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Asset Correlations: Shifting Tides.

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Abstract

The Basel II Accord outlines a general framework for determining regulatory capital requirements for credit risk portfolios. Different obligors usually operate in dependent socio-economic environments and these structural correlations are the main reason why regulatory capital is needed. Therefore, it is not surprising that an important component of the regulatory regime for capital is the asset correlation between obligors. Basel II has set a range for corporate asset correlations from 8 to 24%, the exact value depending on several individual firm characteristics.

We use monthly asset value data to calculate asset correlations and compare these with Basel II as well as results from other papers. Our results are in line with literature but a clear difference is found between the majority of these results and the results from Basel II and some major software providers. We discuss these differences and offer some explanations as an

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attempt to reconcile the differences. The impact of horizon is considered as well.

1 Introduction

There is ongoing pressure from regulators, investors and rating agencies on financial institutions to build appropriate models that allow measurement of the different risks faced. For the financial institutions the implementation of these models is often a first step towards developing what is now often called an enterprise wide risk framework, which can support and reward management on an enterprise-wide basis by integrating all risk components. As far as credit risk is concerned it follows from Sklar's theorem that one is able to assess the risk of the entire loan portfolio provided that the dependency structure or copula is known (as well as the marginal distributions of the individual credit losses). However, whilst the assessment of the marginal risks is now relatively well under control, fitting a copula in a credit context is a difficult exercise due to the relative scarcity of observed defaults. Therefore, most institutions limit themselves to using default correlations when assessing the dependencies and use a variance-covariance framework to asses the credit portfolio risk. It must be noted that in the literature on default correlations it is now standard to use the concept of asset correlation to discuss and to compare the different findings. Indeed, an assumption on joint asset movements (typically using a Gaussian copula) allows one to back out the implied asset correlations from the default correlations; we refer to Crouhy et al (2000) for more details.

Asset correlations are also an important component of the Basel II Accord for regulatory capital requirements of credit risk portfolios. In the Basel Committee on Banking Supervision (BCBS) document of January 2001 (BCBS (2001a), asset correlations were assumed to take a value of 20% for all obligors. The modification later that year (BCBS (2001b)) assumed that asset correlation declined with PD: for the lowest PD the asset correlation was 20% and for the highest PD the asset correlation was 10%. Then finally in the Consultative Document of 2006 asset correlations for sovereigns, banks and corporates were principally assumed to be between 12% and 24%, once again depending on the probability of default. We note that for small and medium sized corporates an extra downward firm-size adjustment up to 4% is made and this brings the effective range of corporate asset correlations between 8% and 24%.

There was limited research at the time of the first Basel II document and as such, it seems that these estimates were at least partly based on industry perception and practice and this is admitted in the document (BCBS (2001a), page 35).

In the subsequent years there have been numerous papers using different approaches and different datasets, the majority of which report dramatically different results. These can be largely separated into two categories. The first uses observed default data to calculate single and pairwise default frequencies from which default correlations are derived. Papers in this category include Gordy (2000), Frey and McNeil (2003), Dietsch and Petey (2004), Jobst and de Servigny (2005) and de Servigny and Renault (2002).

The second starts with the calculation of correlations between firm's asset returns. Next, assuming (for example) that asset returns are bivariate normally distributed and a Merton model of the firm, one can derive default correlations; see again Crouhy et al (2000). Papers in this category include Duellmann *et al.* (2006), Lopez (2002), Pitts (2004) and the software providers Moody's KMV (MKMV) and Fitch Vector 2.0.

A related issue is the choice of the distribution for joint asset value movements. Non-Gaussian distributions for the asset movements have been considered in Frey *et al.* (2001) and since the choice of copula is not the topic of this paper, we will use the Gaussian copula in all cases.

Ultimately, default data is the best source of default correlations as no intermediate process is assumed. However frequently default data is either sparse or unavailable. In this study we use monthly asset value data to derive asset correlations and we compare our results with other results in literature.

Section 2 describes the data used and the methodology applied. Section 3 presents our results and the results of other papers. Section 4 discusses the effect of horizon. Section 5 discusses the various results and interprets the findings. Section 6 concludes and discusses areas for further research.

2 Data and Methodology

The source of the asset value data used is MKMV Credit Monitor. Several papers have used the same data source, such as Pitts (2004) and Duellmann *et al.* (2006). These authors reported that the raw asset data should be corrected for the impact of corporate actions and potential data errors. Therefore, the data was cleaned to remove outliers, asset values were adjusted for debt issues and buybacks and those months where asset value data were not available were removed. The eventual sample of companies was comprised of 20,144 companies with between 40 and 107 months of asset returns each from March 1997 to March 2006. Correlations between companies were only calculated when there were at least 40 months of data for each pair of companies. To the best of our knowledge, this is the largest sample that has ever been used for an asset correlation study.

The companies were aggregated into 336 clusters based on asset size, activity sector, probability of default and world region. Previous studies have shown some evidence that these are factors that may differentiate asset correlation and we note that the probability of default and to some extent asset size do affect the Basel II values for asset correlations; see amongst others Lopez (2002), Duellmann and Scheule(2003), Dietsch and Petey (2004) and BCBS (2006). Then the average of all the asset correlations between companies in each pair of clusters was used as the representative asset correlation between two clusters.

3 Results from Literature

Results from literature are separated into two categories: those using default data and those using asset data. Using default data, one can estimate default correlations directly and then back out the asset correlation with an assumption regarding joint asset value movements. Using asset value data, one can directly estimate asset correlations and then move to default correlations.

3.1 Asset Correlations from Default Data

In Table 1 we report the asset correlations from a variety of studies which have used default data. Where the studies report default correlations, we report the equivalent asset correlations using a Gaussian copula for joint asset movements.

Hamerle it et al. (2003a) used the same data as in Boegelein *et al.* (2002) which comprised default data from Canada, France, Germany, the UK, Italy, Japan, South Korea, Singapore, Sweden and the US.

In addition Vassiliev (2006) uses default data from UBS to calculate asset correlations which "are in the range reported in external studies (e.g., Dietsch and Petey, 2004)".

The results, which use data sets from North America, Canada, Switzerland, France, Germany, Finland, the UK, Italy, Japan, South Korea and

Source Study	Data Source	Results
Gordy (2002)	S&P	1.5% - 12.5%
Cespedes (2000)	Moody's	10%
Hamerle *et al.* (2003a)		max of 2.3%
Hamerle *et al.* (2003b)	S&P 1982-99	0.4% - 6.04%
Frey *et al.* (2001)	UBS	2.6%, 3.8%, 9.21%
Frey & McNeil (2003)	S&P 1981 - 2000	3.4% - 6.4%
Dietsch & Petey (2004)	Coface 1994-2001	0.12% - 10.72%
	AK 1997-2001	
Jobst & de Servigny (2004)	S&P 1981-2003	intra 14.6%, inter 4.7%
Duellmann & Scheule (2003)	DB 1987 - 2000	0.5% - 6.4%
Jakubik (2006)	BF 1988 - 2003	5.7%

Table 1: *Asset correlations from default data*
S&P: Standard and Poor's
DB: Deutsche Bundesbank
AK: Allgemeine Kredit
BF: Bank of Finland

Singapore are largely consistent, yielding correlation estimates in the range of approximately 1% - 10%.

3.2 Asset Correlations from Asset Value Data

There have been several studies which have used asset value data from various sources and the results are presented in Table 2.

Source Study	Data Source	Results
Duellmann *et al.* (2006)	KMV	10.1%
KMV (2001)	Undisclosed	9.46%-19.98%
Fitch (2005)	Equity	intra 24.09%, inter 20.92%
Lopez (2002)	KMV Software	11.25%

Table 2: *Asset correlations from asset value data*

Duellmann *et al.* (2006) calculate 2 year asset correlations using rolling 24-month time windows. However since their study only used 8 years of asset return data (which means 4 distinct 24-month periods), this may be insufficient data for correlation estimates. A similar data source to this paper is used, however they restrict themselves to the universe of European companies. The Fitch Vector model uses equity value data and reports 5 year correlations. MKMV does not release details regarding how they build their asset correlation model or the data used and it is designed to be used in conjunction with their Portfolio Manager software. Lopez (2002) also does not disclose details of the asset data used, only that MKMV Portfolio Manager was used for the analysis.

In addition, De Servigny & Renault (2002) utilize equity correlations to obtain an average correlation of 6%.

3.3 Our results

With our 336 asset clusters as described above, the average intra-cluster asset correlation was 11.1% and the average inter-cluster asset correlation was 6.3%. A graph of the intra-asset correlation grouped by asset size band and client rating is provided in Figure 1. As expected, the correlations are increasing in asset size and also as we expect c orrelations are (almost always) decreasing in probability of default. The four default probability groups, in increasing order, are: blue, green, yellow and red. Figure 2 shows the same information for the average inter-cluster asset correlations.

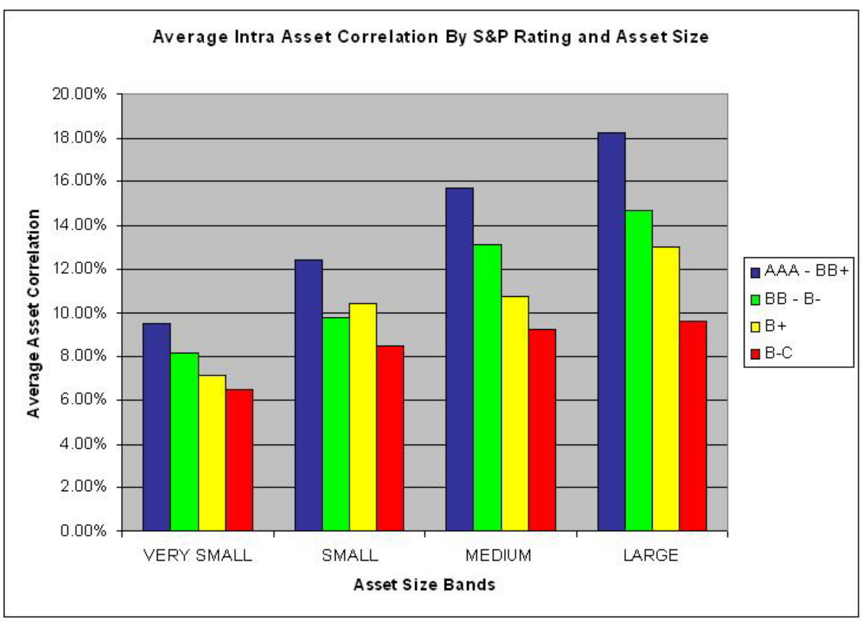

Figure 1: *Average Intra-Cluster Asset Correlations by Rating Colour and Asset Size Bands*

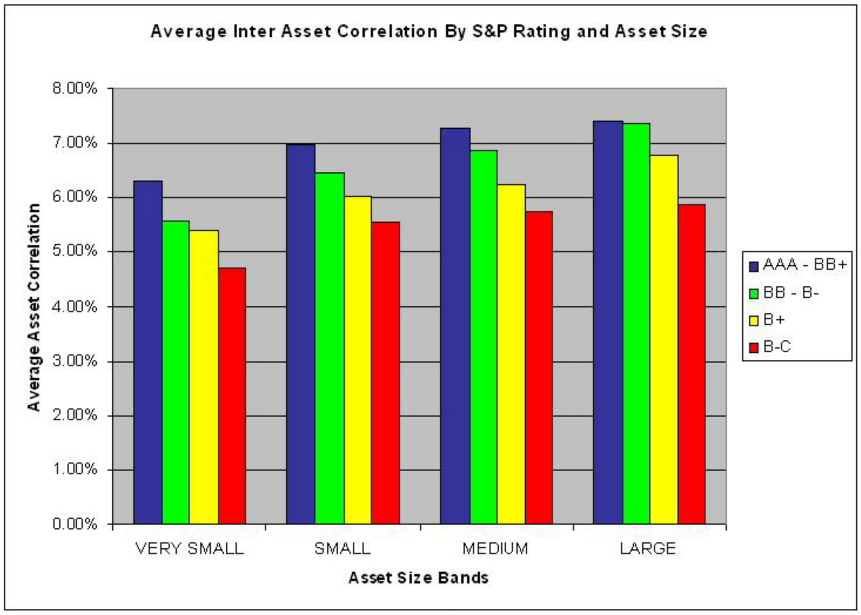

Figure 2: *Average Inter-Cluster Asset Correlations by Rating Colour and Asset Size Bands*

Figures 1 and 2 show that the results using default data and asset value data are broadly similar, both indicating asset correlations typically in the range of 0%-10%. We notice that the studies from MKMV and Fitch show larger results.

The results we obtain from using the monthly asset return data are consistent with the majority of the values from literature.

4 Effect of Horizon

The effect of horizon has been studied for equity correlations (e.g. Koyluoglu *et al.* (2003)) but less so for asset correlations. In large part this is due to data limitations. Default data is generally only available to use at a 1- or 5-year level. In Jobst and De Servigny (2005) whilst default correlations were observed to increase with increasing horizon (using 1, 3 and 5 year time periods) the probability of defaults also increased keeping the asset correlation broadly constant. However in de Servigny and Renault (2002) some evidence for increasing asset correlations was found. Moving from an one year time period to a longer time period shows inconclusive evidence.

Using asset returns requires the use of shorter time periods due to less data being available. Given that it is generally advised to use at least 50 values to estimate a correlation, using annual returns is impossible with the number of years of asset return data available. The commonly used options are to calculate either weekly or monthly asset returns and then use these as annual asset correlations. Some studies such as Duellmann *et al.* (2006) use rolling-window time periods to calculate correlations, that is, where overlapping time periods are used however this does not increase the effective dimension of the calculations. Using rolling 24-month time periods with 8 years of data may lead to more observations, but consecutive observations are now built on almost identical data, differing only by one month at the beginning and one month at the end. One still only has 4 distinct 24-month periods.

Based on the evidence in this paper and the other papers which use monthly asset returns, using monthly asset correlations as a proxy for asset correlations gives results that are in line with default correlations observed from default data. The impact of horizon on asset correlations is certainly a topic that requires further research.

5 Are Asset Correlations Uniquely Defined?

The results from literature are very closely aligned, with the exception of Fitch Vector 2.0, which uses equity correlations as a substitute for asset correlations on a five-year horizon and MKMV. As such, there appears to be a growing consensus in literature on the range for asset correlations. Despite the fact that the current Basel II correlations are lower than in the first release, they are still larger than the results reported in literature. Many previous papers have reported that the Basel II correlations seem to be rather high; see for instance Duellmann and Scheule (2003) and Dietsch and Petey (2004).

This immediately raises the questions of why this might be the case. The most obvious explanation might be that industry perception was for higher asset correlations before substantial research had been done. Some evidence for this is found in the CreditMetrics (1997) technical document (page 93):

Based on conversations with Patrick H. McAllister in 1994 when he was an Economist at the Board of Governors of the Federal Reserve System. Part of his research inferred average asset correlations of corporate & industrial loan portfolios within mid-sized US banks to be in the range 20%-to-25%.

Our own research suggests that it is easier to construct higher correlation portfolios versus lower correlation portfolios, hence a 20%-to-35% range.

A second and more difficult issue that needs to be considered here is the issue of credit loss dependencies. In economic capital calculations and CDO pricing, asset correlations are not used directly. Rather it is the credit loss dependency structure that is ultimately required. Hence, many more modelling assumptions are required to go from default correlations to the entire credit loss distribution.

First of all, since default correlations are related to individual and pairwise but not multiple default probabilities, they do not provide a full picture of the dependency structure or the copula. In fact, for a given set of default correlations or even loss correlations, several copulas that preserve the loss correlations will exist and each of these copulas will give rise to a particular probability distribution function for the total credit portfolio loss S. We refer to Frey *et al.* (2001) or Embrechts *et al.* (1999) for various illustrations within this respect.

Other examples of implicit or explicit model assumptions that affect the computation of loss correlations include whether loss given defaults (LGDs) are deterministic or stochastic, dependence between LGDs and dependence between PDs and LGDs. This means that asset correlation is merely one possible source of loss correlation between obligors; see for instance Bürgisser *et al.* (2001) and references therein for discussions of a portfolio model that incorporates dependent LGDs.

We will further illustrate this through the use of an example. Consider an infinitely large homogeneous portfolio, that is, a portfolio with an infinite number of identical obligors where the goal is to estimate the portfolio loss standard deviation, also called the unexpected loss, as accurately as possible. LGDs here are expressed as a fraction of exposure at default. The first - and most sophisticated - model uses stochastic dependent LGDs and best-estimate asset correlations corresponding to the numbers presented in section 3.3. The second model assumes stochastic independent LGDs and the third assumes deterministic LGDs. Using the second and third models will result in lower unexpected losses. To achieve the best estimate of the unexpected loss (defined as the result from the first model) will require the use of higher asset correlations. This naturally leads to the question: how much higher?

From Dhaene et al. (2005) we have the following equation for the loss correlation between different obligors.

$$\rho^L = \frac{A+B}{Var(L)} \tag{1}$$

where

$$A = \left[\rho^D \sigma^2(I) + q^2\right] \rho^{LGD} \sigma^2(LGD)$$
$$B = \rho^D \sigma^2(I) E^2(LGD) \tag{2}$$

Here ρ^D is the default correlation between different obligors (calculated with a Gaussian copula using an asset correlation and the default probabilities), $\sigma(I)$ is the standard deviation of the default indicator for a given obligor, q is the default probability for obligor i, ρ^{LGD} is the correlation between the LGDs for two distinct obligors, $E(LGD)$ is the expected value of the LGD for an obligor and $\sigma^2(LGD)$ is the variance of the random LGD. Furthermore, the variance of an individual loss is given by:

$$Var(L) = E^2(LGD)q(1-q) + q\sigma^2(LGD).$$

With an infinitely large portfolio as described above, it can be shown that the Portfolio Unexpected Loss (UL) expressed as a fraction of the total amount at risk equals:

$$UL_p = \sqrt{\rho^L var(L)}. \tag{3}$$

We can calculate UL_p with the first model and then calculate what the required asset correlation is for models two and three to reach the same UL_p. Note that from (1) and (2) for an infinitely large portfolio it makes no difference whether LGDs are stochastic and independent or deterministic so the required asset correlations for models two and three will be the same.

We calculated the "corrected" asset correlations for various values of PD, VarLGD and ρ^{LGD}. The LGD was fixed at 50%. 8 results are presented in Table 3 - for the full table, please e-mail the first author. For example the first row considers a portfolio of obligors with a PD of 0.21%, ρ^{LGD} of 25% and VarLGD of 0.25. The best estimate of asset correlation is 13.96% but if a zero ρ^{LGD} is assumed then an asset correlation of 16.84% needs to be used to keep the same value of UL_p.

Using all the scenarios, the relative change from the true asset correlation to the corrected asset correlation was 45%. As expected, the difference is highest for portfolios with high PD and high ρ^{LGD}.

This can explain the possible need to use higher asset correlations. Whilst one might claim to be measuring asset correlations, in fact this is used as an

PD	ρ^{LGD}	**VarLGD**	**True Asset Correlation**	**Corrected Asset Correlation**
0.21%	25%	0.25	13.96%	16.84%
0.21%	100%	0.25	13.96%	23.32%
0.21%	25%	0.042	13.96%	14.48%
0.21%	100%	0.042	13.96%	15.94%
9.75%	25%	0.25	8.45%	16.88%
9.75%	100%	0.25	8.45%	37.53%
9.75%	25%	0.042	8.45%	9.93%
9.75%	100%	0.042	8.45%	14.18%

Table 3: *With an Infinitely Large Portfolio of Clients with a given PD, ρ^{LGD}, VarLGD and Asset Correlation, What is The Corrected Asset Correlation We Need to Use if We Assume $\rho^{LGD} = 0$ to Keep The Same Portfolio Unexpected Loss*

input to calculate the overall credit loss distribution. That is, whilst best estimates of asset correlations might typically be in the region of 0%-10%, to obtain the best estimates of credit loss distributions might require using higher asset correlations (to account for other sources of dependencies).

For example, in the KMV Portfolio Manager software, LGDs seem to be always assumed independent which might require the use of higher asset correlations to prevent potential underestimation of Portfolio Unexpected Loss.

6 Final Remarks

Numerous papers in recent years have reported default correlations which indicate that asset correlations are much lower than suggested by Basel II. This paper reported these findings and also compared them with the results of using monthly asset return data from MKMV.

Whilst there have been many papers reporting asset and default correlations using a variety of datasets, there are still a number of issues which require further research. The most significant could be the issue of horizon, that is, does asset correlation vary significantly over the time horizon used? The evidence thus far is inconclusive.

A more difficult issue is the choice of clustering, in other words, what are the factors that differentiate asset and default correlation and how can they best be grouped? A related issue is the effect of various factors on asset correlation. Basel II recommends increasing correlations with decreasing default probabilities, however there is evidence that world region and sectors are important differentiators of asset correlation.

The role of asset correlations in economic capital calculation was considered, in that asset correlations are merely one source of dependence and if other dependencies are not explicitly modelled (such as dependence between LGDs) then the unexpected loss will be underestimated unless the asset correlations are increased.

Estimation of correlations is a difficult exercise however it is ultimately crucial for economic capital calculation.

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