Monitoring Credit Risk Transfer in Capital Markets: Statistical Implications*

Dennis Hänsel[†], Jan Pieter Krahnen[‡], Christian Wilde[§]

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ABSTRACT

A major objective of banking supervision is to keep the probability of systemic risk at bay. In this paper we emphasize the need for policy indicators that allow to survey joint bank default risk augmenting the current practice of stand-alone Value-at-Risk reporting. The joint default probability, however, while a natural candidate for such an indicator, is substantially affected by the widespread use of credit derivatives and instruments of risk transfer. Monitoring the risk exposure of individual banks as well as the entire banking sector therefore requires a bottom-up strategy for data collection, starting at the level of the individual financial instrument and its major characteristics. Familiarity with industry practice is as much a prerequisite for measurement, as is the knowledge of financial economics. The paper sets out to give a selective account of the type of information that has to be collected if a supervisor wishes to monitor the risk exposure of banks that employ credit securitizations. The conclusions for data management extend to a broader class of derivative financial instruments.

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JEL classification: G21, G28

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[†]Finance department, Goethe-University, Frankfurt. Correspondence: Mertonstr. 17-21 (PF88), D-60054 Frankfurt(Main), Germany, E-Mail: haensel@finance.uni-frankfurt.de.

[‡]Finance department, Goethe-University, and CFS Center for Financial Studies, Frankfurt, and CEPR. Correspondence: CFS, Mertonstr. 17-21, D-60054 Frankfurt(Main), Germany, E-Mail: krahnen@wiwi.uni-frankfurt.de.

[§]Finance department, Goethe-University, Frankfurt. Correspondence: Mertonstr. 17-21 (PF88), D-60054 Frankfurt(Main), Germany, E-Mail: wilde@finance.uni-frankfurt.de.

I. Introduction

Monitoring the stability of financial markets and financial intermediaries is one of the primary objectives of supervisors and central banks, yet it is also one of the more diffuse goals. Intuitively we understand quite well what financial stability means. It entails the smooth functioning of the payment system, the existence of liquid secondary markets at all times, and the absence of concurrent bank break downs. Financial stability in a given market is reflected in the belief, shared among market participants, that the risks faced by financial intermediaries are under control, both internally and externally. This may be achieved through sophisticated risk management at the level of the individual bank, and through financial market regulation and supervision at the level of the economy.

A major element in the above description of financial stability is the ”common belief” that risks are under control, reflecting the confidence of small and large investors in the safety and soundness of the financial system. Evidently, the confidence of market participants has to be continually earned, day after day.

In this paper, we claim that over the past couple of years it has become more difficult for financial market supervisors to assert that ”the financial system risk is under control”. The reason we believe financial stability to be more difficult to communicate than in earlier times rests with the huge amount of derivative claims and liabilities that interconnect the economy today.[1] The immense growth of the credit derivatives industry, credit default swaps and credit securitizations in particular, poses a considerable challenge to the monitoring abilities of regulators and central banks. We will demonstrate, by way of an example borrowed from the booming market of structured finance, that the quantification of the corporate risk exposure of banks requires an analytical understanding of financial engineering, coupled with financial economics. These skills help to scrutinize data requirements and statistical methodology, and they are needed to fulfill the monitoring function of regulators and central banks.

Some numbers shall suffice to convey the immense size of the derivatives market today. The overall (notional) volume of the over-the-counter derivatives market is estimated at $300 trillion, of which some 5-10% are credit derivatives. In the US alone, investment in CDO instruments, a sub-category of credit derivatives, is estimated to reach $290bn at year end

[1]There are, however, conflicting views on the risks involved in the derivatives industry. Alan Greenspan, at the time still Chairman of the Federal Reserve, said on September 27, 2005: ”The new instruments of risk dispersal have enabled the largest and most sophisticated banks, in their credit-granting role, to divest themselves of much credit risk by passing it to institutions with far less leverage. Insurance companies, especially those in reinsurance, pension funds, and hedge funds continue to be willing, at a price, to supply credit protection.” We see the efficiency enhancing capacity of derivative instruments, but we also see that the improved risk management capability may well increase risk appetite along with management potential.

2005 (Bloomberg, August 30, 2005). Of course, this number is not a measure of the true default risks, but it shows that at the end of 2005, the gross sum of underlyings involved in derivative transactions had grown to roughly 24 times the GDP of the US. For the much smaller credit derivatives market these figures add up to 1-2 times US GDP (year end 2005).

While most observers agree that the diffusion of sophisticated risk management instruments among banks goes hand in hand with an increased sophistication in risk management on the part of major banks, there is also growing concern among policy-makers that overall systemic risk may actually rise rather than decrease.[2]

Krahnen/Wilde (2006) argue that a rise in systemic banking risk is the likely consequence of ”leveraged lending”, the use of credit securitization for funding new loans. There is some evidence supporting this claim. De Nicolo/Kwast (2002) find an increase in the degree of correlation between stock prices, owing to consolidation in the industry. In their current research, Hänsel/Krahnen (2006) argue that the use of credit derivatives tends to make financial intermediaries more similar to one another. From a sample of European CDO issuers, they can show that bank systematic risk as measured by their equity beta is rising around the announcement of CDO issues. The rise of beta appears to be robust, and it is consistent with the notion that the market is anticipating an increased appetite for risk by bank management involved in credit securitizations.

Be this as it may, the monitoring of bank risk exposure and credit risk transfer is a necessary requirement for the evaluation of any systemic risk in the economy. In the remainder of the paper we will look at the technique of risk assessment, focussing on the changes of the joint default probability of financial institutions that securitize credit risk. We advocate a bottom up approach to risk assessment, similar that practiced by major rating agencies. With reference to collateralized debt obligations, section 2 will explain how the overall loss distribution of an underlying loan portfolio can be estimated, while accounting for various covenants of the transaction, such as credit enhancement and trigger clauses. Section 3 explains how, on the basis of tranching, the statistical properties of a loan portfolio transform into the properties of individual tranches that make up the issue. Correlation between tranches and between issues will be shown to determine the overall exposure of the issuing institution. Both sections will discuss the data requirement for high quality risk estimation. Section 4 will conclude by addressing the issue of risk migration through securitization. Amongst others, we will make a distinction between inter-sectoral and intra-sectoral risk transfer, which differ with respect to the likely effect on the value-at-risk of the financial system.

[2]Compare the speeches of Alan Greenspan on 27 September 2005 in Chicago (”[...] recent regulatory reform, coupled with innovative technologies, has stimulated the development of financial products, such as asset-backed securities, collateral loan obligations, and credit default swaps, that facilitate the dispersion of risk”) with the more recent remarks of Timothy Geithner, President of NY Fed; ”And there are aspects of the latest changes in financial innovation that could increase systemic risk in some circumstances” (Speech, 28 February 2006-see FRB NY web site).

II. Estimating the loss distribution

A. Modeling CDOs

Asset securitization may have many different forms, so that generalizations about the prevailing structures are notoriously difficult. There is a growing body of literature analyzing why originators are interested in securitizing parts of their loan book, what the effect of the intended risk transfer will be on their financial situation. According to Greenbaum and Thakor (1987), credit securitization allows banks to reduce their risk exposure, and to increase diversification in the economy. Gorton and Pennacchi (1995) show that securitization transforms illiquid assets into marketable assets. [3] Outside observers wishing to assess the risk of these instruments, therefore need an appropriate tool for evaluating the loss distribution of the individual tranches that make up the transaction. The tool should allow the loss distribution to be estimated in a way similar to the assessments done by the originator himself, and the rating agencies.

The basic setup of securitzation deals, referred to as tranching, is largely standardized in the market. Claims on cash flows generated by the collateral, i.e. the underlying asset pool, are split into several classes of notes, according to the principle of subordination. Each class of notes is called a tranche and has absolute priority in cash flows over all more junior classes. For a detailed description of the tranching process, see Plantin (2004) or Firla-Cuchra and Jenkinson (2005). We will now explain how the loss distribution is estimated by means of Monte Carlo simulation. This approach is similar to the methodology used by all major rating agencies, e.g. Standard and Poor's. Our model evaluates the credit quality of tranches, with different levels of rating, given the overall quality of a portfolio of assets. The following information about the underlying loan portfolio is required:

- par amount of each portfolio asset,
- the coupon,
- maturity and amortizing schedule,
- the rating of the individual assets or the entire asset pool (internal ratings have to be mapped into agency ratings),
- type of securitized asset
- characteristics of ultimate borrower that are relevant for the assessment of rating dynamics, such as industry and nationality,

This information is then used as an input for the Monte Carlo simulation. There are two main sources of information about the characteristics of the underlying portfolio of ABS-transactions. First, there is the Offering Circular of a transaction. The OC provides a detailed

[3] For a detailed overview of different motivations of asset securitization see Bluhm (2003). The different structural features of an ABS-transaction are explained by Fabozzi et al., (2002, Chapters 24 and 25).

description specifying all the relevant characteristics of the transaction for the use of investors. Second, the major rating agencies publish at least once, sometimes more than once, a report on the structure of the issue, containing an evaluation of the major features of the transaction, i.e. a pre-sale report and a new-issue report. Institutional investors need ratings from at least two major rating agencies.

In addition to structural information on the specific transaction, the sector correlation coefficients, the table of default probabilities for assets, and the table of default probabilities for CDO tranches are also required as input for the simulation.[4]

B. Asset default probabilities

The single most important information for the risk assessment process is the overall default probability of the asset pool. The latter is derived from individual asset default rates which are determined by, for example, asset type, credit rating, and the maturity of the claim. Empirical studies have shown that ex-ante credit ratings are a valid estimator of ex-post default incidence. Table I is an extract of the asset default table of a major agency (in this case Standard and Poor's), see Standard and Poor's (2003) for further details. We will explain below how a given rating and maturity are translated into a default probability D.

Table I
Implied Asset Default Rates (%)

The default rates reported in this table are based on the time series of bond issue performance. Default rates are by rating notch and by maturity. Historical ABS default rates are lower than corporate rates and are not as sensitive to final maturity. All ABS securities are assumed to have a seven-year weighted-average life.

Security	Maturity	AAA	AA	A	BBB	BB	B
ABS	All	0.25	0.50	1.00	2.00	8.00	16.00
Corporate	Year 4	0.19	0.57	0.81	1.81	9.49	21.45
Corporate	Year 7	0.52	1.20	1.81	3.94	14.20	26.15
Corporate	Year 10	0.99	1.99	3.04	6.08	17.47	28.45

Source: Standard and Poor's (2002)

[4]See Standard and Poor's, 2002.

C. Correlation

Given the industry classification of each portfolio asset and the correlation between industries, we can derive the correlation matrix of the portfolio. The correlation coefficients are modified in accordance with regional concentrations and country-specific characteristics as is documented in Standard and Poor's (2002). For each asset in the portfolio, a random number is drawn from a standard normal distribution, which is multiplied with the Cholesky-decomposition of the asset correlation matrix, yielding a vector of correlated random variables. The correlation between assets can be thought of as being determined by the correlation of the asset values with a common macro factor. Our calculation assumes a between-assets correlation of 0.3, and a between-industries correlation of 0.1, for credit cards and other ABS-portfolios. For corporates, we assume a within-industry correlation coefficient of 0.3, and correlation of 0.0 between industries. This approach follows that of Standard and Poor's.[5]

D. Model

To find the rating changes of the assets, we specify the one year transition probabilities of each rating class in terms of thresholds, again using a standard normal distribution. The vector of correlated random numbers is now applied to S&P's one year rating migration table. Table II shows the average one-year rating transition rates for AAA- and BBB-rated obligors.

Table II
Average One-Year Rating Transition Rates, 1981-2003

Average one-year rating transitions for the rating classes AAA and BBB.

	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/C	Def.	withdrawn
AAA	88,07	3,67	2,62	0,51	0,28	0,17	0,14	0,06	0,09	0,00	0,03	0,03	0,00	0,00	0,00	0,00	0,00	0,00	4,33
BBB	0,02	0,02	0,09	0,06	0,28	0,66	1,43	5,64	75,57	5,92	1,83	1,11	0,49	0,32	0,26	0,04	0,09	0,34	5,82

Source:Standard & Poor (2002)

In order to attribute rating changes completely, we have modified the original S&P matrix according to the formula

$$p^m_{i,j} = \frac{p_{i,j}}{\sum_{i=1}^{N} p_{i,j}} \qquad i = 1,2,...,N-1 \;\; j = 1,2,...,N \tag{1}$$

where $p^m_{i,j}$ is the modified default probability for each rating class and $p_{i,j}$ is the probability in the original migration matrix. The results are shown in Table III.

[5] See Standard and Poor's (2002) for the correlation behavior of corporate obligor.

Table III
Modified Migration Matrix, 1981-2003

Average one-year rating transitions for the rating classes AAA and BBB.

	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/C	Def.
AAA	92,06	3,84	2,74	0,53	0,29	0,18	0,15	0,06	0,09	0,00	0,03	0,03	0,00	0,00	0,00	0,00	0,00	0,00
BBB	0,02	0,02	0,10	0,06	0,30	0,70	1,52	5,99	80,25	6,29	1,94	1,18	0,52	0,34	0,28	0,04	0,10	0,36

Source:own calculation

The threshold values $S_{i,j}$ for a rating class change of an asset are calculated with the modified migration matrix. The basis for this calculation is the standard normal distribution. The transformation of a modified rating probability to a threshold value occurs through the following formulas:

$$S_{i,j} = \Phi^{-1}_{SNV}(\sum_{k=j}^{-1} p^m_{i,k}) \tag{2}$$

after conversion:

$$\begin{aligned} \int_{i,j+1}^{i,j} f(x)dx &= p^m_{i,j} \\ \Phi(S_{i,j}) - \Phi(S_{i,j+1}) &= p^m_{i,j} \end{aligned} \tag{3}$$

recursive initiation:

$$\Phi(S_{i,j}) - \Phi(S_{i,N+1}) = \sum_{k=j}^{N} p^m_{i,k} \tag{4}$$

with $S_{i,N+1} = 7.94 \;\; F(S_{i,N+1}) = F(9,94) \approx 0$

For instance, a BBB-rated company needs a random number value in the range of 3.52 and 7.94 to get an AAA rating. Correspondingly, if the realization is lower than -2.69, a default occurs for the company. For an easier use of the model the maximum threshold value is 7.94. The different values of a rating transition are presented in Table IV.

Table IV
Threshold values for rating changes

Average one-year rating transitions for the rating classes AAA and BBB.

	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/C	Def.
AAA	7.94	-1.41	-1.74	-2.21	-2.39	-2.55	-2.68	-2.85	-2.95	-3.23	-3.23	-3.42	-7.94	-7.94	-7.94	-7.94	-7.94	-7.94
BBB	7.94	3.52	3.34	2.99	2.88	2.58	2.26	1.92	1.36	-1.22	-1.67	-1.91	-2.14	-2.29	-2.42	-2.58	-2.61	-2.69

Source:own calculation

Each asset acquires a rating development that depends on the original rating class of a corporate asset and the calculation as given above.

The coupon of an asset is the same in each rating class. In case of a default, the payment of an asset is dependent on the recovery rate. Standard and Poor's (2002) shows that recoveries of defaulted structured finance securities are based on their rating. With this default matrix, we calculate the future cash flows of the portfolio. The cash flow of a defaulted asset is the product of the recovery rate and nominal value in addition to the interest payments before default. The recovery rate depends on the type of the assets, the country of the debtor, the economical situation, and the initial rating. The cumulated difference between expected cash flows and realized cash flows is the loss of the portfolio. By generating new random numbers, this process is repeated. The different loss realizations from each simulation produce the loss distribution.

E. Data

E.1. Portfolio Data

As is evident from the foregoing discussion, detailed information is required on a loan by loan basis to evaluate portfolio risk. The offering circular contains public information about the ABS-transaction at hand. It summarizes the major transaction characteristics for investors, including information about the risk factors, the notes, the trust agreement, the reference pool, the originator and the trustee. If we follow the general approach of the rating agencies, we can separate the information in the offering circular into two categories. First, we obtain information on the asset pool on a loan-by-loan basis. As an example we consider London Wall 2002-2, issued by Deutsche Bank in 2002. The reference pool consists of a set of claims (loans), originated by the bank, and transferred to a special purpose entity. The composition of the reference pool is determined at a cut-off date. Through a unique identifier, it is possible to trace the characteristics of individual assets in the portfolio, allowing the loss rate distribution of the composite portfolio to then be estimated.

The offering circular provides the major characteristics of the initial reference portfolio; London Wall, for example, consists of 264 claims from 236 debtors. Several features of the underlying loans are displayed as descriptive statistics, rather than on a loan-by-loan basis. Thus, the distribution of loans is reported by industry, by size, by maturity and spread.

For a risk assessment, the default risk of the portfolio has to be estimated. In the case of London Wall 2002-1, the analysis can proceed on the basis of the distribution of initial ratings and of maturities. In other transactions, the information on asset risk is less precise. Often, the only aggregate risk information available is the average rating of the assets, and an internal firm rating by the originator. Without a reliable mapping to external ratings, the information on the rating distribution of the asset portfolio cannot be used to estimate the portfolio loss rate distribution.

If individual claims in the asset portfolio are large, as is the case in the London Wall transaction, then assets can be mapped on a loan-by-loan basis, since the borrowers are rated themselves. Alternatively, if the individual underlying claims are small, as in a SME portfolio with thousands of loans, the risk assessment rests on the internal ratings by the originating institution. Here asset correlations are quite important. Again, taking the London Wall 2002-1 transaction as an example, there is no correlation matrix for the relevant portfolio assets. We therefore adopt the correlation assumption used by rating agencies, accounting for the industries and the regions or origin.

Using a more detailed correlation matrix would imply an obvious improvement for the task of risk assessment.[6] Note that the correlation of assets is arguably the main driver of the loss distribution and of the resulting tranching decision.

For calculating the loss given default (LGD), an estimate of the expected recovery rate of the assets is needed. Many offering circulars contain no assessment of the recovery rates. The by-default assumption (sweeping assumption) of the agencies has then to be used, which is 47.5% in the case of Moody's. However, empirical studies have shown that the recovery rates vary considerably according to the region, the type of the securitized asset, and the current economic situation. A precise historical estimate of the recovery rate does not exist in many banks. Thus, deriving the correct expected recovery rate would also be an improvement over current practice.

Referring to the London Wall 2002-1 example, and following S&P's policy, we take the recovery rate of the reference pool to depend on the country of borrower domicile, and on whether the underlying claim is secured or unsecured. Information about expected prepayments, relating to both their size and their dates, also influence the assessment of overall risk. Usually, historical data is used to back up the estimate, and it also may be required to carry out stress tests. For this reason, the originator should provide historical experience values.

An important further characteristic of an ABS-transaction is the replenishment policy. Replenishment refers to the refilling of a reference pool in case single claims mature early. The replenishment is subject to a pre-specified list of conditions. These conditions refer to a set of threshold values, typically a minimum and a maximum value, applied to the average correlation, the average rating, and the portfolio concentration.

E.2. Credit Enhancement

The precise assessment of the credit enhancement is another building block needed for the determination of the loss rate distribution. It takes a variety of forms, including most impor-

[6] There is one agency, Fitch, that has started to use a detailed correlation matrix.

tantly, the retention of the first loss piece. Here the bank agrees to absorb default losses up to a specified limit called the attachment point, which is determined by the tranching exercise described earlier. The larger the retained tranche, the more important is the deductible. Note that the offering circular does not provide information about the location of the first loss piece. However, unless specified otherwise, we assume the first loss piece to be retained.

In the terminology of structured finance, the subordination of the tranches and the retention of the first loss piece are seen as internal credit support. Other forms of support are the reserve fund, excess spread, overcollateralization and cash account.

Excess spread and overcollateralization are forms of credit enhancements that are difficult to implement in our approach to the estimation of the loss rate distribution. This is because the degree of overcollateralization depends upon the number of defaulted assets. Therefore, the assessment of the credit enhancement has to be based on historical realizations, which are notoriously difficult to calibrate. Typically, the offering circulars and the rating agencies provide no information about the direct effect of particular enhancements on either tranching, or default risk.

A reserve fund is a separate account created by the issuer that reimburses the issuer for losses up to the amount of the reserve. It is funded by an upfront payment, or by cash flows that are accumulated over time, similar to a cash account. It is fairly straightforward to implement such funds in our portfolio risk estimation, provided the offering circular gives a detailed description of how the credit enhancement works. This, however, is not always the case.

III. Tranching

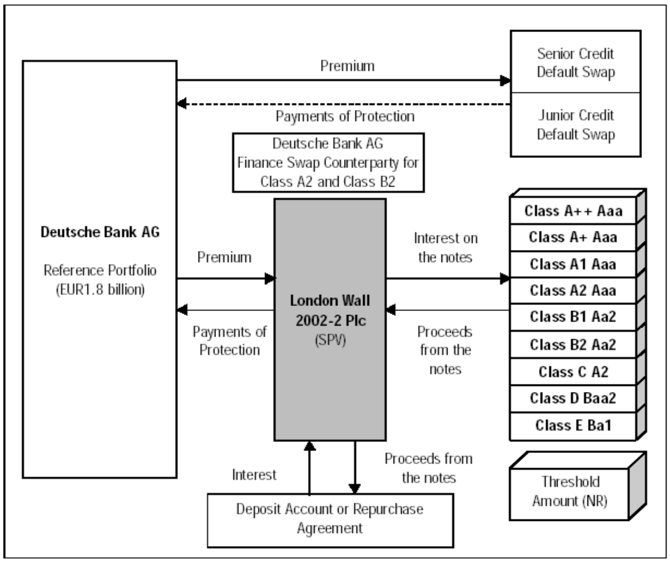
A. London Wall transaction design

To demonstrate the relevant issues when modeling the loss distribution of a transaction, we now, by way of example, examine in detail a real-world transaction. We will continue to rely on the example used earlier, a transaction issued by Deutsche Bank in December 2002 (London Wall 2002-2), which matures in January 2009. Figure 1 gives an overview of the transaction structure. According to the details of the transaction, as specified in the offering circular and in the new issue report, it is a synthetic CLO, i.e. the reference portfolio consists of loans, and there will be no cash flows before maturity.

To transfer the risks embedded in the reference portfolio, the issuer (Deutsche Bank) enters into three credit default swaps, written on the portfolio. The two senior swaps account for 89% of the size of the reference portfolio. The counterparty for the third swap, covering the remaining amount, is the SPV London Wall, exclusively established for this purpose under the jurisdiction of the Republic of Ireland. Based on this transaction, the SPV has issued a total of nine rated tranches, all representing claims on the reference portfolio. These tranches have

Figure 1. London Wall transaction structure

This figure shows the structure of the London Wall 2002-2 transaction. Source: Moody's New Issue Report.



five levels of subordination, i.e. some tranches have the same seniority. The remaining first loss piece has a size of 2.61%.

The losses occurring during the lifetime of the issue are allocated according to their level of subordination to the tranches. London Wall is entitled to call the outstanding tranches before maturity, subject to certain conditions. These conditions may, for example, include changes in tax laws, or the change of capital adequacy regulations. Furthermore, investors have the right to ask for early redemption in the event that London Wall defaults. Finally, Deutsche Bank may demand early redemption starting from April 2007.

The rating quality of the tranches ranges from Ba to Aaa according to Moody's rating scheme (note that the first-loss piece is not rated). With the exception of two tranches tailored to fit the needs of specific investors (and of minor size), denominated in US dollars and New Zealand dollars, all tranches are denominated in Euros.

As pointed out earlier, the reference portfolio consists of 264 outstanding loans, from 224 distinct obligors. The loans in the portfolio cover 32 industries according to Moody's classification and 36 industries according to Standard and Poor's classification. Individual loans in the portfolio are denominated in foreign currency. The portfolio is exposed to country risk, since 62% of the notional amount of all loans is from Western Europe, while 21% is from the USA. 45.19% of the notional amount of all underlying loans are not rated by Moodys. The largest obligor corresponds to 1.25% of the entire portfolio with respect to notional amount.

Figure 2. London Wall summary

This figure shows a summary of the London Wall 2002-2 transaction as of the cut-off date. The figure is based on the offering circular.

Total Outstanding Nominal Amount	1,800,000,000	
Reference Claims	264	
Debtors	236	
Debtor Groups	224	
Moody's Diversity Score	89.44	
Moody's Weighted Average Rating Factor	381	
Fitch Weighted Average Rating Factor	9.52	
Weighted Average Life (years)	2.66	
% of Reference Pool publicly rated by Moody's	54.81%	
% of Reference Pool publicly rated by S&P	62.73%	
% of Reference Pool publicly rated by Moody's and/or S&P and/or Fitch	64.07%	
Moody's Weighted Average Recovery Factor	47.25	
S&P Weighted Average Recovery Rate	36.18	
Fitch Weighted Average Recovery Factor	39.26	
Maximum Debtor Group Balance - AAA / Aaa	21,841,309	1.21%
Maximum Debtor Group Balance - AA- to AA+ / Aa3 to Aa1	22,500,000	1.25%
Maximum Debtor Group Balance - A- to A+ / A3 to A1	18,000,000	1.00%
Maximum Debtor Group Balance - BBB+ / Baa1	18,000,000	1.00%
Maximum Debtor Group Balance - BBB / Baa2	18,000,000	1.00%
Maximum Debtor Group Balance - BBB- / Baa3	9,000,000	0.50%

Note: The calculation of the Weighted Average Life is as of the Closing Date.

Finally, the initial diversity score is 89.44 according to Moody's diversity score calculations.[7] The details of the portfolio are summarized in Figure 2.

The portfolio is called a dynamic portfolio because it is replenishable (subject to certain conditions) during the first four years of the transaction. Thus, the quality may change over time owing to defaults, rating migrations, and replenishment. In order to establish minimum reliable portfolio standards for the investors, the contract provisions as outlined in the offering circular guarantee a certain quality, measured in several categories. First, a minimum diversity score of 70 according to Moody's diversity score calculations is guaranteed to the investors during the lifetime of the transaction. If this is not the case, then the reference portfolio has to be modified. Second, at least 52.5% of the notional amount of the loans in the portfolio have to be rated at any point in time. Third, the share of the largest obligor in the gross portfolio must not exceed 1.5%, provided its rating is Aaa, according to Moody's, or less otherwise. Furthermore, the average rating of the portfolio is to be at least Baa2 according to Moody's rating scheme. Finally, the composition of the portfolio is to be adjusted to attain a minimum weighted average recovery rate of 45%.

B. Implementation

In the implementation, several assumptions regarding portfolio quality have to be made, in particular regarding the replenishment practice. We chose to rely on conservative assumptions regarding replenishment, and this procedure is confirmed by practical evidence.

The simulations are performed with Standard and Poor's rating migration tables and the tranching is performed according to Standard and Poor's loss tables. Note that, according to the loss tables, the default probability of the lowest rated tranche (Ba1) over the relevant time horizon of six years until maturity is not allowed to exceed approximately nine percent. The loss potential of the lowest rated tranche determines the loss the first loss piece has to cover.

B.1. Empirical results

We first examine one transaction (London Wall 2002-2) in more detail. Figure 3 shows the loss rate distribution of London Wall as obtained by a Monte Carlo simulation. It has the typical shape of loan portfolios loss rate distributions, i.e. highly skewed to the right. The mean loss is 1.499% of the transaction volume, and the highest realized loss in our simulations amounted to 6%.

Subsequently, given the loss distribution, the portfolio is divided into tranches. Table V shows the size of the tranches as derived from the simulation exercise, as well as the actual

[7] Moody's Diversity score is a proxy for the diversification achieved in the reference portfolio. This score takes into account the number of different industries as well as the number of loans in the portfolio.

Figure 3. Loss distribution of London Wall

This figure shows the loss distribution of the London Wall 2002-2 transaction as a histogram. Based on information regarding the reference portfolio as provided in the offering circular, the loss rate distribution for the entire reference portfolio is generated by a Monte Carlo simulation. The assumed correlation structure is 0.3 within industries, and 0 between industries. Credit migration risk is modeled according to Standard and Poor's rating migration table. The loss distribution shown in the table is obtained with 50'000 simulation runs. The vertical axis measures the frequency of observations, and the horizontal axis the associated loss rate, truncated at 10%. No observation surpassed this threshold.

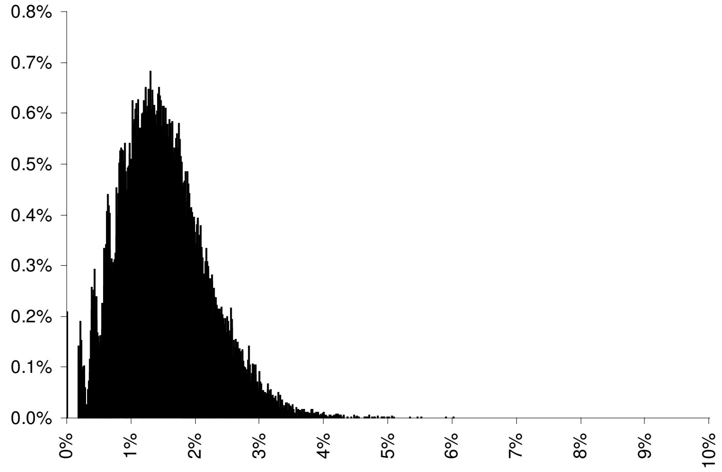


Table V
Tranching results for London Wall

This table shows the tranche size obtained with Monte Carlo simulation in comparison to the actual tranche size.

	Tranche size	
Tranches	Offering circular	Simulation
Aaa	93.20%	96.24%
Aa2	1.40%	0.38%
A2	1.00%	0.15%
Baa2	1.10%	0.31%
Ba1	0.70%	0.46%
NR	2.61%	2.46%

tranche sizes according to the offering circular. The lowest deviation, namely 0.15%, is obtained for the first loss piece, whereas the largest deviation, i.e. 3.04%, can be observed for the senior tranche. The comparison of our estimation with the actual tranching (which is also a result of an estimation) suggests that the rating agencies assume extreme losses to be more likely than we did. This is consistent with the view, often voiced by practitioners, that rating agencies tend to tranche portfolios rather conservatively, assuming a higher level of risk.

Table VI shows the descriptive statistics of the tranches obtained from the simulation exercise. Although the reference portfolio has an average rating of Baa2, it can be split into a large senior tranche, comprising 96.24% of the transaction volume, with excellent credit quality. Its mean loss is only 0.002%, its default probability amounts to 0.36%, and its loss given default is only 0.403%.

The major part of the overall portfolio credit risk is condensed into the first loss piece, which is small, comprising less than 2.5% of the issue. Its mean loss attains 59.383%, its default probability is 99.79%, and its loss given default runs at 59.506%. These numbers illustrate that tranching leads to non-proportional risk sharing, and that loan portfolios can be split into ”vertical” tranches with completely different characteristics, when compared to the underlying asset portfolio.

After presenting in detail the results for one transaction, we now examine the allocation of credit risk to different tranches for a sample of 39 European CDO transactions. Table VII presents summary statistics of the sample. The average maturity of the issues is 6.54 years, and the average volume of the transactions is 1.51 billion euro, the average number of rated tranches that differ by seniority is 3.67. The average portfolio consists of 900 individual securities, with average ratings of the loan reference portfolios that range from B2 (Redwood CBO) to A1 (Dutch Care).

Table VIII presents the tranching results for the sample of 39 European CDOs. The expected loss of the reference portfolio as obtained by Monte Carlo simulation amounts to 3.50% on average, ranging from 0.26% (Dutch Care) to 22.71% (Redwood). The average size of the first loss piece amounts to only 4.0%. The last column shows the multiple of expected loss

Table VI
Tranche statistics for London Wall

This table shows the tranche statistics for the London Wall 2002-2 transaction as obtained using Monte Carlo simulation. Tranche size, mean loss, loss standard deviation, default probability, and loss given default are given in the columns for each tranche. The last row reports the corresponding numbers for the portfolio as a whole.

Tranches	Tranche size	Mean loss	Loss std	Default probability	LGD
Aaa	96.24%	0.002%	0.036%	0.38%	0.403%
Aa2	0.38%	0.616%	7.224%	0.95%	65.141%
A2	0.15%	1.149%	10.291%	1.40%	82.334%
Baa2	0.31%	2.126%	13.446%	3.09%	68.851%
Ba1	0.46%	5.571%	20.727%	8.92%	62.468%
NR	2.46%	59.383%	24.149%	99.79%	59.506%
Total portfolio	100.00%	1.499%	0.676%	99.79%	1.502%

that is covered by the first loss piece. This number is 3.2 on average, ranging from 0.3 to 27.4. In most cases the first loss piece does not fall short of the expected loss of the underlying loan portfolio, but instead, it is usually several times its size.

B.2. Correlations

Figure 4 shows the impact of the correlation assumption on loss distributions. Leaving all parameters constant (homogenous portfolios with 200 individual securities, each with a default probability of 10%), we vary the correlation between individuals securities from 0.01 to 0.4. The resulting distribution function shifts considerably. If the correlation increases, probability mass is shifted to the tails of the distribution. Overall, the results demonstrate the importance of modeling correlations accurately, since even minor changes in the assumptions may have significant effects on the distribution of portfolio losses. Evidently, robustness checks on all simulations are required.

B.3. Data requirements

The data requirements for calculating the loss rate distribution of a structured finance transaction include all the institutional and financial aspects relevant to the Monte Carlo simulation. These comprise, first, individual loan components, such as maturities, the credit quality of the individual loans (i.e. probability of default, represented potentially by the ratings), credit migration probabilities, the correlation structure (correlation within and between industries, macro-factor dependencies), and expected recovery rates at default. Second, they also relate to portfolio components, such as portfolio diversification, credit exposure to various industries, and individual obligor concentration. Third, additional CDO features applicable to dynamic portfolios, such as replenishment provisions and the agreed elements of a possible credit enhancement, have to be taken into account.

Table VII
Summary statistics of the sample

This table shows the summary statistics of the sample used for the empirical analyses. Each row reports the statistics of an individual transaction. Information on maturity, transaction volume, number of rated tranches, number of loans in the reference portfolio, average rating of the reference portfolio, and Moody's Diversity Score are given in the columns.

Name	Maturity in years	Volume in bn Euro	number of rated tranches	number of loans	Average Rating	Div Score
Dutch Care 2001-1	8	1.30	3	169	A1	12.4
Hesperic No. 1 plc	6	1.40	5	104	Baa1	31
IKB Credit Linked Notes 2000-1	10	0.53	3	61	Ba2	33
Leverage Finance Europe Capital I B.V.	10	0.32	4	30	B1	26
London Wall 2002-1 PLC	6	3.00	5	330	Baa2	70
London Wall 2002-2 PLC	6	1.80	5	224	Baa2	70
CLO	**7.67**	**1.39**	**4.17**	**153**		**40.4**
CAST 1999-1 Ltd.	7	2.90	4	4389	Baa3	70
CAST 2000-1 Ltd.	7	4.50	4	1991	Baa3	70
CAST 2000-2 Ltd.	7	2.50	4	5178	Baa3	95
HAT (Helvetic Asset Trust) AG	5	2.50	3	650	Ba2	100
HAT (Helvetic Asset Trust) II Limited	5	2.50	4	1455	Ba2	110
PROMISE-A-2000-1 plc	8	1.00	5	1097	Ba1	90
PROMISE-A-2002-1 plc	8	1.62	6	1277	Ba1	124
Promise-C-2002-1	6	1.50	5	4578	Baa3	90
Promise-Color-2003-1	5	1.13	5	1512	Ba2	80
Promise-G-2001-1	7	0.65	4	100	Ba1	85
Promise-I-2000-1	8	2.50	5	2267	Baa3	80
Promise-I-2002-1	7	3.65	5	4172	Baa3	80
Promise-K-2001-1	5	1.00	5	2916	Ba1/Ba2	100
Promise-Z-2001-1	8	1.00	5	658	Ba1	85
SME CLO	**6.64**	**2.07**	**4.57**	**2303**		**89.9**
ARCH ONE FINANCE LIMITED	4	0.49	2	70	Baa1	47
ARGON CAPITAL PLC - SERIES 1	7	1.38	5	53	Baa1	30
Brooklands Euro Ref. Linked Notes 2001-1	10	1.00	3	100	Baa1	50
Cathedral Limited	5	0.47	3	52	Baa1/Baa2	36
CDO Master Investment 2 SA	5	3.75	3	112	Baa1	66
CDO Master Investment 3 SA	5	2.50	3	86	Baa1	60
CDO Master Investment SA	5	1.63	3	100	Baa1	49
CIDNEO FINANCE Plc	10	0.25	3	57	Baa2	34
CLASSIC FINANCE B.V. (Petra III)	5	2.32	5	232	A3	103
Credico Funding S.r.l.	6	0.89	1	117	Ba1	30
Deutsche Bank United Global Inv. Gr. CDO I	5	1.44	3	148	Baa1	60
DYNASO 2002-1 LTD	5	1.00	3	100	A3	55
Eirles Two Limited Series	7	0.63	3	74	A3	40.8
Helix Capital (Netherlands) B.V. 2001-1	5	0.80	2	80	A3	50
Lusitano Global CDO No.1, Plc	4	1.14	3	218	Baa3	35
Marche Asset Portfolio S.r.l.	3	0.17	3	59	Baa1	12
Redwood CBO	10	0.30	3	100	B2	45
Spices Finance Limited Peas	5	0.95	2	100	Baa2	56
Vintage Capital S.A.	10	0.36	1	76	Baa2	36
Other	**6.11**	**1.13**	**2.84**	**102**		**47.1**
Total	**6.54**	**1.51**	**3.67**	**900**		**61.4**

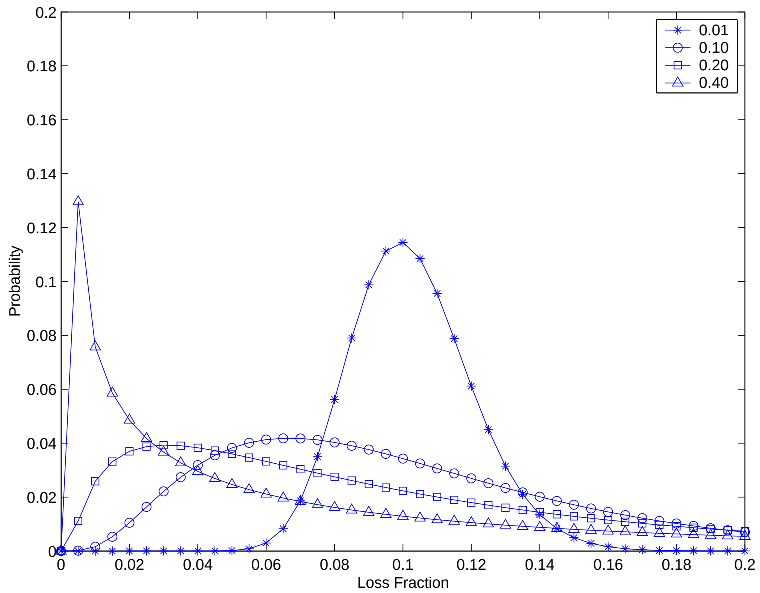
Table VIII
Empirical results

This table shows the results from the empirical analysis. Each row reports the results for an individual transaction. The last row reports average numbers over all transactions. Columns two and three show average loss for the corresponding reference portfolio as well as the first loss piece. Columns four and five report the size of the first loss piece as obtained with Monte Carlo simulation and as observed empirically, respectively. The last column gives the size of the first loss piece divided by mean loss of the reference portfolio.

Name	Average loss		Size of FLP		FLP/E(L)
	Total PF	FLP	Simulation	Empirical	
Dutch Care 2001-1	0.003	0.266	0.009	0.015	5.9
Hesperic No.1 plc	0.010	0.498	0.019	0.019	1.9
IKB Credit Linked Notes 2000-1	0.084	0.849	0.091	0.050	0.6
Leverage Finance Europe Capital I B.V.	0.180	0.894	0.187	0.116	0.6
London Wall 2002-1 PLC	0.015	0.649	0.022	0.026	1.8
London Wall 2002-2 PLC	0.013	0.633	0.020	0.038	2.9
CLO	**0.051**	**0.631**	**0.058**	**0.044**	**2.3**
Cast 1999-1 Ltd.	0.032	0.827	0.036	0.030	0.9
Cast 2000-1 Ltd.	0.032	0.727	0.044	0.024	0.7
Cast 2000-2 Ltd.	0.032	0.742	0.042	0.032	1.0
HAT (Helvetic Asset Trust) AG	0.047	0.666	0.071	0.050	1.1
HAT (Helvetic Asset Trust) II Limited	0.047	0.651	0.073	0.060	1.3
Promise-A-2000-1 plc	0.059	0.820	0.070	0.041	0.7
Promise-A-2002-1 plc	0.059	0.967	0.051	0.017	0.3
Promise-C-2002-1	0.027	0.711	0.037	0.030	1.1
Promise-Color-2003-1	0.047	0.873	0.049	0.018	0.4
Promise-G-2001-1	0.035	0.609	0.057	0.048	1.4
Promise-I-2000-1	0.032	0.749	0.042	0.030	0.9
Promise-I-2002-1	0.032	0.751	0.042	0.030	0.9
Promise-K-2001-1	0.048	0.724	0.065	0.048	1.0
Promise-Z-2001-1	0.059	0.794	0.073	0.045	0.8
SME CLO	**0.042**	**0.758**	**0.054**	**0.036**	**0.9**
ARCH ONE FINANCE LIMITED	0.006	0.191	0.030	0.050	8.8
ARGON CAPITAL PLC - SERIES 1	0.012	0.413	0.029	0.032	2.6
Brooklands Euro Ref. Linked Note 2001-1	0.019	0.562	0.034	0.040	2.0
Cathedral Limited	0.010	0.297	0.032	0.023	2.4
CDO Master Investment 2 SA	0.008	0.344	0.022	0.024	3.1
CDO Master Investment 3 SA	0.008	0.314	0.024	0.022	2.8
CDO Master Investment SA	0.008	0.303	0.026	0.048	6.2
CIDNEO FINANCE Plc	0.026	0.551	0.046	0.058	2.2
Classic Finance B.V. (Petra III)	0.003	0.361	0.009	0.028	8.3
Credico Funding S.r.l.	0.033	0.343	0.096	0.017	0.5
Deutsche Bank United Global Inv. Gr. CDO I	0.008	0.512	0.015	0.030	3.8
DYNASO 2002-1 LTD	0.003	0.195	0.016	0.025	7.9
Eirles Two Limited Series	0.006	0.269	0.021	0.040	7.0
Helix Capital (Netherlands) B.V. Series 2001-1	0.003	0.196	0.016	0.018	5.5
Lusitano Global CDO No.1 Plc	0.014	0.343	0.039	0.022	1.6
Marche Asset Portfolio S.r.l.	0.005	0.141	0.038	0.150	27.4
Redwood CBO	0.227	0.882	0.255	0.103	0.5
Spieces Finance Limited Peas	0.010	0.323	0.030	0.044	4.6
Vintage Captial S.A	0.026	0.407	0.065	0.069	2.6
Other	**0.023**	**0.366**	**0.044**	**0.043**	**5.4**
Total	**0.035**	**0.557**	**0.050**	**0.040**	**3.2**

Figure 4. The impact of correlation on the loss distribution

This figure shows the fractional-loss distributions for different correlation scenarios. The reference portfolios are homogenous portfolios consisting of 200 loans, each with a default probability of 10%. In the four scenarios shown, the correlations between the loans are uniformly assumed to be 0.01, 0.1, 0.2, and 0.4, respectively. The chart shows on the vertical axis the frequency of observations, and on the horizontal axis the associated loss rate, truncated at 20%.



Beyond individual loan components, data requirements for modeling loss rate distributions are taken from two main areas: information on rating migration as well as on detailed empirical correlation structure, covering worldwide fixed-income securities. While the information regarding rating migration is available from the historical data sets of the major rating agencies, there is comparably little published work on the correlation structure in an economy. Although accurate modeling of the correlation structure is crucial to achieving accurate results with respect to the loss distribution and the risk profile, rating agencies have only recently departed from their simple approach of assuming a flat correlation rate of 0.3 (intra-industry) and zero (inter-industry).

IV. Monitoring risk migration in the economy

The preceding section has shown that structured finance instruments have increased the computational skills required by controllers for assessing the risk exposure of financial institutions. The complexity of risk assessment is amplified by the fact that structured finance products greatly enhance the fungibility of the the instruments, and therefore allow risk exposure to be repackaged and transferred. The risk transfer in question may be partial or complete.

A. The fungibility of default risk

As was exemplified with CDO instruments, financial engineering allows banks to pool individual risks in virtual portfolios, to tranche them according to the principle of subordination, and eventually to sell these tranches as bonds to investors in the capital markets. The repackaging and resale of default risks is a significant economic achievement, with the potential to confer considerable welfare gains. However, the emergence of credit risk transfer instruments is likely to reduce the transparency of risk allocation in the economy. These aspects will be discussed in turn.

Through the use of CDOs, banks can create gains of improved risk allocation. First, they are able to leverage their expertise in loan origination and borrower monitoring, leaving funding at least partially to the capital markets.[8] Second, the tranching of default risk separates the extreme default risks contained in the senior tranches from the more moderate risks embedded in mezzanine tranches. These extreme risks, e.g. concurrent failure of several banks following a severe economic downturn, represent a threat to the stability of a financial system.

[8] According to a recent Financial Times article, the funding strategy of Commerzbank, a German commercial bank, consists of securitizing one third of the loan book on a regular basis, in order to expand origination, see FT, Feb. 20, 2006, p.18

Therefore, by selling senior tranches to investors, extreme loss risk may be transferred from the bank to investors outside the banking system.[9]

The cartography of risk distinguishes between the financial system specifically, and the retail financial markets outside the banking system. The former consists of banks, insurance companies, brokers, exchanges, security houses, investment banks and the like, whereas the latter comprise households, pension funds and the like. It is the outer financial markets that are best suited to absorbing extreme and unexpected shocks to the financial system. The former, particularly the financial intermediaries are best suited to allocating funds and risks in the economy.

Against any gains from risk spreading, it is necessary to weigh the potential costs of intransparency. Derivative instruments, like CDO- and CDS, allow the originator of a particular exposure to pass on the assumed risk to a protection seller. This transfer happens on the primary market. To the extent that protection sellers, i.e. the buyer of the issued tranches or the swap counterparty, respectively, make a buy-and-hold investment, the resulting risk allocation can be inferred from the issue list of the investment bank. If, however, there is an active secondary market in the relevant instrument, the ultimate risk allocation cannot be inferred by looking at the primary market alone. Instead, the individual risks as they are traded among investors, or rather as they appear on their balance sheets, must be traced.

The eventual risk allocation in the economy may become quite dissimilar to the initial allocation, before the appearance of structured financial instruments. For example, if banks regularly securitize their loan books and retain the first loss piece, then their risk exposure will effectively rise. As we have argued above, their systematic risk will rise, and with it the systemic risk of the entire banking sector. Alternatively, if asset management companies sell protection in CDO or CDS arrangements, their default risk will typically rise. Note that the alteration of a bank's risk exposure through securitization cannot be simply read out of published accounts, even under fair value accounting[10].

Therefore, considerable financial expertise is required for an assessment of financial institution default risk, together with detailed information on all assets and liabilities, including the derivative positions, on a high frequency basis. For a regulator-controller this implies the need for extensive data collection.

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[9] The recent distress of Delphi, a large vendor of the US car industry, affected a significant portion of outstanding CDOs, causing rating downgrades of 7 percent of all CDOs, see ISDA website, or Kothari's website http://www.vinodkothari.com. A similar experience of wide spread losses was made in Europe when Parmalat, the Italian agroindustrial company, failed in 2004. Parmalat loans were included in many CDO-issues. Thus, risk transfer in these cases has spread corporate default risk around the world.

[10] While the fair value will reflect the expected loss of an instrument, it does not reflect unexpected loss. It is the latter component that typically matters for bank default, not the former.

B. Firm level financial data

The emphasis on the warehousing of micro-level financial data is consistent with the analysis presented in this paper, and in much of the literature on the determination of the value-at-risk of banking firms (see BIS 2003, the literature review therein). The aim is to model the cash flow streams resulting from structured transactions, and to use numerical methods to evaluate the distributional properties of the resulting net wealth positions. The informational requirements are high. The controller needs to know the properties of the underlying assets, and the contractual details of the structured finance transaction in question. As outlined in Section 2 of this paper, the information allows the controller to estimate the expected loss distribution of the derivative securities, and by repeating the analysis on the level of the firm, to estimate the loss distribution of the financial institutions as a whole.

This may turn out to be quite cumbersome. The controller needs information on, for example, the exact contractual format of the transaction, the statistical properties of the underlying assets, the allocation of tranches in an initial public offering, and the possible secondary trading of these instruments. Thus, financial institutions would be required to report their positions in derivatives comprehensively.

Of course, in his assessment, the controller may build on summary information produced by the respective financial institutions itself. This is common practice in the area of market risk reporting, where banks may use their own evaluator to consolidate the risks of the trading book into a single value-at risk number. However, from value-at-risk information alone the controller is not in a position to estimate the statistical dependency between different financial instruments, let alone between different financial institutions.

C. Market level information

The true challenge for a controller-supervisor is systemic risk, i.e. the risk of concurrent failure of several banks, rather than the default of a single financial institution. The joint default of many banks is commonly referred to as a banking crisis. The determination of joint default risk requires the estimation of range-dependent correlations. Such a conditional correlation captures the dependency between bank performance in the tails of the banks' respective return distributions.

As was shown in the preceding section, the estimation of covariance risk, and similarly of conditional covariance risk, requires the cash flows of aggregate portfolios to be modeled. This task can only be accomplished if there is a sufficient degree of firm level information to anchor the estimation[11].

[11] A more general estimation of dependency is possible by using the concept of copulas instead of linear correlations. Copulas are warranted if the underlying distributions are non-normal. However, correlation is the most widely used measure of dependency, and we therefore limit our exposition to it.

The general aim of a controller-supervisor will be to keep the probability of joint defaults of many banks under control. The concept is tantamount to estimating the value-at-risk of the banking system as a whole. If data is available on a cash flow basis, the task consists of modeling the joint default distributions of a given number of financial institutions using a Monte Carlo simulation. Aggregate, or systemic risk may then be kept at bay by pre-specifying a maximum value-at-risk of the system. Alternatively, the control effort may focus on the systematic risk of the banks and, by aggregation, on the beta of the banking system as a whole.

Again, it may be desirable to focus on a range-dependent beta control, requiring the financial institutions to keep their covariance risk under a specified threshold level. The major innovation in this supervisory strategy lies in the control of covariance risk, rather than variance risk. The latter underlies the current policy of controlling each bank's value-at-risk separately. However, systemic risk derives from the degree of dependency between financial institutions in terms of risk exposure. If supervisors would only care for systemic risk, they would only be interested in dependency risk alone.

V. Conclusion

In this paper we have argued that bank risk assessment through outside controllers/supervisors is nowadays even more difficult than it used to be when balance sheet information was more reliable with respect to the risks underwritten by financial institutions. The recent growth of structured finance instruments, together with the practice of risk transfer among financial institutions and to investors outside the financial system, is a true challenge not only for market analysts, but also for supervisors and regulators. Both types of controllers, the market and the regulator, help to shape the public perception of bank risk and bank system risk.

Using the issue of collateralized debt obligations as an example, we have listed the data requirements for a continuous institutional risk analysis. These data are not confined to accounting and market data, but also encompass contractual details of the structured transaction. With this information, it is possible to gauge the distributional aspects of risk transfer.

We have also pointed to a possible addendum to bank risk evaluation that builds on the systematic risk of bank stocks. This method, which is commonly used in corporate finance to estimate the costs of capital, is possibly a first step towards gauging the dependency on the default risk between financial institutions. The beta measure may be aggregated from the level of the individual financial institution to cover the entire financial sector[12].

[12] The data requirements that follow from this approach are simply the time series of all bank stocks plus a representative market index. In compiling such a data set, it may also be useful to establish a historical data base that allows the relationship between individual betas, sector betas and bank health to be estimated. There may be various measures of bank health, ranging from completely safe to individual defaults to collective distress. If there is no stock price, as in the case of savings banks, or cooperative banks, a substitute risk indicator is needed.

A more sophisticated level of transparency in the market for derivatives and structured finance may, in our opinion, become an important contributor to the common belief that ”everything is under control”, i.e. that financial market stability is assured.

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This may take the form of traded subordinate debt. However, in some real world cases, a substitute may simply not be available and, hence, this approach does not work.