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Systemic Credit Risk in the Presence of Concentration

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Abstract

In a Black-Scholes-Merton model of single name default, instability could be seen as the level of volatility that would trigger default, everything else equal. At a portfolio level, for instance comprising all credit liabilities of the corporate sector, potential for instability could be measured by a credit portfolio loss distribution. For such a loss distribution, it should then be possible to define a level of volatility that would trigger instability, for instance by producing credit losses in excess of the aggregate capital of the banking system. This paper analyses the potential for instability in the Euro area by looking at both aggregate and name-level data for the corporate sector. Loss distributions are computed under plausible hypotheses for the underlying default, loss and correlation parameters, and our conclusion is that aggregate bank capital could cover losses at a very high confidence level; in other words, the likelihood of financial instability is negligible. However, we identify a sizable degree of concentration in the aggregate liabilities of Euro zone non-financial corporations. Significant concentration, even at investment grade, augments potential credit losses (measured as Credit Value at Risk) in a similar way to a substantial increase in the aggregate average default probability or the average asset return correlation. Further analysis is warranted in order to assess the level of volatility that could trigger default of a "concentrated exposure" and to better understand under which conditions this could lead to instability.

1. INTRODUTION: VOLATILITY VS INSTABILITY

Dealing with the topic of Financial Instability is a task of daunting complexity. The few academic authors that have taken up the challenge (most notable in recent times are Charles Kindleberger and Hyman P. Minsky) have succeeded in devising an initial taxonomy of financial crises and their causes. However, most would agree that moving beyond classification into a tightly knit and consistent theory of Financial Instability is still work in progress. IMF's twice-yearly issues of the Global Financial Stability Report "provide a regular assessment of global financial markets and identify potential system weakness that could lead to crises" (IMF 2003). Again, the focus is chiefly descriptive, enriched by in-depth analysis of various crisis episodes and related policy responses. Many studies posit a connection between episodes of high volatility in the prices of financial assets and episodes of financial instability. While "volatility, simply put refers to the degree to which prices vary over a certain length of time … Financial system instability is often linked to concerns about key financial institutions becoming illiquid or failing …" (IMF, 2003). The motivation of this paper is to explore a formal, however narrow, link between the related concepts of volatility and instability via the Black-Scholes-Merton model (BSM) of default, in the version popularised by Moody's|KMV (2003) and RiskMetrics (1997). In the BSM model, a company will default whenever the value of its assets falls below the nominal value of the liabilities. Everything else equal, an increase in asset volatility augments the likelihood of such an occurrence. The attractiveness of the BSM framework is that it features a discontinuity (i.e. a default) along a path of increasing volatility in asset returns. In a model of single name default, instability could be seen as the level of volatility that would trigger default, everything else equal. At an aggregate level, the joint process of default of a portfolio of names can be derived by their joint asset dynamics. Thus, if one thinks of systemic Financial Instability as entailing the joint default of a number of companies and banks, a BSM model of an economic system could represent a relevant "laboratory" test for systemic risk.

Gray, Merton and Bodie (2003) have extended the BSM framework to a macroeconomic setup. While being more limited in a number of ways, our analysis differs in that we utilise explicitly the concept of a *loss distribution* and we study the implications of *concentration* on financial instability. A portfolio model is first and foremost a tool to quantify the likelihood of a given level of losses on a credit portfolio, over a definite time horizon. This measure is typically read off a *loss distribution*. If this portfolio is assembled at the level of a single bank, one can derive the loss distribution in order to assess the likelihood that the bank will remain solvent over the period, which is given by the probability of losses not exceeding the bank's capital and reserves. The same concept can be applied at a macroeconomic level, for instance, taking aggregate loans from the financial sector to the corporate sector. The resulting loss distribution could be used to evaluate the solvency of the financial system as a whole, thus translating the general concept of systemic risk into a less general, but also more concrete concept of Financial Instability. While the analysis in Gray, Merton and Bodie (2003) encompasses all macroeconomic sectors and quantifies the risk of instability at a macroeconomic level, this paper explicitly models liabilities issued by the major corporates[1] and banks in the Euro area. By computing loss distributions for a specific portfolio, we are able to explore a dimension that, to

[1] We use the shorthand noun "corporate/s" in this paper to refer to one/several non-financial corporation/s.

the best of our knowledge, has received little attention in the literature, and that is *concentration.* Among recent episodes of single name instability are the LTCM debacle and the period following the TMT bubble collapse, including the Enron and WorldCom defaults. These were large institutions, with a non-negligible weight on either the financial system or an important market or both. We believe that the concept of *concentration* is key when trying to assess the link between volatility and instability. Generalized defaults of numerous small actors may weaken, but unlikely threaten the financial system, whereas the orderly resolution of the default of one single institution, at the center of a large number of financial transactions like LTCM, turned out to require the coordinated intervention of major US banks. Portfolio models, applied to the economy-wide portfolio of private credit claims not only enable quantifying potential losses in a probabilistic way, but also help spotting the largest sources of potential losses, the entities about which the largest lumps of credit risk are concentrated.

After having hopefully made a case for the use of loss distributions in the analysis of systemic risk and the impact of concentration, we need to establish at least a suggestive link to the economic implications of volatility and instability. The former could impact the real economy because of losses in the wealth of a sector, which can in turn affect macroeconomic flows. Financial instability will instead affect macroeconomic flows directly. Disruptions in the payment system following bank defaults can impair the efficient allocation of resources upon which a modern economic system with deep capital markets thrives. Such disruptions will likely translate in lower macroeconomic flows. Unlike the destruction of wealth brought about by volatility, which could sometimes amount to a mere redistribution within a sector, disruptions of economic flows will have direct effects on the level of economic activity. While a more detailed analysis of these issues is beyond the scope of the paper, the distinction between flows and stocks should be kept in mind when interpreting our results.

The remainder of the paper is organized as follows. Section 2 introduces the sample, a credit portfolio comprising the largest names in the Euro zone, based on an "anonymous" member list of the EuroStoxx50 index, and examines its actuarial characteristics using the Expected Loss (EL) measure. In Section 3, we present a simplified framework based on a CreditMetrics application of the BSM framework, which enables introducing the main Value at Risk (VaR) concepts for analysing concentration. In section 4, these concepts are applied to derive measures of the solvency of a banking system. Section 5 concludes.

2. NAÏVE CONCENTRATION ANALYSIS

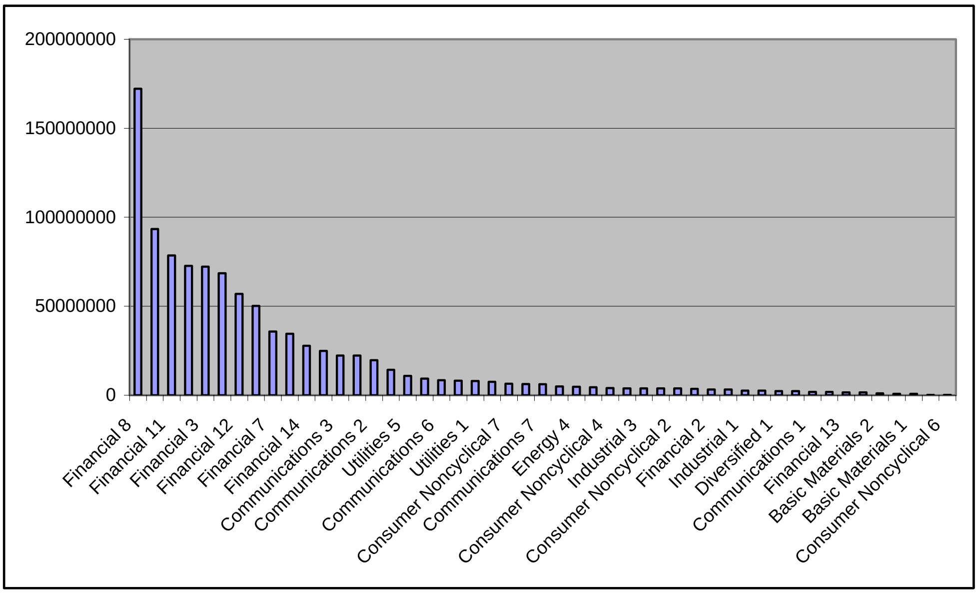
It is instructive to begin this study with a standard Expected Loss (EL) calculation. This is given by the product of the Exposure at Default (EAD), the Loss Given Default (LGD) and the Probability of Default (PD), which are the building block of most credit portfolio models and the natural starting point for any analysis of credit risk concentration. For the sake of brevity, we illustrate each of these concepts by direct application to the sample portfolio.

Exposure at Default (EAD)

A breakdown of the EUROSTOXX50 Index at the end of 2001 into its member components, after consolidating two companies that are part of the same group, provides 49 names representing 49 groups with only minority ties to each other. The sample displays high variation in terms of credit quality, as it contains a richer mix than the current index, including three speculative grade companies. For each name, total debt is defined as in the standardized balance sheet classification available in Bloomberg, which excludes deposits in the case of banking names and account payable for all corporates. EAD are defined in nominal terms, with only one exposure per name, for a total exposure of EUR 3trn. This is possibly an oversimplification, as the total debt numbers extracted from Bloomberg comprise a wide variety of instruments and maturities. Moreover, there is a question of comparability between the total debt of a bank and the analogous measure for a corporate, even if deposits and trade credit are excluded. In this respect, however, we are following mainstream regulatory practice.

For convenience, total debt issued by the names in the sample is normalized to EUR 1bn, and we imagine to hold a single instrument issued by each name in proportion to the debt in its balance sheet. Figure 1 depicts the nominal holdings, with each member identified by its sector and an ordinal number (see Annex 1 and 2 for a full list). The sample is highly concentrated, with the largest issuer accounting for over 17% of total nominal holdings, and with the top ten issuers representing three quarters of the portfolio. A widely used measure of concentration, the equivalent number of assets[2], indicates that the actual portfolio of 49 exposures is as concentrated as a portfolio of 14 identical ones.

Figure 1. Nominal composition of the portfolio by name. Normalized amounts.

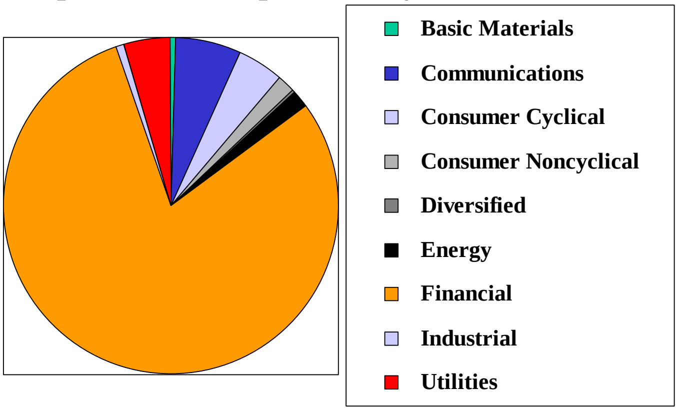


With all major financial exposures in the sample, it is not surprising that over three quarters of the portfolio is attributable to either banks or insurance companies, which

[2] The equivalent number of assets is defined as the reciprocal of the Herfindhal-Hirshman index, which in turn is equal to the sum of the squares of each name's share in the portfolio.

in Figure 2 have been grouped under the "Financial" sector. The share of the other sectors (Communications, Utilities, etc.) amounts to only a handful of percentage points. One may thus conclude that, at first sight, debt issued from EUROSTOXX50 names is highly concentrated both along a name dimension and along a sector dimension. The country dimension is less relevant, as it only represents the country of incorporation, irrespective of the actual geographical distribution of business. However, based on such narrower definition, the portfolio is also concentrated geographically, with 40% of the exposure in Germany, 20% in France, 15% in the Netherlands, and the remaining part more or less equally split among Italy, Belgium and Spain.

Figure 2. Nominal composition of the portfolio by sector



Loss Given Default (LGD)

There is a general agreement, documented by extensive studies[3], that only a fraction of the principal is lost upon default. On the basis of such studies, and the statistics reported in Table 1, one cannot reject the standard working hypothesis that LGD has been on average of 50% historically for senior unsecured publicly traded debt instruments, like bonds. The central estimates are quite similar for bonds, letters of credit and receivables and are somewhat lower for loans.

Table 1. Summary Statistics from LGD Studies

Security	Study	Recovery Rate (%)	Recovery Rate Standard Deviation
Senior Unsecured Bonds	Altman & Kishore [96]	48	27
Senior Unsecured Bonds	Carty & Leiberman [96]	48	26
CDS, LC, Receivable	Carty & Leiberman [96]	48	26
CDS, LC, Receivable	Altman & Kishore [96]	48	27
Loans/ Commitments	Asarnow & Edwards [95]	65	38
Loans/ Commitments	Carty & Leiberman [96]	71	21

Source: RiskMetrics

Additionally, all studies document an important volatility of recoveries across different names, periods and samples. Again, one cannot reject the standard working hypothesis that the standard deviation of the LGD is 25%. Throughout what follows

[3] See for instance, Carty & Leiberman (1996) or Altman & Kishore (1996) on bond recovery and Asarnow & Edwars (1995) on recovery for loans and loan commitments.

we assume a uniform average LGD of 50% and a standard deviation of 25%, regardless of the type of debt composing the portfolio and regardless of the counterpart's nature. While there is evidence that recovery varies across economic sectors and that it is lower for financial institutions than for corporates, we consider such refinements outside the scope of the present work. LGD variation over the business cycle is instead discussed in section 4.

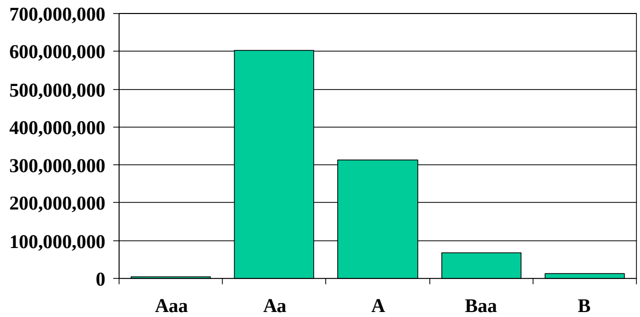
Rating distribution and Probability of Default (PD)

Following standard practice, and taking advantage of the fact that most names in the portfolio issue public debt, relative creditworthiness is measured in terms of long-term senior-unsecured issuer ratings as assigned by Moody's or Standard&Poor's. Agency ratings are a qualitative and ordinal measure of creditworthiness, which is defined in quite general terms. For instance, Moody's defines its ratings scale as follows:

"Obligations rated Aaa are judged to be of the highest quality, with minimal credit risk. Obligations rated Aa are judged to be of high quality and are subject to very low credit risk. Obligations rated A are considered upper-medium grade and are subject to low credit risk. Obligations rated Baa are subject to moderate credit risk. They are considered medium-grade and as such may possess certain speculative characteristics. Obligations rated Ba are judged to have speculative elements and are subject to substantial credit risk. Obligations rated B are considered speculative and are subject to high credit risk. Obligations rated Caa are judged to be of poor standing and are subject to very high credit risk"

For ease of exposition Moody's notation is used throughout the paper. Figure 3 depicts the distribution of ratings in the sample, revealing that well over half of the exposures are associated to names of high credit quality (Aa or above), as primarily determined by exposure to banks and other financial institutions. Over three quarters are at least upper-medium grade (A). The small exposure to speculative grade names (B) comes from companies that have experienced financial difficulties in recent years.

Figure 3. Nominal composition of the portfolio by rating. Normalized amounts.



The next step, to associate a PD to each rating for use in credit portfolio analysis, is both delicate and controversial. Choice will generally depend on (i) the horizon that is most relevant to the issue being analysed; (ii) the degree of discrimination that is warranted, given the heterogeneity of the portfolio; (iii) the available data. For regulatory purposes, the horizon will be one year; there should be a minimum of seven rating grades for non-defaulted borrowers; and data should span a period of at least five years. For the purpose of our analysis, criteria (ii) and (iii) will be satisfied by using historical estimates of default probabilities associated with letter grades. Such estimates are published by the rating agencies, and are typically based on historical samples starting in the 1970s. Series going back to the 1920s are also available, but arguably, they span economic episodes that are not relevant to the immediate future[4]. Realizing that there might be important differences across obligations rated within the same letter grade, in 1983 Moody's introduced the "rating qualifiers" 1, 2 and 3, which are added after the letter grade to obtain an alphanumeric rating. For instance, the highest rated obligations within the letter grade Aa are rated Aa1, the lowest, Aa3. Historical default rates are also estimated for alphanumeric grades; however, the loss of degrees of freedom in estimating 17 instead of 7 PDs increases the volatility of central estimates. Default frequencies for alphanumeric grades often violate the basic requirement to be increasing along the rating scale.

Concerning the risk horizon, the purposes of this exercise are best served if instead of the regulatory standard one-year horizon, a longer one is considered. Table 2 illustrates the reason for this choice. At a one-year horizon, the cumulative default probabilities for Aaa, Aa and A rated names are both negligible and indistinguishable. As the risk horizon increases, the number of default observations increases, thus rendering the estimates more reliable. Only reaching a three-year horizon the probability of default of Aa rated names ceases to be negligible and a clear distinction between this class and the two neighbouring ratings emerges. The difference in PD across ratings classes becomes more and more marked as the horizon increases, but arguably, pushing the horizon beyond 3-5 years will diminish the relevance of the study, as the reference sample becomes less and less representative of the Euro zone economy.

Table 2. Average Cumulative Default Rates 1970-2002 (Issuer Weighted)

Fraction of issuers defaulting by the horizon (%)

Horizon (years)	1	2	3	4	5
Aaa	0	0	**0**	0.04	0.12
Aa	0.02	0.03	**0.07**	0.16	0.26
A	0.02	0.09	**0.22**	0.36	0.51
Baa	0.22	0.61	**1.08**	1.69	2.25
Ba	1.28	3.51	**6.09**	8.76	11.36
B	6.51	14.16	**21.03**	27.04	32.31
Caa-C	23.83	37.12	**47.43**	55.05	60.09
Investment-Grade	0.08	0.24	**0.45**	0.72	0.98
Speculative-Grade	4.99	10.05	**14.66**	18.67	22.18
All Corporates	1.59	3.19	**4.64**	5.9	6.96

Source: Moody's 2003. Exhibit 44.

It is noteworthy that default frequencies at a three-year horizon are of the same order of magnitude as "worst-case-one-year" default rates. The highest one-year default rate was recorded in 2002 for Investment Grade Corporates at 0.49% and in 2001 for Speculative Grade ones at 10.60%. As the sample consists mostly of the former, taking a three-year cumulative horizon is also representative of how much things did go wrong historically in one year over the 1970-2002 period. Most researchers refer to average cumulative default rates as "unconditional" default probabilities, since they span several business cycles. A "worst-case-one-year" default rate is instead thought of having a nature of "conditional" default probability. For instance, the aforementioned default rate of 0.49% recorded for investment grade issuers can be

[4] One could certainly argue that there is a non-zero probability of a repeat of the Great Depression or a World War over the next thirty years, but most would agree that the probability of any such event hitting the Euro area over the next two-three years is indeed negligible.

interpreted to be conditional on the phase of the business cycle prevalent in 2002. Wilson (1997) has suggested a way in which the PDs used in credit portfolio modelling could be expressed as a function of economic conditions. His model could be used to derive PDs that are conditional on current economic conditions, and also for stress testing that is based on a range of macroeconomic forecasts. These concepts are further discussed in section 4.

Expected Loss Analysis (EL)

Under the hypothesis that the default and recovery processes are independent, the EL can be computed by simple multiplication of the EAD times the LGD times the PD. Its interpretation is of a PD-weighted LGD and it provides a more accurate indicator of credit risk concentration than it is the case for nominal exposures. It should be noted that PD and LGD fully determine the capital allocation in the latest version of the New Basel Capital Accord, Internal Ratings Based Approach (2003, §241). In that formula, exactly like in our EL calculation, the LGD enters linearly; capital allocation depends instead from the PD in a non-linear, but nevertheless monotone increasing relationship. Table 3 compares the EL contributions of each sector to the corresponding nominal contributions. Most noteworthy, the financial sector, which accounts for 80% of the total nominal exposure, takes up only 20% when weighted by its PD. Conversely, the communication sector, whose exposure contribution is only 6% of the total, accounts for over half of total EL. The latter fact is explained by the presence of a normalized EUR 8m exposure to B-rated Communications 1 and 7 as well as two large BBB-rated exposures (Communications 2 and 3). The large contribution of the Consumer Non-Cyclical Sector (including retailing and pharma) is mostly due to a normalized EUR 4m exposure to B-rated Consumer Cyclical 4 in the sample.

Table 3. EL vs Nominal Exposure Contribution

Sector	EL EUR	EL %	Exposure %
Communications	1,109,159	51%	6%
Consumer Noncyclical	441,218	20%	2%
Financial	436,449	20%	80%
Utilities	80,570	4%	4%
Consumer Cyclical	64,143	3%	4%
Energy	24,193	1%	2%
Industrial	16,303	1%	1%
Diversified	12,467	1%	0%
Basic Materials	4,175	0%	1%
Total	**2,188,677**	**100%**	**100%**

In relative terms, total EL amounts to slightly over 2% of total nominal exposure. A capital allocation based purely on the EL would fall short of current regulatory capital requirements[5] and it would amount only to a fraction of the largest exposure in our portfolio (recall that the nominal weight of the largest issuer in the portfolio is over 17%). Also, losses originating from default of any except the smallest exposures would be sufficient to wipe out half of such allocation (see Figure 1). This

[5] Even considering risk-weighted assets (RWA) of 20% for all financial institutions, average RWA would be 80%*20%+20%*100%=36% and regulatory capital 8%*36%~=3%.

shortcoming is due to the fact that EL accounts for neither default correlation among exposures, nor the degree of concentration in the portfolio. To correct for the former, the proposal under the Basle II Internal Rating Based Approach, introduces an analytical formula that de facto augments the PD whenever correlation is non-zero[6]. Analytical approximations (e.g. the so "granularity adjustment" in Gordy (2002)) have also been proposed for portfolios that are not infinitely granular. In the next section, these issues are illustrated via numerical simulation.

3. THE EFFECT OF CORRELATION AND CONCENTRATION

Loss distributions for credit portfolio risk are highly skewed and with fat tails, due to the relative infrequency of default events and to the fact that in unfavourable economics situations defaults tend to occur jointly. A model of correlation is needed to incorporate joint default risk in our sample portfolio. Once such a model is established, it is possible to compute a loss distribution by numerical methods and to discuss a set of portfolio-based concentration measures. A number of frameworks for this type of analysis have been proposed over the last few years and are surveyed in Saunders and Allen (2002). Koyluoglu and Hickman (1998) demonstrate that, subject to proper parameterisation, most frameworks could be harmonized to yield similar results. We rely on their argument to choose the model that is simplest to calibrate and implement, so that attention can be focussed on the results of the computations.

A correlation model « à la CreditMetrics »

Within the BSM framework, default occurs when negative asset returns bring the asset value below the nominal value of liabilities. The CreditMetrics methodology calibrates asset returns as a function of normally distributed equity returns. In practice, it is assumed that returns for each obligor are determined by an idiosyncratic factor as well as one or more stock market indexes. In this paper, each obligor is associated to only one such index; for instance, Financial 10 is mapped to the Morgan Stanley Capital International (MSCI) Banks Index for its country of incorporation, while Financial 14 is mapped to MSCI Banks Index for a different country. The asset correlation between these two banks will depend on the correlation between the two stock market indexes as well as the weights of each respective idiosyncratic factor. Following the methodology suggested in the CreditMetrics (1997 and 2003) documentation, we determine the latter weight as an inverse function of the size of the obligor, measured by its total assets. Annex 1 contains the full list of obligors, their total assets, and the weight of the stock index mappings (measured in terms of the R-squared in a univariate regression). On average, asset correlation across obligors in the sample is substantial, of the order of 40%, as one would expect, due to the fact that equity returns across blue chips in the Euro area are highly correlated. Once asset returns are thus calibrated, the value of the default barrier is inferred as the percentile

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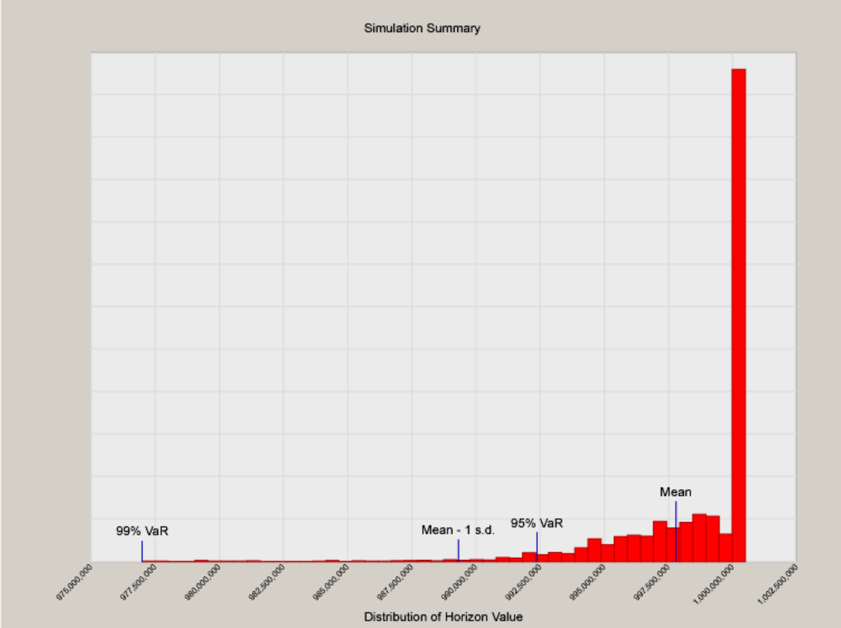
[6] The formula is $\Phi\left(\dfrac{\Phi^{-1}(PD)+\sqrt{\rho}\,\Phi^{-1}(0.999)}{\sqrt{1-\rho}}\right)$, where Φ represents the cumulative function for the standard normal distribution and Φ^{-1} its inverse, and ρ the average asset correlation in the portfolio. It is easy to see that, in the presence of zero correlation the formula returns PD (and the Basel formula reduces to a multiple of the EL). The result is greater than PD, for positive correlation.

of the asset return distribution corresponding to the PD associated to each obligor's rating. Thus, default correlation is ultimately driven by a modified correlation of equity index returns.

Figure 4. Horizon Value Distribution



Based on this model, Figure 4 plots the Horizon Value Distribution, which is the complement of the Loss Distribution to the nominal value of the portfolio. The mean value of the loss distribution is the one already discussed and obtained by subtracting the Mean Portfolio Value from the nominal value of the portfolio. The percentiles, also know as Value at Risk (VaR) are obtained as the difference between the corresponding percentiles of the Horizon Value Distribution and the Mean Portfolio Value. The VaR (in loss terms) at a 99% confidence is estimated at EUR 20,796,782 ± 3%. Due to simulation error, the VaR is estimated slightly less precisely as the confidence level increases[7], yet the central estimate grows to approximately EUR 34m at a 99.5% confidence level and EUR 142m at 99.9%.

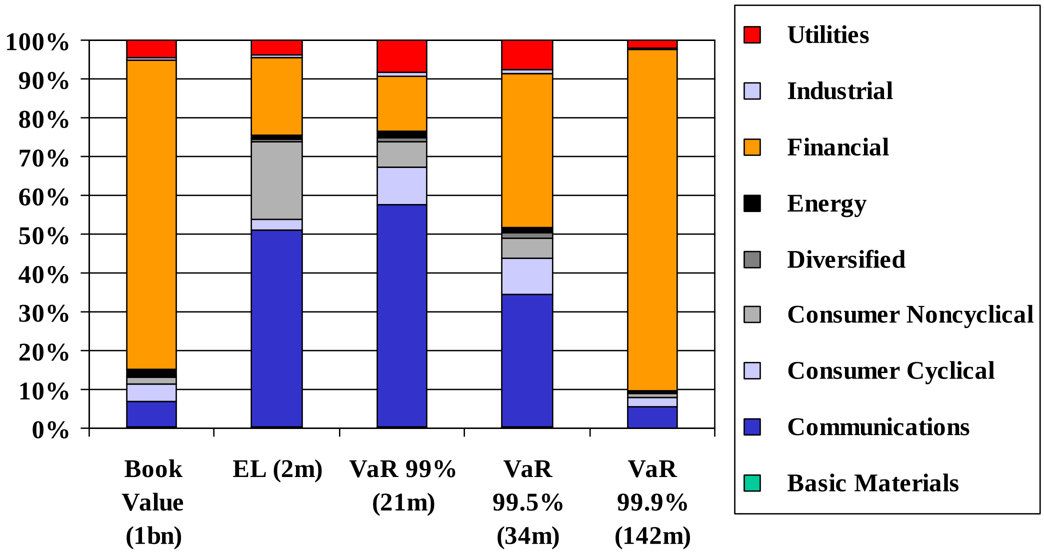
Sector and name concentration

Consider any interval in the loss distribution (the complement to nominal value of the histogram pictured in Figure 4). It measures the frequency of all scenarios producing total losses in such an interval. The average loss associated with a given obligor across all of these scenarios measures its contribution to total loss in that interval, also called VaR contribution. Finger and Xiao (2003) explain how this computation could be accomplished numerically. Looking at VaR contributions at different levels of confidence enables building further intuition on the main sources of credit risk in the sample. Figure 5 presents the breakdown by sector at different levels of confidence. While, as already discussed, the relative EL contribution of the Financial sector is only a quarter of its nominal EAD, its importance grows moving forward into the tails

[7] The results have been obtained by using importance sampling techniques and 5,000,000 repetitions in the CreditManager software by RiskMetrics. See Finger and Xiao (2003) for details on importance sampling.

of the loss distribution. At a 99.9% confidence level, the Financial sector represents approximately 90% of the total Value at Risk.

Figure 5. Exposure, EL and VaR Contribution by sector



The explanation is straightforward, but nevertheless quite central to the understanding of systemic risk. As loss scenarios are ordered by increasing loss and decreasing likelihood along the distribution, one will encounter defaults of relatively riskier borrowers at low confidence levels. At higher confidence levels, less risky exposures begin to default. At very high confidence levels joint default begin to occur. Systemic risk is encountered at these higher percentiles in the loss distribution. This reasoning, however, only holds if no single obligor dominates the portfolio.

Table 4. Top VaR contributors at different confidence levels

Top ten contributions	VaR 99.5%	Top ten contributions	VaR 99.9%
Communications 2	3,333,232	Financial 8	67,372,534
Communications 3	3,259,372	Financial 9	10,902,895
Communications 7	3,224,454	Financial 10	8,462,587
Financial 11	2,691,770	Financial 1	6,903,279
Financial 14	2,271,389	Financial 12	5,322,734
Consumer Cyclical 1	1,824,415	Financial 11	5,235,778
Financial 3	1,560,210	Financial 15	5,096,058
Consumer Noncyclical 4	1,422,554	Financial 3	4,680,736
Utilities 2	1,050,698	Financial 14	3,862,672
Financial 1	972,450	Communications 7	2,336,584
Total	**33,984,931**	**Total**	**141,982,236**

An analysis of VaR contribution by name (see Table 4 and also Annex 2) clarifies the point further. The top contributors to the VaR99% and VaR99.5% are Baa-rated Communications 2 and 3 and B-rated Communications 7 with a total normalized exposure of less than EUR 50m. The top contributor to the VaR99.9% is instead a bank, A-rated, but with the largest normalized exposure in the portfolio of EUR

170m[8]. Whenever a default scenario involving such a large exposure is drawn, losses are "pushed to the tails" of the distribution. To understand why, let us recall that the VaR99.5% amounts to EUR 34m, while on average, LGD on this exposure will be EUR 85m. Thus, most of the increase from VaR99.5% to VaR 99.9% (i.e. from EUR 34m to EUR 142m) is explained by the additional EUR 85m of potential losses on the largest exposure in the sample. The intuition is further reinforced by observing that the second largest contributor at a 99.9% confidence, also a bank, is Aa-rated but with LGD that is only half the former. It seems that the highest tail contributions tend to come either from very large exposures, independently of their creditworthiness, or from highly rated exposures, everything else equal. There is thus something fundamentally different about large concentrations, that is not easily captured by any single capital allocation measure, but that instead requires in-depth analysis of the tails of the distribution at different confidence levels. The assumption of a granular portfolio, underlying the capital requirements proposed in the Consultative Paper on the New Basel Capital Accord (2003), may thus warrant reconsideration[9].

Other than exposure size and high ratings, an additional reason for the disproportionate weight of the financial sector at the highest confidence level is that average return correlation is significantly higher between financial institutions (60%) than it is within other sectors. This is a mechanical consequence of the CreditMetrics correlation model, where the larger the obligor the higher its weight in any given stock market index and consequently, the higher the systematic component of its returns. Higher return correlation increases the relative likelihood of infrequent events like joint defaults. Again, this implies that regulatory capital may need to consider contributions at different confidence levels.

4. MEASURING THE SOLVENCY OF A BANKING SYSTEM. DOES CONCENTRATION MATTER?

Overall, the 49 names in our sample have outstanding debt (excluding deposits) in excess of EUR 3trn. The sample contains nine Aa-rated banks (Financials 3, 6-7; 9-12, 14 and 15) and two A-rated ones (Financials 8 and 14). Collectively, these banks have total capital in excess of EUR 300bn, that is, in excess of 10% of nominal exposure. Such an order of magnitude is comparable to the estimates of risk computed in the previous section, where we found that the VaR at a 99.5% (99.9%) confidence level (over a three-year horizon) is approximately 3% (14%) of the normalized portfolio. Does this finding allow one to infer that the largest banks in the Euro area are solvent at a confidence level that is higher than 99.5% but lower then 99.9%, that is, there is more than one (but less then five) chance(s) in one thousand that cumulative losses on the portfolio over a three year period (or over one worst case year) will exceed their aggregate capital at EUR 300bn?

While the above reasoning can only be taken as suggestive, one could argue that it is both too conservative and not conservative enough. One the one hand, the portfolio of these banks is much more diversified, as it extends well beyond the EUROSTOXX50

[8] Since a considerable fraction of the liabilities of the bank in question is constituted by Aaa rated covered bonds, our results considerably overstate the concentration effect at this level of confidence. Once more, we should emphasise that any reference to a specific name is for illustrative purposes only.
[9] The point is made explicitly in the IMF Staff Comments on the April 2003 Consultative Paper (2003).

names and, additionally, there are banks and capital market investors outside the EUROSTOXX50 which share the risk on these large corporates, either in a direct form or in the form of a credit derivative. This is particularly true since the portfolio is largely composed by bank bonds, a substantial part of which is held by the household sector. On the other hand, the portfolio of a specific institution might be more concentrated than the average on a risky corporate, contributing disproportionately to systemic risk. Aggregate flow-of-funds date provide some additional elements. In its Monthly Bulletin, the European Central Bank publishes statistics on loans to the government, non-financial corporations and households. At the end of the second quarter of 2003, total loans outstanding exceeded EUR 8trn, with EUR 1trn taken by the government sector, and the remaining EUR 7trn split halfway between the corporate and household sector. Of the total loans, over EUR 7trn had been extended by Euro Area Monetary Financial Institutions (MFI). Interestingly, outstanding bonds, issued by the corporate sector, amount to little over EUR 0.5trn. The total capital and reserves of the aforementioned MFI exceed EUR 1trn. Thus, if one omits loans granted outside the Euro area, capital and reserves cover approximately 14% of the outstanding face value of MFI loans. An interesting question to ask is at which level of confidence such capital and reserves would be sufficient to ensure solvency of the banking system taken as an aggregate. We believe there is a meaningful way in which such a question could be addressed. For the sake of illustration, analysis is restricted to the corporate sector, leaving retail and inter-bank exposures as a topic for further research. The first subsection below presents the main argument, while the second sub-section discusses the robustness of the results under stress tested parameter values.

Should concentration make a difference to the capital requirements?

Participating banks to the several Basle II Quantitative Impact Studies have been asked to estimate capital requirements using the IRB formulas, that is, under the assumption that their portfolios were infinitely granular. One should be able to perform a similar exercise, based on aggregate data from the ECB Bulletin, by properly segment the total exposure, for instance by country and by rating class, and to obtain a reasonable estimate of the aggregate loss distribution. However, overlooking the presence of potential concentration in the credit aggregates might lead to a systematic underestimation of aggregate risk. Together, the thirty-eight corporates in our sample have outstanding debt close to EUR 1trn, so that they represent approximately one quarter of total corporate debt outstanding, including both loans and bonds. The largest debt, excluding banks, is Aa-rated Financial 3's at EUR 230bn (approximately 5% of a total corporate debt of EUR 4trn), followed by A-rated Consumer Cyclical 1 with EUR 80m and Baa-rated Communications 3 with EUR 70m. Some further exploration thus appears to be justified.

In order to assess the potential impact from concentration, we fix the attention on total corporate sector debt, which, for illustrative purposes, we quantify at EUR 4trn and compute loss distributions under several hypotheses for average PD, LGD, and asset correlation. Loss distributions are initially computed under the assumption that the portfolio is infinitely granular, using an approximation analogous to the IRB formula, which is built in the CreditManager software[10]. Subsequently, we explicitly model the exposure represented by the thirty-eight corporate names in the EuroStoxx50 and compare the resulting loss distributions at various levels of confidence to assess the impact of concentration.

The parameters for the infinitely granular portfolio are calibrated as follows:

- **PD.** The recently released Moody's study "Default and Recovery Rates of European Corporate Bond Issuers, 1985–2002" estimates an average default rate of 2.9% for all corporates in 2002, the worst year in the sample. While cumulative default rates are not yet available for European corporates, the study observes that one-year transition matrices for European and US bond issuers are quite similar. Thus, consistently with our hypothesis derived from casual observation of US data, that "worst-case-one-year" default rates are of the same order of magnitude as three-year cumulative default rates, we estimate average credit quality of European bond issuers to be lower then Baa (3y default rate of 1.08%) but higher than Ba (3y default rate of 6.09%). For illustrative purposes, two sets of simulations are run using the IRB formula, the first one based on a PD of 3% and the last on 6%. The latter, higher level is possibly more reflective of companies that do not issue public debt, but only have access to bank credit.
- **Asset correlation.** Based on Moody's¦KMV data for listed European companies and calibrating loss distributions for a single factor, Lopez (2002) estimates correlation as low as 10.0% and as high as 22.5% depending on the size of the companies as well as their PD. This range is well below the average correlation applied to our EuroStoxx 50 portfolio, but consistent with the fact that the sector includes obligors of different sizes and from diverse countries. Lopez (2002) also finds that lower asset correlations tend to be associated to higher PDs. Applying the most recent IRB formula for correlation to our chosen range of PD between 3% and 6% one finds asset correlation as high as 15% and as low as 9%, respectively. For illustrative purposes, we tabulate two round levels of correlation (10% and 20%).
- **LGD.** The working hypothesis of 50% average LGD, with a standard deviation of 25% is maintained.

The first figure in each cell in the first row of Table 5 reports the VaR[11] estimates for an infinitely granular portfolio of EUR 4trn. The second figure in each cell of the same table, obtained by assuming that a loan pool of approximately EUR 3bn plus our sample of 38 non-bank obligors make up the total portfolio of EUR 4trn, should gauge the impact of concentration. The < or the > sign separates the two figures, the

[10] Xiao and Finger (2003) demonstrate that, with proper parameterisation, the IRB-type formulas enable approximating the loss distribution for a portfolio with a large enough number of homogeneous obligors.

[11] The CreditManager software requires input of the number of exposures comprising a loan pool, but Xiao & Finger (2003) find that a couple thousand exposures are sufficient to ensure convergence of the loss distribution, under most parameter values. Estimates of the equivalent number of corporate exposures for the Euro area would probably yield an order of magnitude of at least several hundred thousands, which is well beyond the number needed for convergence. As a consequence we arbitrarily set the number of exposures at 2,000. Sensitivity tests run using 5,000 and 10,000 exposures confirm the intuition.

former indicating an increase in VaR at any given confidence level. Several observations can be made on the basis of this simple experiment.

Table 5. Concentration effects in the European Corporate Sector

	PD = 3%			PD = 6%		
	VaR99	**VaR99.5**	**VaR99.9**	**VaR99**	**VaR99.5**	**VaR99.9**
$\rho = 10\%$	168<170	202<208	278<323	268>246	317>297	419<434
$\rho = 20\%$	288>262	357>326	511>504	446>387	534>463	719>662

Firstly, as the average credit quality of the EuroStoxx50 sample is much higher than the credit quality in the loan pool[12], and this is reflected in the assumption of lower PDs, no major increases are observed and actually the VaR decreases in a majority of cases. Still, the joint effect of concentration and of a higher average correlation[13] is evident further into the tails of the loss distribution, especially in the first row of the table, corresponding to a less correlated pool. The largest effect is found in the case of a 3% PD for the pool, at a 99.9% confidence level, where the Value at Risk increases by 15% from EUR 278bn to EUR 323. It is also interesting to notice that, always at a 99.9% confidence level, despite having substituted higher rated names for EUR 1trn of exposure otherwise at a 6% PD, the VaR still increases by almost 4%, from EUR 419m to EUR 434m.

Secondly, VaR always decrease at the higher level of pool correlation as reflected in the bottom row of Table 5. Intuitively this is because a higher level of correlation produces thick tails in the loss distribution of the loan pool. The impact of name concentration on tails that are already thick appears to be negligible. Note, however, that, in the case of an average pool PD of 3%, and at a 99.9% confidence level, the VaR decreases by less than 2%, from EUR 511m to EUR 504m, a further demonstration that the higher concentration and correlation among EUROSTOXX50 names more than compensates their lower PDs. We should also note that the second row of Table 5 might be less representative of actual economic conditions. To see why, one could compare a VaR of EUR 288bn at a 99% level of confidence with total capital and reserves of Euro area banks, amounting to approximately EUR 1trn. Even assuming a cumulative default rate of 3% for the pool over a three-year period, in the presence of an average correlation of 20%, there would be a chance in one hundred that over a quarter of total capital and reserves of Euro banks are wiped out. This fraction grows to half, at the same confidence level, if one considers a PD of 6% for the pool.

For this reason, let us focus on the more plausible assumption of a 10% average correlation. At this level, it is easier to distinguish the impact of concentration from the higher correlation within EUROSTOXX50 names. Items (i) and (ii) in the first row of Table 6 report the VaR figures from the first row of Table 5, for the case of a 3% average cumulative default probability for the pool. The corresponding items in the second and third row are the contributions from the pool and from the most concentrated exposure, the latter being largest non-bank exposure in the index, at

[12] If one excludes B-rated Communications 1 and 7 and Consumer Non-cyclical 4, the average PD is close to the average cumulative 3-year default rate for investment grade names. Including those, the average PD is close to the average cumulative 3-year default rate for Baa-rated names.
[13] Average bilateral assets return correlation among the 38 corporate names is of the order of 40%.

EUR 230m, accounting for over 5% of the total portfolio of EUR 4trn. Recall that the pool accounts for three quarters of the total portfolio. At the actual rating for the largest exposure (Aa), VaR contribution from the pool is close to three quarters, in line with its nominal contribution.

Table 6. Comparative static, (i) EUR 4trn Loan Pool, EUR 3trn Loan Pool with EuroStoxx50 names and (ii) largest exposure rated Aa or (iii) Baa

$\rho = 10\%$; **PD = 3%**	**VaR99%**	**VaR99.5%**	**VaR99.9%**
Absolute value	(i) 168< (ii) 170< (iii) 208	202 < 208 < 281	278 < 323 < 408
Loan pool contribution	(i) 100% (ii) 78% (iii) 69%	100% 75% 60%	100% 69% 53%
Largest exposure contribution	(i) 0% (ii) 0% (iii) 8%	0% 0% 17%	0% 1% 26%
Note:			
$\rho = 20\%$; **PD = 6%**	(i) 446 > (ii) 387 < (iii) 426	534 > 463 < 515	719 > 662 < 735

Furthermore, due to its high rating, the largest exposure barely shows any contribution to the VaR except at the highest confidence level of 99.9%; still, at 1% this VaR contribution is much lower than its nominal contribution of almost 6%. Suppose, however, that the largest exposure were rated Baa instead of Aa[14], still at investment grade and a much higher credit quality than the pool. One should not think of this as a downgrade but, rather, of an exercise of comparative static, with two different portfolios being compared. There would be now a probability of slightly over 1% (see Table 2) that a loss of EUR 115bn (50% of the exposure of EUR 230bn) could be added to the portfolio. Items (iii) in Table 6 show that such a concentration makes its partial impact felt already at a 99% confidence level, with an increase in the VaR of 25%, from EUR 168bn to EUR 208bn. The full impact of the additional loss is instead visible at the 99.9% confidence level, with an increase of 50% in the VaR, to EUR 408m, relative to the case without concentration. The second and third rows of Table 5 indicates that the VaR contribution of the loan pool falls from 69% at a 99% confidence level, to only 53% at 99.9%, while contribution from the largest exposure rises from 8% to 26%. At this higher level of confidence, the lower rating of has a similar effect as doubling the average PD, as it may be seen by comparison with the cell in the upper-right corner of Table 5 (EUR 419m), or a substantial increase in the average correlation. A similar intuition comes from the last row of Table 6, which could be read to indicate that a lower rating of the largest concentrating exposure yields similar value at risk as the original full loan pool in the high-PD high-correlation environment. Our third comment is that, even at investment grade level, a nominal concentration of 5% of the total Euro area corporate portfolio has a considerable impact on the total VaR. Indeed concentration seems to matter at systemic level!

The fourth and final point is that, in none of the cases considered above VaR estimates exceed the level of overall capital and reserves of the Euro area banking

[14] This hypothesis is for illustrative purposes only.

system (approximately EUR 1trn) and that estimates are closest only at levels of confidence that are 99.9% or higher. The next subsection tests the robustness of this result, by considering stress scenarios for the main parameter values.

Cyclical effects and parameter calibration

While the illustrative purpose of our exercise is served by the simplest of assumptions, and the main conclusions are unlikely to be overturned by a more sophisticated parameterization, recent research on (i) the probabilities of default, (ii) the asset return correlations and (iii) the recovery rate is worth discussing. In particular, we should consider implications of the extensive literature, surveyed in Allen and Saunders (2003) and Altman, Resti and Sironi (2003), which has studied interrelated parameter variation over the business cycle. The aforementioned conclusion, that bank reserves for the Euro area are sufficient to cover losses at all but quasi-certain confidence levels, is found to be robust under a wider range of parameters as suggested in the literature.

Unconditional vs conditional probabilities of default

We have tabulated results for PD levels (a low level of 3% and a high level of 6%) that are based on historical default frequencies for European non-financial rated corporates. The assumptions are consistent with three-year cumulative default frequencies as well as worst-year frequencies. According to Moody's global statistics, three-year average cumulative default frequencies for all rated bonds amounted to 4.65% in the 1920-2003 period, 4.71% in 1970-2003 and 6.06% during the latest cycle (1994-2003). The corresponding figure for annual default frequencies (post 1970) attained the maximum value in 2001 globally and for the US, respectively at 3.8% and 4.7%, and in 2002 for European names, at 2.9%. In "dollar-weighted" terms, the global maximum was 5.29%, again in 2001. This long historical record supports our chosen range of PDs.

Average cumulative default frequencies are typically interpreted as "unconditional" default probabilities as opposed to year-by-year default frequencies, which are "conditional" on the macroeconomic environment in a given year. With particular reference to default time series for speculative grade ratings, both Wilson (1997) and Moody's (1999) are able to fit regressions with very high R-squares, explaining default rates for speculative names in terms of a parsimonious set of variables (macroeconomic in Wilson (1997), both macroeconomic and rating variables in Moody's (1999)). An even more parsimonious characterization is provided by Moody's¦KMV EDF methodology, where default frequencies are expressed a non-parametric fit to "distance-to-default" measures, in turn derived from a Black-Scholes-Merton setup (see Moody's¦KMV (2003)). These methods yield "forward-looking" default probabilities and at a first look, one might be tempted to dismiss our results on grounds that we are using unconditional and backward looking default probabilities instead of conditional, forward looking ones. Such a dismissal would be only superficially correct, for at least three sets of reasons. Firstly, our assumed range includes worst-year PDs, which are by their nature conditional on the economic environment of the year in which they are produced. Secondly, long-term cumulative averages are conditional on long-term averages for the explanatory variables. Thirdly, even if we were to employ a formal model of conditional default probabilities, as long as such a model is estimated on the historical period and on the available data, predicted default frequencies will be in the range that has been historically observed.

A more serious concern to be addressed is whether the economic environment that is implicitly assumed by our calculations (i.e. worst year since 1970s or average year since the 1920s) provides a satisfactory characterization of future credit risks. If one looks for worst-year default frequencies all the way back to the 1920s, a maximum value of 8.4% is recorded for all corporates, presumably in the late twenties or early thirties[15]. This should be interpreted as being conditional on a severe recession coupled with a prolonged stock market crash, an extreme monetary tightening and bank runs. Such conditions have neither being repeated since, nor are representative of the average economic environment underlying the average cumulative defaults. For the sake of illustration, one could re-run simulations for a fully granular portfolio in the presence of a 9% PD and assuming a 20% asset correlation. The VaR at a 99.9% attains EUR 849 bn, still short of total capital and reserve of the Euro area banking system.

Asset vs default correlation

The assumed levels for asset correlation, a low level of 10% and a high level of 20% are not out of line with available estimates over a long time horizon. Moody's¦KMV (2002) estimates median asset return correlation of approximately 20% for Utility firms in their global database of listed companies, 18% for the largest Industrial firms and 10% for all Industrial firms. Considering that the European Corporate sector is mostly composed of unlisted companies, which are likely to be smaller and less correlated, the assumed range appears to be conservative enough. Similar considerations apply to the correlation model "à la CreditMetrics" applied to EuroStoxx50 companies. This yields a median asset correlation in excess of 40% for the 38 corporate names, which is, if anything too conservative[16].

What, however, matters for computing a loss distribution is not asset, but rather default correlation, and the latter depends on both the former and the assumed PD level. Under jointly normally distributed assets returns, the default correlation between any two identical obligors is approximately 3%, for PD=3% and asset correlation of 10% and it grows to approximately 6%, for PD=6% and asset correlation of 20%. Based on the S&P default database and on the period 1981-2001, De Servigny and Renault (2003) estimate an average default correlation of 0.1% and 1.7% annually and respectively for US investment grade and speculative grade names. Using the same data on the period 1981-1999, Nagpal and Bahar (2001) had previously found a default correlation of 0.02% and respectively 1.08% for investment grade and speculative grade names at a one-year horizon, growing to 0.29% and 5.50% over a seven-year horizon. Zhou (2001), consistently with Lucas (1995), estimates a 6% default correlation between Ba rated companies at a two-year horizon[17]. Since average cumulative default frequencies for all corporates are

[15] Moody's (2004), Exhibit 25 - Annual Global Issuer-Weighted Default Rate Descriptive Statistics, 1920-2003.

[16] These levels result from applying the model in Finger and Xiao (2003). The logical concern that overestimating correlation could lead to a similar overestimation of concentration was addressed by the comparative static in Table 6.

[17] Unfortunately, Zhou's (2001) does not provide estimates over a three-year horizon for Ba names.

typically found to be lower but close to the corresponding frequencies for Ba-rated names, one could consider these findings to provide an upper bound. In conclusion, the default correlation ranging between 3% and 6% that is implicit in our analysis appears significantly more conservative than justified available historical experience.

Anecdotic evidence is still often cited that both equity correlation and default correlation increase during downturns. To gain a quantitative insight on the implications of this claim, we have run an infinitely granular EUR 4trn portfolio under a PD of 9% and an asset correlation of 30%, both extreme, but plausible in a depression scenario. Default correlation levels are much higher, at least of the order of 15%. We find that losses at a confidence level of 99.9% exceed EUR 1trn, while they are still well below at a 99.5% level. In other words, only a truly depressed scenario, characterized by both high PDs and abnormally high asset correlation could endanger solvency of the Euro area banking system on aggregate; and, even then, only with a probability of one-in-a-thousand times.

Countercyclical Loss Given Default

If one measures LGD from distressed bond values following a default event, it is only natural to find a strong positive correlation driven by the business and credit cycle. Moody's (2004) documents a long-term average recovery rate of 40% on corporate bonds in the period 1982-2003, with peak levels close to 50% in 1987 and again in 1997, and troughs below 30% in 1990 and again in 2000 and 2001. Altman, Sironi and Resti (2002) study in detail the determinant of this relationship and its implications on regulatory capital.

To examine the potential impact of this dynamics on our results, we apply the same test performed by Altman, Sironi and Resti (2002), who use "a second-degree polynomial to model the link between LGDs and empirical default rates, so that LGD is 50% when default rates are at their 20-year average (2%), LGD is 60% when default rates hit their 20-year maximum (5%) and LGD is 40% when default rates hit their 20-year low (0%)". If an average LGD of 60% is used to replicate Table 5 and 6 above (while keeping constant the standard deviation of LGD), all percentiles of the loss distribution increase by 10%, with none of the key findings being affected.

5. CONCLUSIONS AND FURTHER RESEARCH

Significant concentration, even at investment grade, augments potential credit losses (measured as Credit Value at Risk) in a similar way to a substantial increase in the aggregate average default probability or the average asset return correlation in a credit portfolio. We are however sceptical about presence of any systemic threat in the Euro area. Firstly, aggregate capital and reserves of the Euro zone banking system should cover potential losses at a very high confidence level under normal economic conditions. Secondly, having heuristically demonstrated that concentration does have an impact on the capital requirements of the banking sector, one should also recognise that such an impact was measured only in terms of "potential" rather than "actual" losses. Thirdly, even when highly concentrated defaults occur in practice, like it has been the case over the past business cycle, the ability of the banking system to spread losses across different institutions, including sellers of credit protection outside the banking sector, is such that the solidity of the system should still be preserved. Thus, if only a fraction of the Euro zone banks' capital is at risk, and such a risk only comes with a small probability, the likelihood of systemic insolvency has to be limited.

A number of caveats qualify the aforementioned. Firstly, the analysis is greatly simplified and it relies on standardized parameter calibration. A recent assessment of the state of the art in estimating PDs and especially correlations (Koyluoglu, Wilson and Yague 2003) makes a strong case for being humble about achievements to date. Secondly, historical, backward looking default probabilities and correlations are at the base of our model. In a full application of the BSM framework, both default probabilities and correlations are determined by the corporate asset values and by their volatility in a forward-looking way. Thirdly, one needs embedding the problem within a macroeconomic framework. There is a tight relationship between default rates and macroeconomic variables (Wilson 1997), suggesting that one should be able to embed default dynamics in a macroeconomic model, via explicit modelling of corporate asset values. The idea has been expressed in a different and more general context by Tobin (1980, 1992), whose lifelong work was centred on understanding the interaction between asset stocks, assets flows and macroeconomic activity in the presence of uncertainty.

The interest of the latter exercise would be to model the borderline between a situation that is not threatening (e.g. a circumscribed corporate or banking default episode) and a system-wide financial crisis. Within the BSM framework for credit risk analysis, such borderline is measured in terms of volatility. High levels of volatility translate into higher probability that asset values will fall below the default barrier for a higher number of obligors; these higher potential losses in turn increase uncertainty and further depress asset prices. Along a path of increasing volatility, losses at higher levels of confidence will be realized. However, the impact will be radically different in a concentrated portfolio from a granular one. In a granular portfolio, losses will build up gradually. In a concentrated portfolio, one might observe large losses in correspondence of defaults from concentrated exposures, along a path of increasing volatility. Thus, instability will be more likely in an economy characterized by concentrated credit risk than in one where credit risk is more granular, everything else equal. In the absence of significant concentration, and in the presence of well functioning automatic stabilisers, corporate insolvencies associated with an economic downturn may weaken the banking sector and affect the wealth of bondholders and shareholders. Presumably this will lead to increased precautionary savings and lower consumption. Negative pressure on consumption will also derive from the likely temporary upsurge in unemployment; but this negative effect on aggregate demand will likely be softened by higher public expenditure for unemployment benefits. What if instead a large concentrated default were to occur on top of economic conditions characterized by higher default rates and higher correlation? Such an episode would be more likely to trigger insolvency in the banking sector, which, other than further destroying accumulated financial wealth, would also likely disrupt resource allocation and impact economic flows.

Progress in analysing these questions is well under way. Regulators, Statistical Agencies and Rating Agencies are devoting important resources to the task of collecting and analysing credit risk data. While these studies have to date been chiefly employed in business applications, an increasing number of economists in various institutions is focusing on credit risk and financial instability. Notably, Gray, Merton and Bodie (2003) have initiated the extension of contingent claim analysis from the corporate sector to a wider macroeconomic framework. Dynamic stochastic general equilibrium models developed for monetary policy analysis now often include financial asset dynamics. Some of these models might suffer from aggregation fallacies and their empirical application is still quite limited, but clearly have the potential to take up the challenge.

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ANNEX I – EUROSTOXX 50 SAMPLE DATA (figures in EUR bn)

Name	Rating	Exposure	MSCI Index (distinct by country of incorporation which is omitted in the table)	Total Assets	R-squared
Financial 8	A	549	... Banks	678	92%
Financial 9	Aa	298	... Banks	710	92%
Financial 11	Aa	250	... Banks	350	88%
Financial 1	Aa	232	... Diversified Financials	556	91%
Financial 3	Aa	230	... Insurance	852	92%
Financial 10	Aa	218	... Banks	758	92%
Financial 12	Aa	181	... Diversified Financials	716	92%
Financial 15	Aa	160	... Banks	501	90%
Financial 7	Aa	114	... Banks	324	88%
Financial 6	Aa	110	... Banks	279	87%
Financial 14	A	88	... Banks	204	85%
Consumer Cyclical 1	A	79	... Automobiles & Components	187	84%
Communications 3	Baa	71	... Telecommunication Services	107	80%
Financial 16	Aa	71	... Banks	213	85%
Communications 2	Baa	63	... Telecommunication Services	125	81%
Consumer Cyclical 3	A	46	... Automobiles & Components	109	80%
Utilities 5	A	35	... Utilities	84	77%
Utilities 4	A	30	... Utilities	100	79%
Communications 6	A	27	... Telecommunication Services	67	75%
Utilities 3	A	26	... Utilities	68	75%
Utilities 1	A	25	... Utilities	113	80%
Utilities 2	Baa	24	... Utilities	48	72%
Consumer Noncyclical 7	A	20	... Food, Beverage & Tobacco	45	71%
Communications 7	B	20	... Utilities	69	76%
Communications 5	Baa	19	... Telecommunication Services	14	56%
Energy 1	Aa	16	... Energy	66	75%
Financial 5	A	14	... Insurance	445	90%
Consumer Noncyclical 4	B	13	... Retailing	25	64%
Consumer Cyclical 2	Baa	12	... Household & Personal Products	30	66%
Industrial 3	Aa	12	... Consumer Durables & Apparel	78	77%
Energy 2	Baa	12	... Energy	38	69%
Consumer Noncyclical 2	A	12	... Retailing	39	69%
Energy 3	Aaa	11	... Energy	87	78%
Financial 2	A	10	... Diversified Financials	238	86%
Basic Materials 3	A	10	... Pharmaceuticals & Biotech	42	70%
Industrial 1	A	8	... Materials	30	66%
Financial 4	A	8	... Insurance	234	86%
Diversified 1	Baa	7	... France	21	61%
Industrial 2	Baa	7	... Technology Hardware & Equip	32	67%
Communications 1	B	6	... Technology Hardware & Equip	26	64%
Consumer Noncyclical 3	A	6	... Food, Beverage & Tobacco	16	58%
Financial 13	Aa	5	... Insurance	196	85%
Consumer Noncyclical 1	A	5	... Pharmaceuticals & Biotech	31	67%
Basic Materials 2	Aa	4	... Materials	35	68%
Consumer Noncyclical 5	Aa	3	... Household & Personal Products	13	56%
Basic Materials 1	Aa	2	... Materials	11	53%
Energy 4	Aa	1	... Energy	85	78%
Communications 4	A	1	... Technology Hardware & Equip	23	63%
Consumer Noncyclical 6	Aa	0	... Pharmaceuticals & Biotech	9	50%
Total		**3,170**		**9,127**	

ANNEX 2. VaR CONTRIBUTIONS FOR THE EUROSTOXX50 SAMPLE

All figures in EUR (normalized)	Book Value	EL	VaR Contribution		
			99.0%	99.5%	99.9%
Financial 8	172,303,071	189,533	-222,490	-30,812	67,372,534
Financial 9	93,429,329	32,700	118,742	729,840	10,902,895
Financial 10	68,511,472	23,979	211,638	772,246	8,462,587
Financial 1	72,692,860	25,443	123,220	972,450	6,903,279
Financial 12	56,872,401	19,905	167,879	887,483	5,322,734
Financial 11	78,485,396	27,470	139,808	2,691,770	5,235,778
Financial 15	50,165,667	17,558	254,917	908,260	5,096,058
Financial 3	72,286,933	25,300	197,812	1,560,210	4,680,736
Financial 14	27,701,263	30,471	1,002,932	2,271,389	3,862,672
Communications 7	6,163,301	648,071	2,665,525	3,224,454	2,336,584
Financial 7	35,712,331	12,499	249,728	802,680	2,131,633
Communications 2	19,677,858	106,260	3,788,407	3,333,232	2,050,334
Financial 6	34,481,554	12,069	251,313	780,400	2,021,112
Consumer Cyclical 1	24,836,547	27,320	1,189,133	1,824,415	1,746,768
Communications 3	22,253,121	120,167	4,211,880	3,259,372	1,659,779
Financial 16	22,187,790	7,766	173,365	498,743	1,347,724
Consumer Noncyclical 4	4,052,044	426,072	1,140,309	1,422,554	1,220,589
Utilities 2	7,517,645	40,595	745,126	1,050,698	1,122,553
Consumer Cyclical 3	14,316,050	15,748	530,368	882,080	912,193
Utilities 5	10,844,955	11,929	313,958	572,094	806,999
Financial 5	4,413,705	4,855	131,507	315,264	702,861
Communications 1	1,815,524	190,902	635,282	827,495	670,274
Communications 5	6,359,829	34,343	404,031	573,618	576,508
Consumer Cyclical 2	3,902,859	21,075	275,662	438,207	511,331
Financial 2	3,201,890	3,522	96,805	227,787	507,995
Diversified 1	2,308,726	12,467	222,064	385,699	486,700
Communications 6	8,382,573	9,221	220,689	375,375	443,544
Utilities 4	9,382,458	10,321	276,950	418,347	351,705
Energy 2	3,852,691	20,805	235,146	351,716	351,647
Utilities 1	7,927,339	8,720	228,978	351,285	300,680
Consumer Noncyclical 7	6,418,222	7,060	116,676	190,586	266,366
Industrial 2	2,231,811	12,052	132,568	196,904	253,552
Utilities 3	8,186,341	9,005	159,412	205,977	217,034
Industrial 1	2,631,458	2,895	60,452	117,380	214,269
Consumer Noncyclical 2	3,782,745	4,161	76,014	132,573	161,790
Financial 4	2,572,343	2,830	51,102	87,485	150,007
Energy 4	4,788,551	1,676	41,403	76,665	134,434
Basic Materials 3	3,194,670	3,514	50,040	77,366	102,039
Financial 13	1,565,941	548	11,216	28,112	80,680
Energy 1	4,892,152	1,712	33,989	44,151	63,574
Consumer Noncyclical 1	1,491,850	1,641	19,339	35,760	56,883
Industrial 3	3,875,923	1,357	18,271	31,680	51,564
Basic Materials 2	1,143,407	400	9,816	20,903	47,704
Consumer Noncyclical 3	1,770,003	1,947	23,752	38,423	44,575
Basic Materials 1	745,894	261	4,935	9,723	19,306
Consumer Noncyclical 5	830,721	291	4,493	8,450	13,563
Communications 4	177,063	195	2,137	3,546	4,633
Consumer Noncyclical 6	130,600	46	482	895	1,476
Energy 3	3,531,124	0	0	0	0
Total	1,000,000,001	2,188,678	20,796,782	33,984,931	141,982,236