds as underlyings, and Non-SME CLOs are a mixture of the two asset classes, comprising corporate bonds and loans to large firms. The numbers in the table are averages across the transactions listed in the column. Total volume is the amount in EUR of the portfolio underlying the transaction, the number of tranches is the number of issued tranches, excluding the FLP. Size FLP is the nominal value of a tranche relative to the nominal amount of the issue in funded and unfunded transactions, Size Senior Tranche is the nominal value of a tranche relative to the nominal amount of the issue in funded and unfunded transactions, FLP/E(L) is the size of the FLP tranche relative to expected loss E(L) of the underlying portfolio, and the FLP quantile is the cumulative density of losses not exceeding the size of the first loss piece.

	SME CLO	Non-SME CLO	CBO
Total volume (bn EUR)	2.068	1.392	1.126
Number of claims	2.303	153	100
Portfolio rating (median)	Ba1	Baa2	Baa1
Most junior rated tranche (median)	Ba2	Ba1	A3
Size FLP (in %)	6.7	8.61	5.93
FLP/E(L)	1.34	1.74	3.36
FLP quantile (cdf)	0.87	0.87	0.96
Number of tranches	4.57	4.17	2.85
Size Senior Tranche (in %)	91.11	87.79	92.89

Table 2: Reinvestment of securitization proceeds: Simulation results for the loss rate distributions

This table summarizes the results of a simulation exercise. The original portfolio consists of 50 B-rated loans of equal par value with one year to maturity, split evenly across five industries. The new portfolio is obtained by securitizing the original portfolio retaining a first loss piece of 10.11 percent and reinvesting the par value of the original position minus the first loss piece in another portfolio which has the same characteristics. The loss given default is assumed to be 52.5 percent. There are three scenarios in the table, which differ by their correlation assumptions. The lower panel shows the first four moments of the resulting loss rate distribution for the bank's loan book, including the retained first loss tranches, for the three scenarios. The first column (original portfolio) describes the loan book before securitization, the second (new portfolio) describes the loan book after the securitization transaction.

Panel I: Assumptions regarding correlations						
Within industries	0.3		0.5		0.7	
Between industries	0.0		0.0		0.3	
Panel II: Moments						
	Original portfolio	New portfolio	Original portfolio	New portfolio	Original portfolio	New portfolio
Mean	5.67%	10.51%	5.70%	10.30%	5.64%	9.52%
Standard deviation	3.52%	5.43%	4.29%	6.61%	7.63%	11.26%
Skewness	0.81	0.44	1.00	0.52	2.03	1.34
Kurtosis	0.68	-0.32	1.04	-0.46	4.76	1.13

Table 3: Change of loss rate distribution due to securitization

This table summarizes the results of a comparison of loss rate distributions before and after the securitization of a loan portfolio. It is assumed that the securitization proceeds are reinvested in a new loan portfolio of the same quality as the old portfolio. The figures in the table refer to the results of a simulation exercise with 10,000 runs. The original portfolio consists of 50 B-rated loans of equal par value with one year to maturity, split evenly across five industries. The new portfolio is obtained by securitizing the original portfolio retaining a first loss piece of 10.11 percent and reinvesting the par value of the original position minus the first loss piece in another portfolio which has the same characteristics. The loss given default is assumed to be 52.5 percent. The pairwise within-industry correlations are 0.3, while pairwise between-industry correlations are assumed to equal 0.0. The benchmark loss rate in the first column specifies a level of loss rates, while the figures in the two remaining columns refer to the frequency of loss rate exceedances in the simulation exercise, relative to the benchmark. Column 2 reports the frequency for the original loan portfolio, whereas column 3 lists the frequencies after securitization and reinvestment.

Benchmark loss rate	Before securitization: Prob (realized loss rate > benchmark)	After securitization: Prob (realized loss rate > benchmark)
40%	0.02%	0.59%
30%	1.13%	12.53%
20%	15.91%	62.34%
10%	69.32%	97.22%
5%	94.64%	98.88%
1%	99.95%	100.00%
0%	100.00%	100.00%

Table 4: European CDO data set: descriptive statistics

This table presents descriptive statistics of the CDO data set. The numbers (except no. of issues) are averages across transactions. The upper panel uses information of 74 of the 77 issues underlying the estimations in section 3. For the remaining three issues there were no balance sheet data available on Datastream, the source of these data. The lower panel represents a subsample, which contains only those issues that did not experience a repeat issue by the same issuer within five months after the first transaction. There are two issues without balance sheet data in Datastream, leading to 51 issues included in Panel II. 'Size' is the Euro volume of collateral assets underlying the issue, "Number of tranches" is taken from the offering circulars. All tranches, including non rated tranches, are considered. "Share of balance sheet assets" divides Size by total assets of the bank. "Equity (book value)" is the sum of equity and open reserves, according to Datastream.

Panel I: European data set (n=74)					
Year	Number of issues	Size (collateral assets, € bn)	Number of tranches	Share of balance sheet assets, in %	Equity (book value, € bn)
1999	10	1.682	6,4	0.54	12.5
2000	17	2.586	5.53	1,42	11.7
2001	20	2.629	5.60	2,08	14.7
2002	27	1.940	6.30	0.95	15.0
Panel II: Detailed data set (n=51)					
Year	Number of issues	Size (collateral assets, € bn)	Number of tranches	Share of balance sheet assets, in %	Equity (book value, € bn)
1999	7	1.675	5.43	0.66	10.3
2000	14	2.640	5.36	1,52	10.8
2001	15	2.850	5.67	2,66	12.4
2002	15	1.912	6.60	1,48	9.6

Table 5: Announcement effects: regression results

This table reports the results of the event study relating to the announcement of CDO issues. A SUR estimation of the determinants of excess stock returns of the issuing banks was employed. The first regression (A.1) is a time series estimation with 75 events over a window of 240 trading days. The second regression (A.2) has 51 events, excluding overlapping events by the same issuer (multiple issuers). All regressions use data from the period January 1999 to December 2002. The dependent variable in both regressions is $R(it)$, the daily return on 27 banks (from Datastream). The explanatory variables are $R(mt)$, $D(event)$, $D(other\ event)$ and $D(after)$. $R(mt)$ is the return on the EuroStoxx taken from Datastream. $D(event)$ equals one for the event window $[-20,+20]$, where the event is the announcement date of the CDO issue, $D(other\ event)$ equals one for all other event windows in the period $[-120,+120]$, and $D(after)$ equals one for the period $[+20,+120]$. Wald-statistics (p-values) are in parentheses.

$$R_{i,t} = \alpha_i + \beta_{1,i} R_{m,t} + \gamma_{1,i} D^{event} + \gamma_{2,i} D^{other\ event} + \beta_{\Delta,i} D^{after} R_{m,t} + \varepsilon_i$$

	$\bar{\alpha}_i$	$\bar{\beta}_1$	$\bar{\gamma}_1$	$\bar{\gamma}_2$	$\bar{\beta}^{\Delta}$
A.1 (n=75) w/overlap	-0,0003 (0,982)	0,7413 (0,000)	-0,0003 (0,360)	0,0003 (0,456)	0,05097 (0,003)
A.2 (n=51) w/o overlap	-0,0003 (0,943)	0,6597 (0,055)	0,0165 (0,343)		0,00175 (0,094)

Table 6: Announcement effects: second stage regression results

This table reports the results of the event study relating to the announcement of CDO issues. A SUR estimation of the determinants of excess stock returns of the issuing banks was employed. The regressions in this table are cross-sectional estimates of the determinants of delta-beta and gamma 1 from the regression in Table 5, i.e. the change in systematic risk after an event, and the cumulative abnormal return in the event window. The explanatory variables are D(dyn), D(syn), D(CLO), D(CBO), D(other), D(99), D(00), D(01). D(dyn) equals one for a managed issue, D(syn) equals one for a synthetic issue. D(CLO), D(CBO) and D(other) equal one when the collateral portfolio consists of loans, bonds, or other assets. Mortgage backed securities are the reference group. D(99), D(00) and D(01) equal one for the issue year 1999, 2000 or 2001. p-values are in parentheses. As in Table 5, the estimation is with 75 events over a window of 240 trading days. All regressions use data from the period January 1999 to December 2002.

$$X_j = \alpha_j + \lambda_{1,j} * D^{\phi^m} + \lambda_{2,j} * D^{\text{syn}} + \lambda_{3,j} * D^{\text{CLO}} + \lambda_{4,j} * D^{\text{CBO}} + \lambda_{5,j} * D^{\text{other}} + \lambda_{6,j} * D^{99} + \lambda_{7,j} * D^{00} + \lambda_{8,j} * D^{01} + \varepsilon_j$$

X_j	α	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8
β^Δ	0.061 (0.65)	-0.165 (0.02)	0.129 (0.16)	0.006 (0.95)	-0.111 (0.45)	-0.057 (0.62)	-0.282 (0.01)	0.172 (0.04)	-0.017 (0.83)
γ_1	-0.0009 (0.55)	0.0004 (0.61)	-0.0015 (0.18)	0.0019 (0.16)	0.0023 (0.20)	0.0018 (0.19)	0.0023 (0.06)	0.001 (0.31)	-0.0003 (0.72)
$adj.R^2$		$\left\{ \begin{array}{l} \beta^\Delta: 0.235 \\ \gamma_1: 0.048 \end{array} \right.$							

Table 7: List of European CDO issues used for loss rate estimation

This table summarizes descriptive statistics of the issues that have been used to calculate the loss rate distribution for the sample of European CDOs.

Name	CBO/CLO	Maturity	Volume in bn.€	#rated tranches	#years	Average Rating	Div Score
Dutch Care 2001-1	CLO	8	1.300	3	169	A1	12.4
Hesperic No. 1 nk	CLO	6	1.400	6	104	Baa1	31
IKB Credit Linked Notes 2000-1	CLO	10	0.534	3	61	Ba2	33
Leverage Finance Europe Capital I.B.V.	CLO	10	0.315	4	30	B1	26
London Wall 2002-1 PLC	CLO	6	3.000	5	330	Baa2	70
London Wall 2002-2 PLC	CLO	6	1.800	5	224	Baa2	70
ARCH ONE FINANCE LIMITED	other	4	0.490	2	70	Baa1	47
ARGON CAPITAL PLC - SERIES 1	other	7	1.382	5	53	Baa1	30
Brooklands Euro Ref. Linked Notes 2001-1	other	10	1.000	3	100	Baa1	50
Cathedral Limited	other	5	0.466	3	52	Baa1/Baa2	36
CDO Master Investment 2 SA	other	5	3.750	3	112	Baa1	66
CDO Master Investment 3 SA	other	5	2.500	3	86	Baa1	60
CDO Master Investment SA	other	5	1.625	3	100	Baa1	49
CDNEO FINANCE Plc	other	10	0.250	3	57	Baa2	34
CLASSIC FINANCE B.V. (Petra III)	other	5	2.320	5	232	A3	103
Credito Fudizis S.r.l.	other	6	0.890	1	117	Ba1	30
Deutsche Bank - United Global Inv. Gr. CDO I	other	5	1.436	3	148	Baa1	60
DYNASO 2002-1 LTD	other	5	1.000	3	100	A3	55
Erke Two Limited Series	other	7	0.628	3	74	A3	40.8
European Dream 2001-1	other	7	1.069	3	59	Aa1	26
Helix Capital (Netherlands) B.V. 2001-1	other	5	0.800	2	80	A3	50
Luximmo Global CDO No. 1, Plc	other	4	1.145	3	218	Baa3	35
Marche Asset Portfolio S.r.l.	other	3	0.168	3	59	Baa1	12
Redwood CBO	other	10	0.300	3	100	B2	45
Spices Finance Limited Peas	other	5	0.950	2	100	Baa2	56
Vintage Capital S.A.	other	10	0.360	1	76	Baa2	36
CAST 1999-1 Ltd.	SME CLO	7	2.900	4	4389	Baa3	70
CAST 2000-1 Ltd.	SME CLO	7	4.500	4	1991	Baa3	70
CAST 2000-2 Ltd.	SME CLO	7	2.500	4	5178	Baa3	95
HAT (Helvetic Asset Trust) AG	SME CLO	5	2.500	3	650	Ba2	100
HAT (Helvetic Asset Trust) II Limited	SME CLO	5	2.500	4	1465	Ba2	110
PRIMISE A-2000-1nk	SME CLO	8	1.000	5	1097	Ba1	90
PRIMISE A-2002-1nk	SME CLO	8	1.618	6	1277	Ba1	124
Promise-C-2002-1	SME CLO	6	1.500	5	4678	Baa3	90
Promise-Color-2003-1	SME CLO	5	1.130	5	1512	Ba2	80
Promise-G-2001-1	SME CLO	7	0.850	4	100	Ba1	85
Promise-I-2000-1	SME CLO	8	2.500	5	2267	Baa3	80
Promise-I-2002-1	SME CLO	7	3.850	5	4172	Baa3	80
Promise-K-2001-1	SME CLO	5	1.000	5	2916	Ba1/Ba2	100
Promise-Z-2001-1	SME CLO	8	1.000	5	668	Ba1	85

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