

An Empirical Analysis of Equity Default Swaps (I): Univariate Insights¹

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Abstract

The aim of this paper is to describe a new methodology to assess the risk of any Equity Default Swap (EDS). We show that as credit ratings can measure counter-party risk, it is technically possible to provide a quantitatively derived “through the cycle” risk estimate for EDSs. Whereas in the case of CDSs, the assessment is relevant at an issuer level, for EDSs it makes sense at an issue level. The reason for such a difference is that unlike for pure credit risk, the risk on EDSs directly depends on equity market conditions at origination and is therefore not fully counter-party specific. The outcome of this paper is that though this new methodology is purely quantitative, its level of performance is surprisingly high with superior results compared to previously developed techniques.

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Introduction

The objective of this paper is to offer a methodology to assess the risk of any Equity Default Swap (EDS) over its life conditional on the information available at a specific point in time (e.g. its issuance). This piece of research is followed by a second one focussing on EDS correlation, see Jobst and de Servigny (2005).

Equity-credit hybrid derivatives – called Equity Default Swaps – have recently been introduced by a number of banks in CDOs and in EDS / CDS carry trades. New in the credit environment, EDSs are known in equity markets as deep “out of the money” long dated digital American puts with regular instalments. These instruments offer significantly higher spreads than comparable vanilla Credit Default Swaps (CDS). While a payment is triggered on a CDS when a credit defaults, a payment is triggered on an EDS when the underlying equity price falls below a predetermined level⁴. This price decline is often referred to as an equity event, analogous to a credit event within a CDS contract. While any combination of trigger level and recovery rate could be considered, EDS contracts are typically structured in the market with a trigger level set at 30% of the value of the share at inception and a fixed recovery rate of 50%.

From a pricing perspective, EDS evaluation techniques are mainly derived from stochastic equity models using local volatility features or from extensions of credit valuation models (e.g. Medova and Smith (2004) and Albanese and Chen (2004)). From a risk perspective, several techniques have already been proposed in order to assess the quality of EDSs, see for example, Jobst and Gilkes (2004). These are usually based on deriving the behaviour of the instrument using Garch techniques for volatility estimation. Although interesting, these techniques are rarely employed for long-term assessment of risk. This means that for an EDS with a typical horizon of 5-years, (qualitative) adjustments may be required. In addition, some of the available information at the time the EDS is originated might not be factored in. As an alternative to these Garch modelling techniques, we explore here some simple pattern recognition/scoring techniques in order to discriminate the risk profiles of EDSs. These techniques are usually used in the traditional credit risk universe. We discuss the validity of such credit techniques to assess the risk of these types of equity-based instruments. Based on our findings, we consider that this new approach is more robust and comprehensive than any of the previous ones for two reasons. Firstly, it tries to extract in a systematic way, the predictive power embedded in the full set of available information. Secondly, it encompasses the period running from inception to the maturity of the EDS instrument.

In what follows, we start by explaining the approach we retain to estimate probabilities of default as well as probabilities of an Equity Event. We then focus on some key explanatory factors that are expected to contain relatively high predictive power. We move ahead to more systematic scoring techniques, and discuss how close an EDS is to a pure credit instrument. We then extract an equity event risk assessment meant to be somehow comparable to a credit rating. We ultimately work on a database of EDS prices provided by a bank in order to evaluate the consistency between the current prices and the corresponding level of EDS risk measured using the methodology developed in this paper.

⁴ EDSs are for this reason part of the family of the so called “one-touch” options.

1 Estimating Probabilities of Default

A common approach for rated companies is to derive historic average default or rating transition probabilities by observing the performance of groups of companies – frequently called cohorts – with identical credit ratings⁵. These estimates are particularly suitable in the context of long-term “through-the-cycle” risk management, which attempts to dampen fluctuations due to business cycle and other economic effects.

We start by considering all companies at a specific point in time t (e.g. December 31, 2000). We denote the total number of companies in the k th cohort at time t by $N_k(t)$, and the total number of observed defaults in period T (i.e. between time $t+T-1$ and time $t+T$) by $D_k(t, T)$. We then obtain an estimate for the (marginal) probability of default in year T (as seen from time t):

$$P_k(t, T) = \frac{D_k(t, T)}{N_k(t)}.^6$$

Repeating this analysis for cohorts created at M different points in time t allows us to obtain an estimate for the unconditional probability of default in period T ,

$$\bar{P}_k(T) = \sum_{t=1}^M w_k(t) P_k(t).$$

These unconditional probabilities are simply weighted averages of the estimates obtained for cohorts considered in different periods. Typically, $w_k(t) = \frac{1}{M}$ (each period is equally weighted),

or $w_k(t) = \frac{N_k(t)}{\sum_{m=1}^M N_k(m)}$ (weighted according to the number of observations in different periods).

One way to obtain unconditional cumulative default probabilities is to replace the (marginal) number of defaults in period T , $D_k(t, T)$, with the cumulative number of defaults up to period T ,

$D'_k(t, T) = \sum_{m=1}^T D_k(t, m)$. Unfortunately, this estimator “loses” more and more information as T

increases.⁷ An alternative method, which incorporates all available information, is to calculate the unconditional (weighted average) cumulative probabilities $\bar{P}_k^{cum}(T)$ from the unconditional marginal probabilities $\bar{P}_k(T)$. Such an estimate is given by:

$$(1) \quad \bar{P}_k^{cum}(T) = \bar{P}_k^{cum}(T-1) + (1 - \bar{P}_k^{cum}(T-1))\bar{P}_k(T).$$

$$\text{and } \bar{P}_k^{cum}(1) = \bar{P}_k(1)$$

Table 1 shows the cumulative default probabilities for time horizons of up to 10 years, estimated from the Standard & Poor’s CreditPro[®] database. The database contains the ratings history of 9,740 companies from December 31, 1981 to December 31, 2003, and includes 1,386 defaults. Figure 1 plots the results for rating classes “AAA” to “B”.

⁵ The cohort analysis outlined here is based on the global ratings performance data contained in Standard and Poor’s CreditPro[®] Version 6.60 (<http://creditpro.standardandpoors.com/>).

⁶ Some companies will have their rating withdrawn during the course of the year. It is common to treat these transitions to NR (not rated) as non-informative with respect to the credit quality. Hence, companies that have their rating withdrawn during the period of interest are ignored in the subsequent analysis.

⁷ For $T=5$ years, for example, the last cohort that can be considered is December 1998 as the last entry in the database corresponds to December 2003.

Rating	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10
AAA	0.00	0.00	0.03	0.06	0.10	0.17	0.25	0.38	0.43	0.48
AA	0.01	0.04	0.10	0.19	0.31	0.43	0.58	0.71	0.82	0.94
A	0.05	0.15	0.28	0.45	0.65	0.87	1.11	1.34	1.62	1.95
BBB	0.37	1.01	1.67	2.53	3.41	4.24	4.94	5.61	6.22	6.93
BB	1.36	4.02	7.12	9.92	12.38	14.75	16.65	18.24	19.84	21.00
B	6.08	13.31	19.20	23.66	26.82	29.29	31.33	33.01	34.21	35.41
CCC/C	30.85	39.76	45.47	49.53	53.00	54.30	55.50	56.11	57.59	58.44

Table 1: Cumulative default probabilities (in %) 1981 – 2003. Source: Standard & Poor's

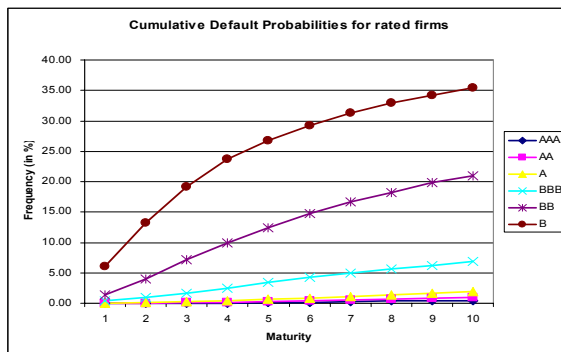


Figure 1: Cumulative default probabilities (AAA to B) 1981 – 2003. Source: Standard & Poor's

The estimates for “AAA” companies over short horizons reveal one of the main drawbacks of cohort analysis. The approach is not capable of deriving non-zero probabilities if no defaults have been observed in the past. However, it is clear that there is a chance (however small) that even a highly rated company will default within the course of one or two years. Duration (or hazard) modelling techniques are frequently employed to overcome the shortcomings of cohort analysis, see for example Lando and Skodeberg (2002), Jafry and Schuermann (2003) and Jobst and Gilkes (2003), and Couderc and Renault (2004).

2 Estimating equity event probabilities

We apply now the cohort approach to estimate the unconditional long-term average probability of an equity price decline to a level of $k\%$ of the initial price. This probability is referred to as the *equity event probability* (EEP), which obviously depends on the value of the barrier level k .

Looking at different barriers is important, as a standard EDS with a 30% barrier today is likely to correspond to an EDS with, say, a 10% or a 40% barrier in six months, following changes in the underlying stock value during that period.

The analysis is performed using the Standard & Poor's Compustat[®] (North America) database, which contains data on approximately 56,500 corporations trading in the US or Canada between 1962 and 2003. Of course, not all of these companies are listed, and we therefore focus on companies that have listed equity with prices quoted regularly on a major exchange. If multiple equity issues are available, we focus on the primary issue and also exclude “non-vanilla” equities such as American Depository Receipts (ADRs), over-the-counter (OTC) traded equity, mutual or investment trust funds, or exchange traded funds. In addition, we impose a constraint to exclude

companies with a market value below 50 million.⁸ We also exclude companies for which the equity price time series is incomplete, i.e. we require all prices between the first observation and the last observation⁹. In total, this results in approximately 12,000 equity time series with approximately 120,000 yearly observations¹⁰.

The cohort analysis is then performed as follows. For each company in a given cohort at a specific point in time t (e.g. Dec 1980), we register the price P_t at that point in time and count the number of companies that would have triggered an equity event in period T . This is done by comparing the running minimum monthly price¹¹ between time $t+T-1$, P_{t+T-1}^- , and time T , P_{t+T}^- , to the EDS barrier $B_t = k \cdot P_t$. In the following, we register the prices on December 31 of every year and follow the time-series for up to 10 years. Note that an annual observation frequency is chosen as a compromise between frequency and independence of observations. Instead of December, any other month could have been chosen. Initial investigation reveals noticeable differences. For example, EDS event rates are slightly higher when selected annually in May or June. Within this framework, several different types of cohorts can also be selected.

In what follows we try to measure the impact of the most intuitive factors on the level of EEPs. We start with volatility and subsequently consider ratings as drivers of Equity Event risk.

3. Identifying the impact of some key factors on Equity Event Probabilities

3.1 Historic volatility grouping

In the first stage of the analysis, we group all companies with similar historic volatility into different time cohorts. In particular, we split the companies into quintiles¹². Quintile 1 contains 20% of companies with the highest historic volatility, calculated using 5 years of monthly data.¹³ Quintiles 2, 3, 4, and 5 (which contains 20% of the companies with the lowest volatility) are created accordingly. Figure 2 (left panel) shows the unconditional cumulative equity event probabilities for a barrier of 30%.

⁸ The outcome of the analysis does not change significantly if this constraint is relaxed.

⁹ We recognize that a slight survival bias might be introduced here. From section 4 of this paper onwards, we do not exclude defaulted companies anymore

¹⁰ We retain here one observation per year, on 31 December.

¹¹ The minimum is retrieved from time-continuous trading information recorded in the monthly low price in Compustat.

¹² From one time cohort to another, a company can move quintile depending on the observed level of volatility during the period considered.

¹³ A monthly data frequency was mainly chosen because of the larger coverage of monthly prices in the database. Although monthly data may “smooth” some uncertainty in historical equity prices, we believe that this frequency is adequate for long-term risk measurement.

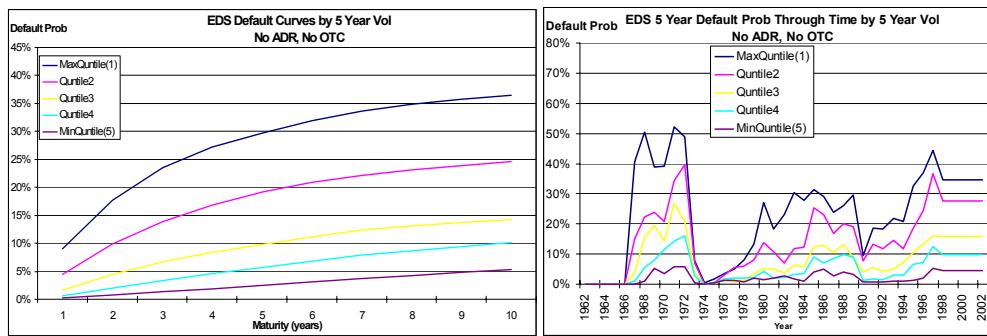


Figure 2: Cumulative EEPs (left panel) and historic behaviour of 5-year EEPs (right panel).

The figure reveals a very strong link between historic volatility and the probability of an equity event, namely the price of a company falling to 30% of its current value (i.e. a total fall of 70%). The right panel of Figure 2 shows the 5-year equity event probability through time, that is, the probability of a 70% drop within 5 years of the cohort selection date (December each year). Note that the last cohort for which five years of data is available is December 1998, as the last price contained in the database corresponds to December 2003. This figure reveals that for every year considered in our sample companies with higher historical volatility are more likely to suffer a severe price drop than less volatile companies. Note that the differences in volatilities are substantial, with the average annualized volatility of companies in quintiles 5 to 2 equal to 24.2%, 31.7%, 40.9% and 53.9% respectively, and the volatility in quintile 1 exceeding 100%.

3.2 Equity event probabilities for different barriers and maturities

The previous analysis shows that equities with higher volatility are more likely to suffer a 70% price drop. In this section, we investigate this relationship for different price barriers and maturities. The left panel of Figure 3 shows historic average probabilities of equity prices falling below 10%, 30%, ..., 90% barriers over a time horizon of 5 years. Cohorts are analysed in relation with historic volatility. This time, volatility is defined as the exponentially weighted moving average (EWMA) volatility¹⁴ and grouped into nine cohorts.

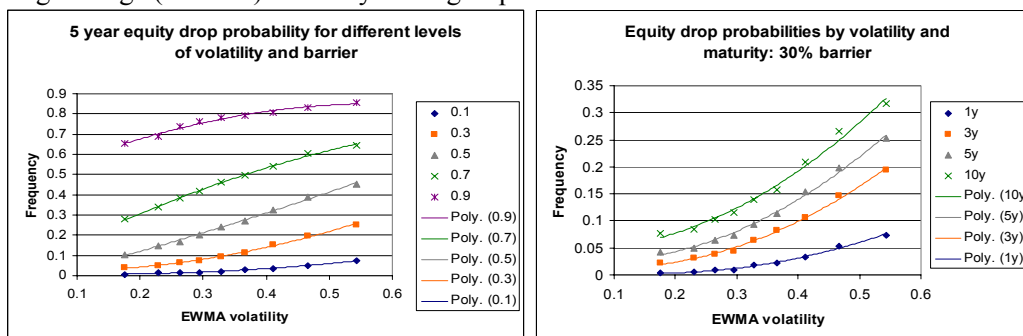


Figure 3: Left Panel: Equity event probabilities by volatility for different barriers. Right panel: Equity event probabilities by volatility for different horizons.

¹⁴ The exponential decay factor was chosen as equal to 0.985. The choice of EWMA volatility shows that the performance is not dependent on the particular definition of 5-year volatility. Similar results are derived for other volatility measures, such as the 1 or 3 year historical volatility.

The figure shows clearly that EEPs increase with increasing levels of volatility for all barriers levels. This is encouraging, given the relatively small differences in volatilities within the 9 cohorts considered. Depending on the barrier level, this increase is concave (high barrier), almost linear (e.g. 50% barrier) or convex (low barriers). Figure 3 (right panel) confirms the relationship between volatility and 5-year equity event probability (30% barrier) for different maturities. It is also apparent that the largest jump in probability occurs when moving from a one-year horizon to a three-year horizon.

3.3 EDS for rated companies

Throughout this section, we apply the cohort approach to a subset of companies with rated debt outstanding. Altogether, we identified approximately 4,500 companies that were also contained in the CreditPro ratings database. Approximately 2,300 of these also have continuous price data (monthly closing and minimum) in Compustat. Figure 4 displays the cumulative EEPs (30% barrier) for companies with different ratings¹⁵. It is clear that the equity price of highly rated companies is less likely to suffer a severe decline than that of lower rated companies, which can be partly explained by the volatility differences between companies with high and low ratings.

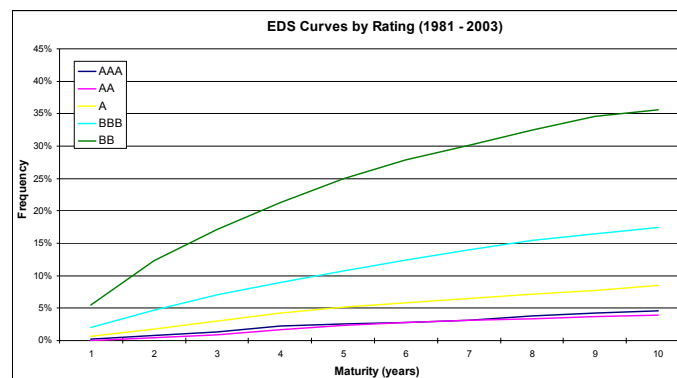


Figure 4: Equity event probabilities for equities of rated firms.

3.4 Credit Ratings and Volatility

In this part of the analysis, we differentiate between companies with high, medium and low equity volatility within a given rating class.¹⁶ Figure 5 reveals that in the case of both investment grade and non-investment grade companies, higher volatility results in a greater chance of hitting the 30% barrier for all maturities. The effect of volatility seems to be more pronounced for investment grade companies, where the equity prices of the most volatile companies (with an average EWMA volatility of 38%) are approximately 3 times more likely to fall by 70% within 5 years than the least volatile companies (with an average EWMA volatility of 21%). From this analysis we can conclude that volatility is also very important for equities of rated companies in the context of EDS risk analysis.

¹⁵ Given the smaller sample of rated companies, the total number of companies in each cohort varies significantly. Whereas only 10-20 “AAA” companies are considered in each annual cohort, between 150 and 350 are observed for “A” and “BBB” rated companies. For that reason, the subsequent analysis focuses mainly on “AA” (30-100 companies), “A”, “BBB”, “BB” (80 – 300 companies), and “B” (60 – 200 companies).

¹⁶ Three volatility “buckets” are chosen due to the relatively small number of companies within one rating Category. However, an analysis based on quintiles is in line with these findings.

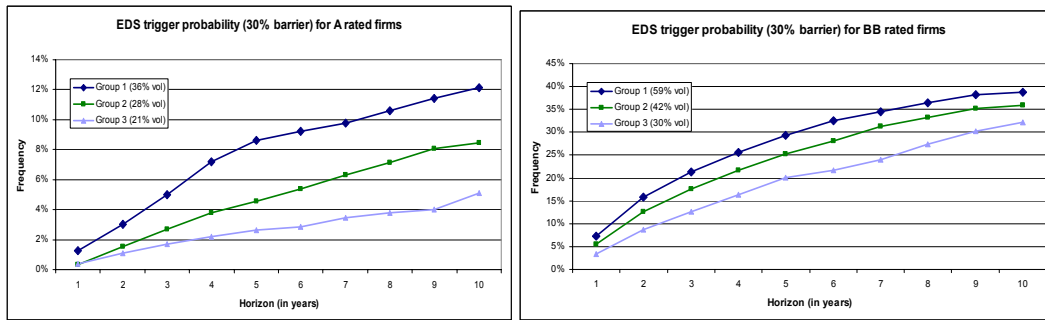


Figure 5: EDS trigger probabilities for A (left panel) and BB (right panel) rated firms by volatility.

Figure 6 plots the 5-year EEP for “AA”, “A”, “BBB”, “BB”, “B” and all companies (rated and non-rated) for different levels of historic average EWMA volatility. The figure reveals that there are substantial differences between the EEPs of highly rated firms and those of lower rated firms. Ratings therefore add valuable information in the analysis of EDS.

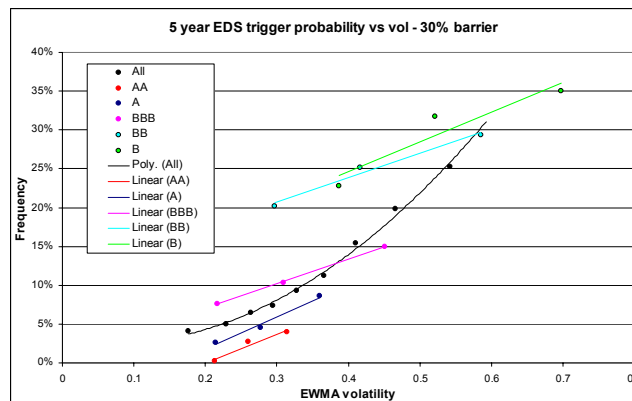


Figure 6: Equity event probability (5 year horizon) by volatility.

It is also interesting to note that within a rating class, EEPs appear to increase almost linearly with volatility confirmed by R-squared values of 94%, 98.5%, 99.9%, 98%, and 89% from linear regressions to the results for “AA”, “A”, “BBB”, “BB” and “B” ratings, respectively. Repeating this analysis for different maturity levels and barriers confirms this relationship. (See Jobst and Gilkes (2004) for further discussion)

Comparison to PDs

Table 2 compares the historic average 5-year default probabilities to 5-year EEPs (30% barrier) for “AA”, “A”, “BBB” and “BB” ratings. Each row of the table corresponds to a different equity volatility quintile (decreasing from Q1 to Q5). Whereas the default probabilities depend only on the rating¹⁷, the EEPs decrease monotonically with decreasing volatility, as shown earlier.¹⁸ We

¹⁷ While the impact of volatility on defaults could also be investigated, it is common in the credit universe to estimate long-term default probabilities based on ratings, only.

¹⁸ Some estimates were adjusted slightly to be in line with the linear relationship found earlier. Small inconsistencies may occur on a few occasions due to the smaller cohort sizes in a quintile-based study. In general, however, the quintile-based study confirms the linearity.

also calculate the ratio of EDS trigger probability to default probability, which yields ratios from 1.6 to 15.1.

	AA			A			BBB			BB		
	PD	EEP	Ratio	PD	EEP	Ratio	PD	EEP	Ratio	PD	EEP	Ratio
Q1	0.3%	4.6%	15.1	0.7%	9.0%	13.8	3.4%	16.9%	5.0	12.4%	32.1%	2.6
Q2	0.3%	3.0%	9.8	0.7%	6.5%	10.0	3.4%	13.2%	3.9	12.4%	27.4%	2.2
Q3	0.3%	2.5%	8.2	0.7%	4.9%	7.6	3.4%	10.9%	3.2	12.4%	24.9%	2.0
Q4	0.3%	1.6%	5.1	0.7%	3.8%	5.8	3.4%	8.8%	2.6	12.4%	22.6%	1.8
Q5	0.3%	0.9%	2.8	0.7%	1.8%	2.8	3.4%	6.8%	2.0	12.4%	19.8%	1.6

Table 2: A comparison of unconditional default and equity event probabilities – 5-year horizon – 30% barrier.

Note that the absolute numbers are not directly comparable across ratings as the average (or median) volatility of equities within a specific quintile (e.g. Q1) differs per rating class. Overall, however, the results of this section highlight the importance of both ratings and volatility information, in the risk analysis of EDS.

We now investigate in a more thorough way what other factors might also improve the risk analysis on EDSs.

4. Towards a more systematic approach of relevant factors: using scoring techniques

In this section, we review in a systematic way a large set of available factors that can bring predictive power in the estimation of EEPs. The set of factors considered is exhibited in Appendix 1¹⁹.

The population we work on corresponds to all US based Compustat observations for which an S&P rating and all other risk factors are available. It corresponds to 2067 firms and 17,256 yearly observations. An observation is defined as the combination of a time t and a set of information (the factors) corresponding to a given company at this time t . For each company, there are as many observations as there are times t . In this case, as we define in our database, time t as being the yearend, the number of observations related to a company corresponds to the number of years in Compustat on this company²⁰. In addition, for each company we have collected default and equity event dates.

4.1 Presentation of the methodology and of the initial findings: assessing the risk of Equity Event on EDSs with a 30% barrier

Based on the full set of factors described in Appendix 1 (including ratings), we calibrate different logit models for different time horizons. The level of barrier we initially consider, in order to define what an Equity Event²¹ is, is 30%. (See Appendix 2 - box 1 for a description of the linear logit technique)

¹⁹ We have excluded the reference to industry categories for two reasons: first, the industry impact seems to be largely included in the rating and volatility assessments already; second in order to use industry as a factor, a classification of industry risk is necessary. This classification typically depends on the barrier level considered to measure a default or an equity event. In our case where multiple barriers are considered, any classification would be subjective.

²⁰ This approach is consistent with the cohort approach defined in part 1, with the weighted average based on the real number of observations per year.

²¹ An Equity Event is a comparable of a Default: i.e. the share value breaching the barrier.

Performance results are expressed both in terms of rank ordering (Gini Coefficient – see Appendix 2 - box 2) and Calibration (GMP, see Appendix 2 - box 3)

The out-of-sample level²² of performance of this model at a 1-year horizon is:

Gini All	70.81%
GMP All	89.06%

And the level of Equity Events represents 3.48% of the total population.

The out-of-sample level of performance of this model at a 5-year horizon is:

Gini All	53.99%
GMP All	74.92%

And the level of Equity Events represents 7.9% of the total population.

We should note that the population for which ratings exist (2,067 firms in the database we consider) corresponds overall to a restrained sample of larger firms with lower risks, compared with the full Compustat database. As a consequence, Equity Event ratios on the full US Compustat database (12,400 firms) represent 4.5% at a 1-year horizon instead of 3.48% and 12.5% at a 5-year horizon instead of 7.9%. This does not impact the calibration of scoring models, but the analysis of results that we could report on the rated universe might not be fully applicable to the full listed US universe reported in Compustat.

Beyond this simple model, we also use more advanced logit techniques described in Cangemi, de Servigny, Friedman (2003). In addition to being more refined these models include in addition a regularisation feature that helps reducing over-fitting and improves accordingly the performance of the linear logit model. The models we run with this regularisation feature are:

- A linear logit model
- A quadratic logit model
- A Full logit model, i.e. a combination of linear + quadratic + Kernel features

By doing so, we reduce model risk and can better analyse the real predictive power of the data independently from the specification of the scoring function.

In table 3 below, we display the results obtained at a five-year horizon, using all the available factors described in Appendix 1.

5-year horizon	GMP		Gini	
	In-Sample	Out-of-Sample	In- Sample	Out-of-Sample
Barrier 30%				
Linear	74.964%	74.667%	61.10%	59.45%
Quadratic	75.606%	75.051%	64.23%	61.41%
Full Model	75.832%	75.262%	65.34%	62.39%

Table 3: 5-year performance results, with the full set of factors

A two-risk factor approach: Rating and Volatility

We now use the same models with two factors only: the One-year Volatility and the Rating. These factors were those considered in section 3 as the most intuitive ones.

At the one-year horizon, results are described in the table 4 below:

²²For in / out-of-sample see Appendix 2, box 2.

1-year horizon Barrier 30%	GMP		Gini	
	In-Sample	Out-of-Sample	In-Sample	Out-of-Sample
Linear Logit Model	88.421%	88.567%	68.12%	69.74%
Quadratic Logit Model	88.468%	88.640%	68.47%	70.43%
Full Model	88.559%	88.715%	68.96%	70.56%

Table 4: 1-year performance results, with two factors only

At the five-year horizon, results are described in the table below:

5-year horizon Barrier 30%	GMP		Gini	
	In-Sample	Out-of-Sample	In-Sample	Out-of-Sample
Linear	73.726%	73.583%	53.54%	52.57%
Quadratic	73.767%	73.592%	53.66%	52.58%
Full Model	73.816%	73.637%	53.99%	52.89%

Table 5: 5-year performance results, with two factors only

From the previous sets of results, we can observe that though one-year volatility and ratings have a strong predictive power, they provide lower performance levels (particularly for extended horizons) than models integrating the full set of information described in Appendix 1. (There is a significant 9.5% difference in the Gini coefficient at the 5-year horizon, comparing tables 3 and 5²³)

A six-risk factor approach

As a consequence, the retained solution is to select a minimum set of relevant factors that is necessary in order to keep close to the highest possible performance levels. A process of selection of optimal factors leads to select the following six factors²⁴:

	Factor number in Appendix 1	Expected sign²⁵
3	One Year Return	-
27	SP-High-Ratio	+
7	One Year Volatility	+
15	Rating (dummy variable, an increase in the dummy variable means a decrease in the credit quality)	+
16	Market Capitalisation	-
18	Debt Over Equity	+

Among these 6 factors, 4 are of particular interest. We find both the rating and the one-year volatility that were considered in section 3 as the most intuitive factors. We also obtain the debt-equity ratio that usually matters from the perspective of structural models²⁶. The SP High Ratio²⁷ illustrates how current equity market conditions compare with the highest historical levels.

²³ A 9.5% difference in Gini coefficients is substantial according to the common statistical standards.

²⁴ This process is comparable to the one described in the working paper by Cangemi, de Servigny, Friedman (2003). It is however more judgmental, given the fact that we have to focus simultaneously on different time horizons for the models.

²⁵ If an increase in the factor leads to an increase in the EEP, the sign is a (+). If an increase in the factor leads to a decrease in the EEP, the sign is a (-)

²⁶ E.A. Medova & R.G. Smith (2004)

In order to characterize the factors more precisely on a multivariate basis, we review the bivariate linear correlation matrix (table 6).

	OneYearReturn	SPHighRatio	OneYearVol	RatingCode	MktCap	DebtOverEquity
OneYearReturn	1.00	0.16	0.00	-0.03	0.13	-0.06
SPHighRatio	0.16	1.00	-0.14	-0.06	0.02	0.00
OneYearVol	0.00	-0.14	1.00	0.53	-0.27	0.11
RatingCode	-0.03	-0.06	0.53	1.00	-0.60	0.31
MktCap	0.13	0.02	-0.27	-0.60	1.00	-0.21
DebtOverEquity	-0.06	0.00	0.11	0.31	-0.21	1.00

Table 6: Bivariate linear correlation

Three of the factors appear as significantly correlated: the one-year volatility, the rating, and the market capitalization. The low number of factors enables however to avoid partly over-fitting in the linear logit set-up. When the full logit model is used, linear correlation becomes much less of a relevant criterion²⁸, enabling large Gini coefficient pick-ups. In addition, we can observe that there is little correlation among credit related factors (the rating, the Debt Equity ratio, the 1-year return) as well as among equity factors (1-year volatility and the SP High Ratio).

4.2 Barrier dependence of EDS scoring models

Based on this selection of factors, we run linear logit models on a wider basis, i.e. for various barriers and at different time horizons. Out-of-Sample performance results²⁹ in terms of Gini are presented in table 7a below.

Linear Model without regularisation

GINI (Barrier / Year)	10%	20%	30%	40%	50%
1 Year	80%	74%	69%	61%	54%
3 Years	69%	64%	56%	47%	41%
5 Years	62%	56%	49%	41%	35%

Table 7a: performance results for simple linear logit models trained with the 6 factors mentioned above

At a five-year horizon, performances tend to be too low according to common standards (see Box 2). We therefore rerun models for the six bottom right categories in yellow on the table using the full model with the regularisation feature mentioned above (see Table 7b).

Full logit model with regularisation (same factors) for 3 / 5 years and 30%, 40%, 50%

GINI (Barrier / Year)	10%	20%	30%	40%	50%
1 Year	80%	74%	69%	61%	54%
3 Years	69%	64%	64%	56%	52%
5 Years	62%	56%	56%	53%	49%

Table 7b: performance results, using the full logit model with regularisation in the yellow cells (6 factors).

As expected, results improve very significantly and can now be considered as acceptable from a credit perspective.

²⁷ We could have considered other equivalent ratios, using for instance the de-trended historical level. We could also have looked at the ratio on an industry basis in order to better identify some industry specific bubbles.

²⁸ The more advanced models focus on non linear patterns

²⁹ Without using the regularisation feature

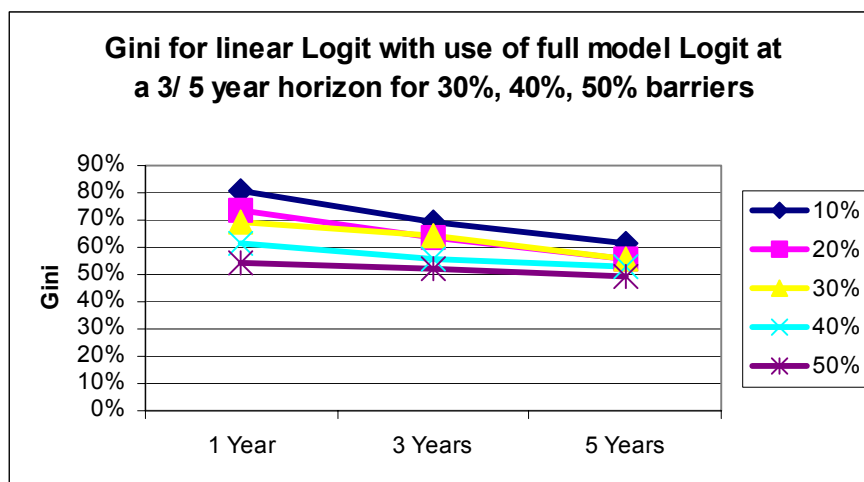


Figure 8: Performance of linear logit models, based on Table 8.

The first conclusion of this exercise is that with the six factors we have selected initially, we keep a reasonably good predictive power for EDS with barriers between 10% and 50%.

The rank-ordering performance of these models remains reasonably stable over time and model recalibration should not be frequently required. This can be seen in the table 8 below where the Gini coefficient of a one-year, 30% barrier linear logit model is computed for a comparable sample of companies considered over 3 different time periods.

Gini observations 1996 to 2002	68.19%
Gini observations 1997 to 2002	66.46%
Gini observations 1998 to 2002	67.75%

Table 8: stability of performance for different time periods

Looking at barriers above 50% (see table 9), we observe that the level of prediction decays and rapidly becomes substandard, relative to expectations in the credit universe³⁰.

Linear Model without regularisation

Gini coefficient	60%	70%	80%	90%
1 Year	44.09%	33.65%	22.09%	11.88%
3 Years	32.64%	24.89%	16.39%	8.78%
5 Years	28.71%	22.04%	14.33%	7.65%

Table 9: performance results beyond 50% barriers.

Previous empirical research showed that one reason for this is that the higher the default or event rate, the more difficult achieving a good rank ordering level is. Table 10 below shows that for barriers over 50%, event rates start to move to and above 30%. In such cases the conditions

³⁰ Using the full logit model with the regularisation feature typically brings between 8 and 12% to the Gini coefficient. Even with this enhancement, the performance would tend to remain under 50%.

observed at the origination of the EDS seem to lose predictive power. As market volatility is typically in the area of 30%, many non-credit related factors start to impact EDSs such as liquidity, market cyclicality etc. The EDS behaviour becomes closer to the underlying equity itself. This analysis on regime switching³¹ around barrier levels of 50% to 60% is consistent with the findings of Jobst and de Servigny (2005) on EDS correlation.

Horizon (year)	Barrier (%)	Event Rate
1	10	0.71%
3	10	2.72%
5	10	3.58%
1	20	1.86%
3	20	5.51%
5	20	6.89%
1	30	3.48%
3	30	9.14%
5	30	11.24%
1	40	6.17%
3	40	14.60%
5	40	17.41%
1	50	10.05%
3	50	21.11%
5	50	24.10%
1	60	16.64%
3	60	30.26%
5	60	33.05%
1	70	26.99%
3	70	41.67%
5	70	44.12%
1	80	42.61%
3	80	55.89%
5	80	57.70%
1	90	65.23%
3	90	73.67%
5	90	74.68%
1	100	98.56%
3	100	99.02%
5	100	99.15%

Table 10: Event Rate per time horizon and barrier level

4.3 Analysis of the relative contributions of the different scoring factors in the Logit models, depending on the EDS barrier level

The analysis of the relative contribution of each of the factors, at various barrier levels, provides a view on the key drivers of EDS event probabilities. This analysis is possible because the linear Logit models we have used are based on rank transformed and normalized factors³². As a

³¹ The move from a debt like instrument to an equity like one

³² The input considered in the models corresponds to a transformation of the initial input. For each factor the data is ranked ordered and rescaled between 0 and 1.

consequence, the weights on the factors translate into a ranking of each of these factors for different barriers (see figures 9, 10, 11).³³

- The two most informative factors to assess the risk of an EDS event are clearly the Rating and the One-year Volatility. Interestingly, in the short term the rating dominates for barriers below 50% and for longer-term assessments it remains very influential for 50% barriers and beyond. At a five-year horizon for instance (figure 11), Ratings appear to be always more informative than other factors. The consequence of this analysis is that assessing the riskiness of an EDS in a robust way without the credit rating (or at least an estimate of this rating) of the underlying company would prove quite a challenge. An interesting point is that while the impact of volatility is increasing with the barrier level, it is the opposite with ratings. This is again in agreement with the view that EDSs move from a debt like behaviour to an equity like one.
- Market Capitalisation seems little sensitive to changes in the barrier, whatever the horizon. It is however an important factor in the risk assessment of EDSs.
- Two factors, the One-year Return and the Debt over Equity, bring some value for low barriers, i.e. in a credit like environment. As soon as the barrier increases to levels up to 30% - 50% the contribution of these factors seems to decrease significantly. In addition, these factors receive low weights in the scoring function. This shows that the debt to equity ratio, that is usually considered as representative of the structure of a company and that gives some indication about its distance-to-default, could actually prove to be slightly less relevant than expected. Some caution is however required here, as some of the debt / equity information might already be factored in the credit rating.
- The last factor, corresponding to the ratio of the current level of the S&P 500 compared with its highest level over the past 10 years, does not initially appear to be very relevant in a credit like environment and up to 50% barriers but then picks up significantly for higher barriers. This feature means that market conditions at the moment the EDS is originated becomes of paramount importance in the medium term when the EDS navigates in regions of over 50% barriers due to a downturn of equity markets in general or a collapse of the stock itself, following the origination of the EDS.

³³ Two caveats here: in the calibration of logit models, there is no unique optimal result for the weights and as some equity based factors are correlated with some credit factors, there is additional uncertainty.

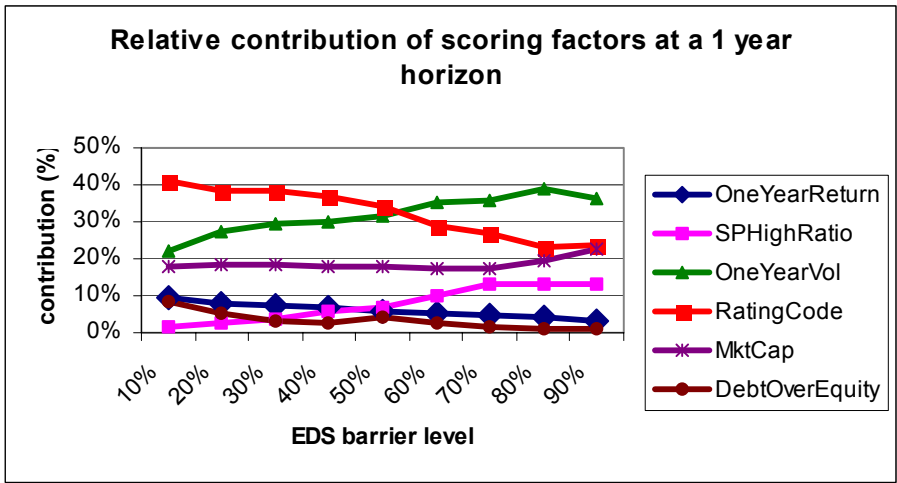


Figure 9: factors contribution at a 1-year horizon

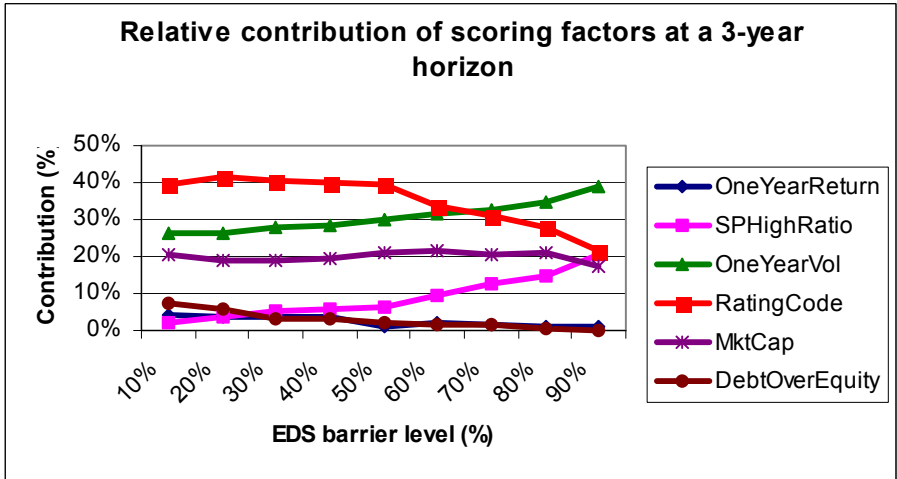


Figure 10: factors contribution at a 3-year horizon

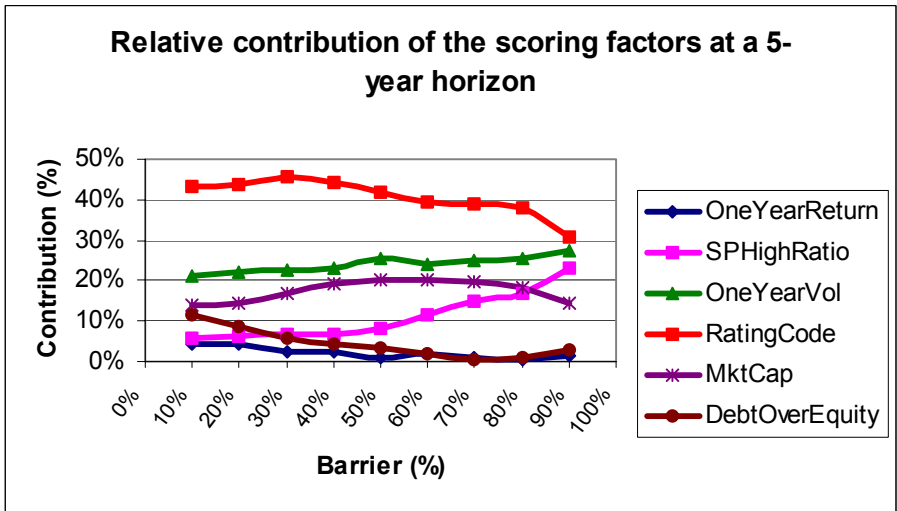


Figure 11: factors contribution at a 5-year horizon

4.4 Are EDS more credit like or more equity like?

What is clear from the above analysis and from figure 12a is that EDSs with barriers under 50% are more debt like products than equity like products. The figure provides the split between the relative weight of credit based factors (rating, Debt over Equity, one-year return³⁴) vis-à-vis the equity based factors (one year volatility of equity, SP High Ratio) per barrier and horizon levels. We exclude the market capitalisation that can be considered as either debt or equity like. Another point to focus on is that beyond 50% barriers, the factors we are using start to lose predictive power. As a result, the relative weight of debt and equity features is probably only indicative. At the 5-year horizon, the crossing of the curves is observed for higher barriers as on the equity side there are no such long-term factors as the rating is for credit factors.

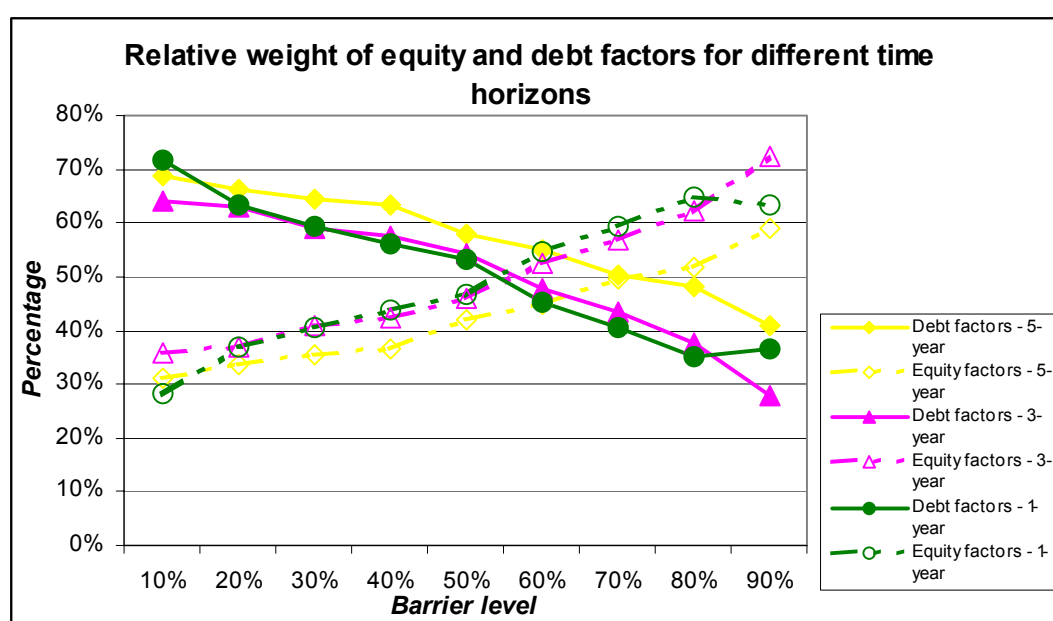


Figure 12a: relative weight of debt / equity factors in EDSs for different barriers

4.5 Trying to answer the question from a different perspective: looking at Kendall's Tau between defaults and equity events for different barriers³⁵

As can be observed using a particular specification of Kendall's tau³⁶, a default and an EDS event are close for low barriers and tend to diverge with increasing barriers, as can be seen in figure 12b.

³⁴ The one-year return typically matters from a credit perspective, we acknowledge that it could also be considered as an equity related indicator

³⁵ Whereas in most approaches on EDS correlations (see Jobst, de Servigny (2005)), we have excluded non-vanilla equity issues such as OTC traded equity, ADRs etc, we include them in this section to obtain a higher number of (credit) default. In the current database, we have in total approximately 850 defaulters, while this number is limited to approach 320 in this section because of the necessity of ratings/default as well as equity price data. (For comparison, if OTC traded equities are excluded, we end up with approximately 100 defaulters.)

³⁶ For more information on the Kendall's tau see A. de Servigny and O. Renault (2004), p. 177. Note also that Kendall's tau is more frequently applied within the context of continuous random variables, see, for example, Nelsen (1999).)

Let us define notations first.

$d(i,t,T)$ is the indicator (0/1) of default of (rated) firm i within T year from time t . Usually, t is December of each year from 1980 to 2002 (23 years) and $T = 1$ year.

$e(i,b,t,T)$ is the indicator of equity default (drop to a barrier of $b\%$) of (rated) firm i within T year from time t . Usually, t is Dec of each year from 1980 to 2002 (23 years) and $T = 1$ year.

Let us consider only $n(t)$ pairs $(d_{i,t}, e_{i,t})$ and define concordant and non-concordant pairs as follows:

Concordant: $d_{i,t} = e_{j,t}$

Non-concordant: $d_{i,t} \neq e_{j,t}$

Counting the number of concordant and non-concordant pairs gives the Kendall's Tau estimator

τ_t the usual way: $\tau_t = \frac{c_t - \bar{c}_t}{c_t + \bar{c}_t}$.

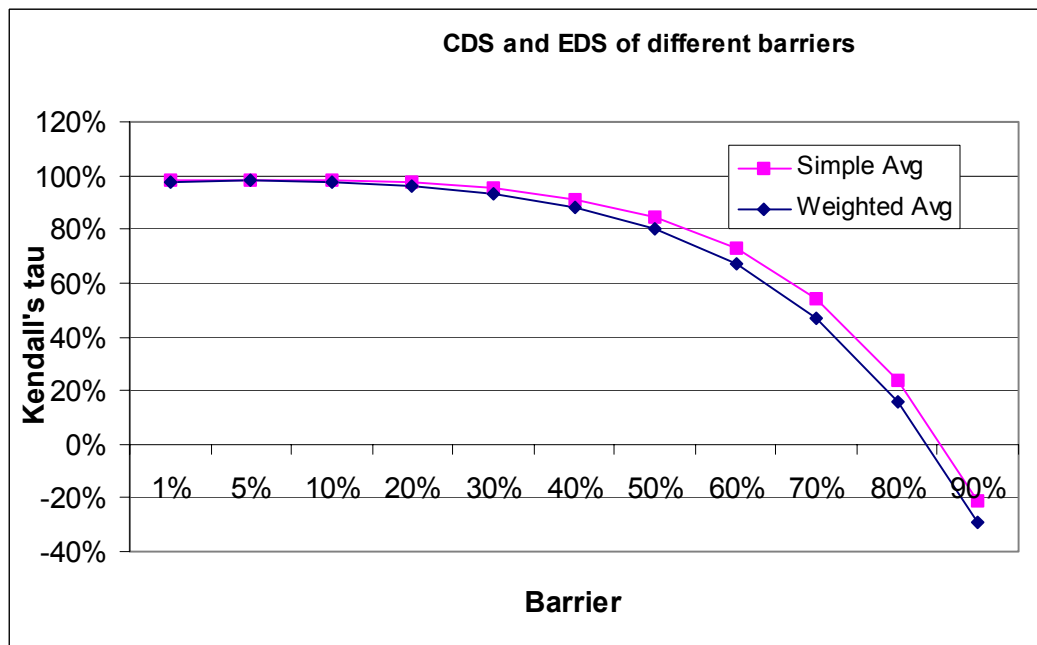


Figure 12b: how close EDSs are from debt instruments

The two curves are computed using different weights of yearly averages.

EDSs are undoubtedly different from CDSs, especially with the increase of the barrier level. What is interesting is that similar risk assessment techniques seem to be usable with the two instruments.

4.6 Stability of scores over time

There is a large literature on the instability of scores over time. Scores are often called “point in time” as opposed to “through the cycle” measures (e.g. ratings)³⁷. The major weakness of “point

³⁷ See de Servigny and Renault (2004)

in time” indicators is that they usually convey little information beyond the time horizon they have been built on. On the contrary “through the cycle” indicators give not only a default / an event likelihood indication at a given time horizon, but also indications of riskiness at several different time horizons. A “through the cycle” measure can therefore be characterised by a curve defined in terms of cumulative probabilities of default / event. S&P rating categories are for instance linked to a term structure of default probabilities.

We know that “through the cycle” assessments are available for credit instruments. We now investigate if for EDSs we could also develop a comparable “through the cycle” assessment of event risk of companies, whatever the barrier and the time horizon considered.

5. Beyond scoring, towards a stable EDS risk classification³⁸

The initial sample on which we operate is the same as before, it contains 17,256 yearly observations spread over 18 years. The starting point is obviously the set of scores we have computed in the last paragraph. We then reduce this population to a sub-sample of observations. We indeed require that for any company there is a minimum of 5 subsequent observations³⁹. The new population reduces to 12,082 yearly observations.

As opposed to ratings that are issuer specific, we focus here on an issue (EDS) specific risk estimate.

In the first instance, we define an origination date t for the EDS. We compute EDS scores at different horizons and classify them by performance quintiles, conditional on the definition of a barrier level. We focus on the 10%, 30% and 50% barriers as well as the 1, 3 and 5-year time horizon. We therefore define 9 possible combinations of pairs (barrier, horizon), corresponding to 9 models. In order to illustrate this, we describe the process for the first pair at a 10% barrier level and at a one-year horizon

- The first quintile of observations corresponds to the top lowest 20% scores observed
- The second quintile of observations corresponds to the 20% to 40% following scores and so forth for the lower quintiles.

An EDS on a company will be said to be in Category one (I) at time t , if for all nine instances the scores have been found in the first quintile. More generally, an EDS on a company will be said to be in Category (X) at time t , if in the nine instances the scores have been either in quintile⁴⁰ X or in a higher one.

As a result of this operation, we obtain the split of EDSs per “through the cycle” risk Category. The main finding is that around $\frac{1}{4}$ of companies have been excluded from Category I as they did not exhibit sufficient stability over the various sets of combinations.

Category I	14.50%
Category II	19.08%
Category III	21.25%
Category IV	20.98%
Category V	24.18%

Table 11: The split of EDSs per Category

³⁸ We use here the results of the linear logit models, without regularisation. We do so to increase simplicity, though we recognize that the use of the results of full-logit models would have improved the performance of this classification.

³⁹ By excluding companies with less than 5 years of rating, we know we could bias the sample by excluding some recently rated low sub investment grade companies. These companies may not however be the principal target population for EDSs.

⁴⁰ Excluding EDSs already in lower Categories.

5.1 Sensitivity analysis of EDS Categories to EDS factors

5.1.1 Comparison of categories with the rating classification

We now try to evaluate ex post how good an indicator of EDS quality an S&P rating is, by looking at the distribution of ratings per EDS Category (figures 13 to 17):

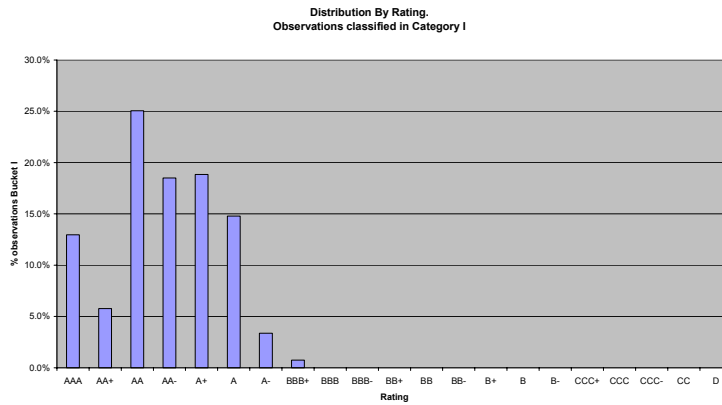


Figure 13: Distribution of ratings in Category I

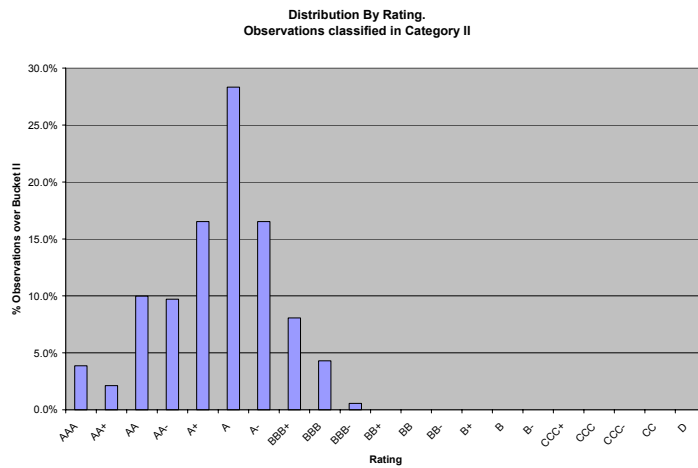


Figure 14: distribution of ratings in Category II

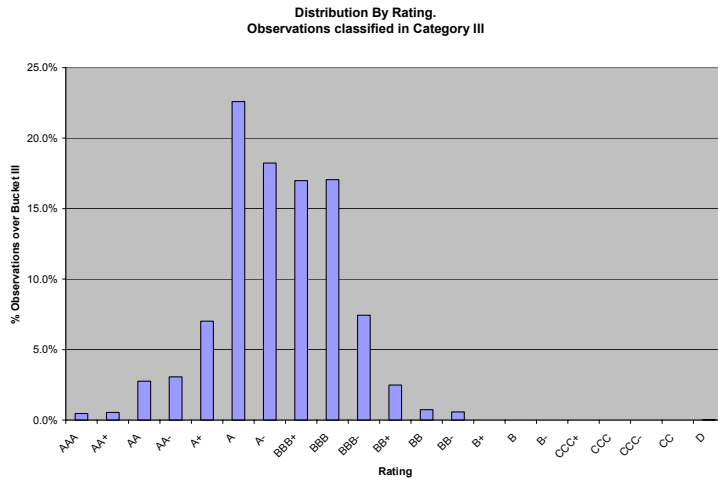


Figure 15: distribution of ratings in Category III

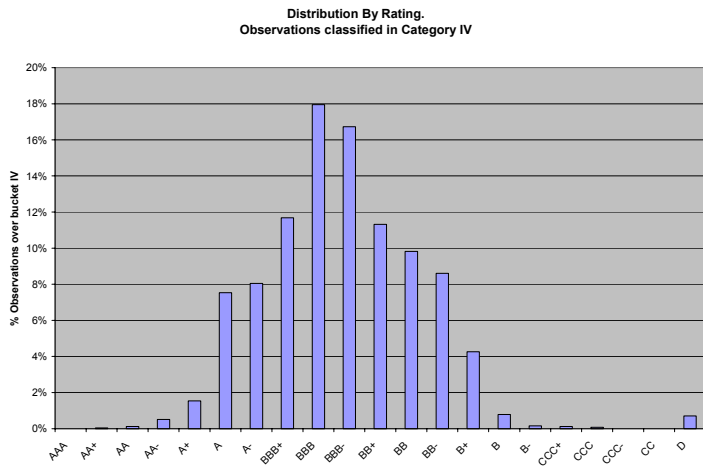


Figure 16: distribution of ratings in Category IV

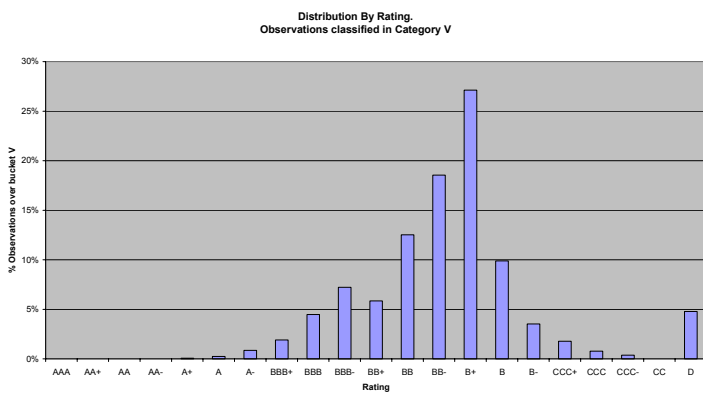


Figure 17: distribution of ratings in Category V

As expected, though credit ratings and EDS Categories are meant to provide a “through the cycle” assessment of risk, we can see that ratings are not sufficient indicators to discriminate among EDS categories.

5.1.2 Analysis of the impact of volatility on Categories

In this section, we want to understand how stable the volatility patterns are for an EDS. In order to do so, we try to drill down into equity volatility, checking for any sort of regime switching behaviour. We consider the period of 23 years defined in Section 4 and measure the likelihood of a company with its one-year volatility positioned in a given quintile to remain in the same one-year volatility quintile a year after. We perform this analysis on the two samples we have defined in Section 4: in table 12a, we refer to the full Compustat universe (All Companies) and in table 12b, we consider the universe of rated companies (Rated Companies).

Overall, the likelihood to remain in the same quintile appears as rather limited, apart from Quintile 1 in the case of rated companies that tends to exhibit a more stable pattern (with a 56% probability of stability over 1 year). We can also observe, that for 80% of companies, volatility moves by one notch only (i.e. stay in the same quintile or move to the adjacent upper or adjacent lower quintiles).

We can however observe around 20% of companies exhibiting very different volatility patterns from one year to another. This means that we tend to observe some regime switching patterns, and ideally, one would want to track these companies.

Despite the informative power of volatility for EDS risk classification, it is clear that it is not sufficient, especially with respect to longer time-horizons, given the presence of such volatility behaviour. The use of additional information, in particular credit rating, as discussed previously, leads to a significant performance improvement by better identifying and then filtering these volatility jumps. A second layer of filtering is subsequently introduced in Section 5, with the EDS Categories. The use of different models calibrated on different barriers and different maturities is indeed meant to catch not only extreme volatility jumps, but also more benign diffusion like dynamics.

Overall, due to the existence of volatility jumps that might not be fully anticipated by our approach, we know that Categories might exhibit higher migration patterns than credit ratings.

One Year - All Companies	End Q1	End Q2	End Q3	End Q4	End Q5
Initial Q1	50.28%	28.72%	14.11%	5.31%	1.58%
Initial Q2	26.26%	31.17%	24.82%	13.20%	4.56%
Initial Q3	12.17%	22.56%	28.50%	24.62%	12.15%
Initial Q4	5.02%	11.87%	22.80%	32.97%	27.35%
Initial Q1	1.66%	4.46%	11.25%	26.38%	56.25%

12a: Stability of volatility quintiles over one year on the Compustat database

One Year - Rated Companies	End Q1	End Q2	End Q3	End Q4	End Q5
Initial Q1	56.24%	26.28%	11.06%	4.99%	1.43%
Initial Q2	22.87%	32.01%	24.06%	14.80%	6.27%
Initial Q3	10.55%	21.28%	27.91%	24.83%	15.43%
Initial Q4	4.66%	13.58%	24.36%	32.00%	25.40%
Initial Q1	2.05%	6.34%	13.50%	26.06%	52.05%

12b: Stability of volatility quintiles over one year on the rated universe defined in Section 4

5.2 Analysis of the performance of EDS Categories

We now try to review the performance of EDS categories / Risk Estimates from two perspectives: the quality of calibration and the quality of rank ordering (Gini). We first perform an analysis of cumulative average probability of equity event (EEP or PE) and of Events Rates (ER) per EDS Category, for given barrier levels in order to evaluate calibration differences (figures 18 to 20). We then measure the Gini coefficients per barrier and time horizon.

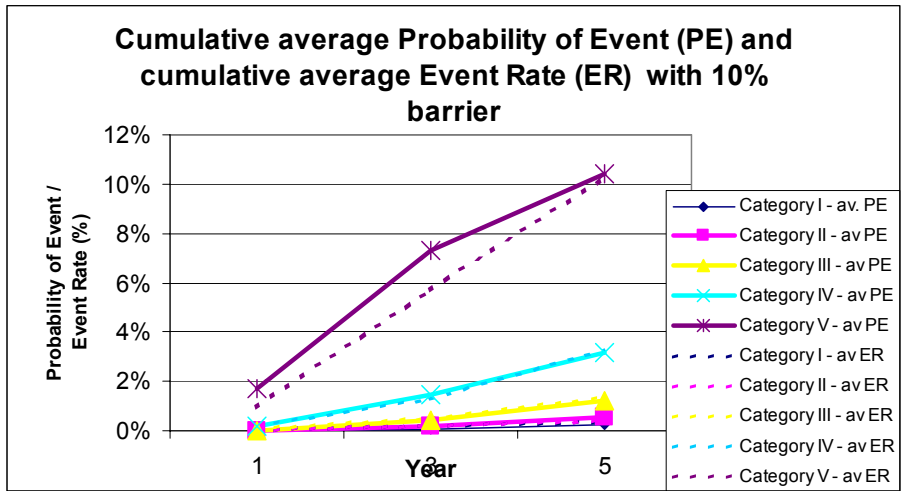


Figure 18: comparison for 10% barrier

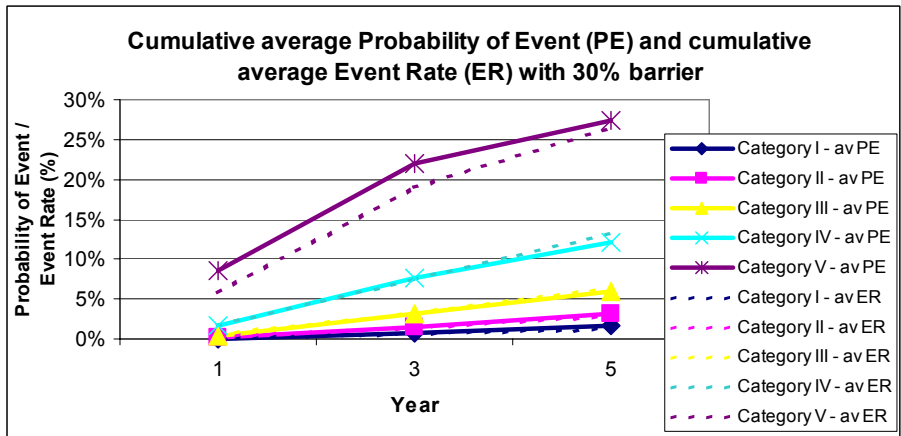


Figure 19: comparison for 30% barrier

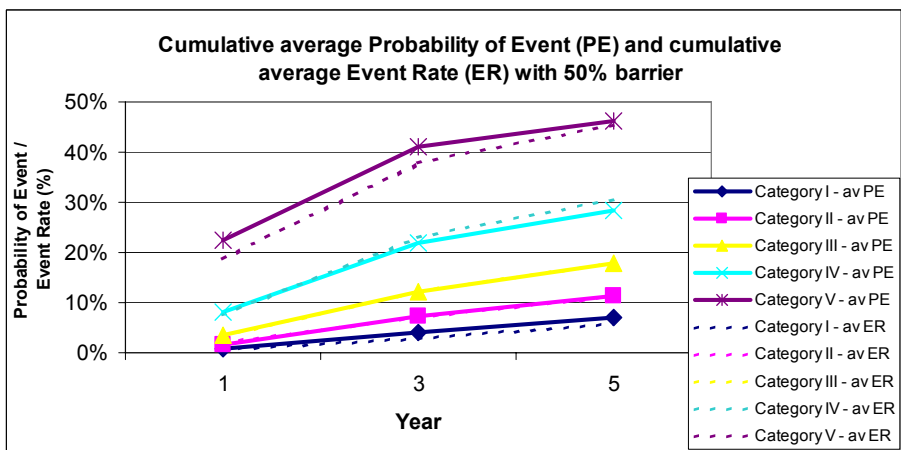


Figure 20: comparison for 50% barrier

We can observe in tables 13a and 13b that cumulative PEs per EDS Category are well differentiated and that differences between categories I, II and III widen with the increase of the barrier level.

Event Rate												
10% Barrier				30% Barrier				50% Barrier				No. Observations
Category	1 year	3 year	5 year	Category	1 year	3 year	5 year	Category	1 year	3 year	5 year	
I	0.00%	0.17%	0.29%	I	0.06%	0.63%	1.14%	I	0.63%	2.57%	5.76%	1,752
II	0.00%	0.17%	0.39%	II	0.17%	1.39%	2.86%	II	1.87%	7.11%	11.06%	2,305
III	0.04%	0.47%	1.36%	III	0.62%	3.12%	6.31%	III	3.19%	12.07%	17.76%	2,568
IV	0.16%	1.30%	3.27%	IV	1.70%	7.50%	13.18%	IV	7.50%	23.00%	30.45%	2,535
V	0.99%	5.75%	10.30%	V	5.78%	19.06%	26.52%	V	18.55%	37.95%	45.38%	2,922
												12,082

Probability of Events												
Barrier: 10%				Barrier: 30%				Barrier: 50%				No. Observations
Category	1-year	3-year	5-year	Category	1-year	3-year	5-year	Category	1-year	3-year	5-year	
I	0.00%	0.05%	0.26%	I	0.06%	0.68%	1.66%	I	0.82%	4.06%	7.08%	1,752
II	0.01%	0.15%	0.57%	II	0.17%	1.46%	3.16%	II	1.71%	7.19%	11.44%	2,305
III	0.03%	0.43%	1.23%	III	0.46%	3.11%	5.89%	III	3.46%	12.22%	17.74%	2,568
IV	0.16%	1.45%	3.16%	IV	1.62%	7.59%	12.15%	IV	7.98%	21.93%	28.44%	2,535
V	1.73%	7.31%	10.42%	V	8.53%	21.90%	27.38%	V	22.56%	41.08%	46.30%	2,922
												12,082

Tables 13a and 13b: calibration of Categories

We can also observe that the calibration per EDS Category is very robust with only a small overestimation of probabilities of events vis-à-vis event rates in Category V.

Regarding the predictive power of EDS categories, we measure in table 14 the quality of their rank ordering by computing the Gini coefficients related to EDS categories for all 9 (horizon, barrier) pairs in the table below.

EDS Categories	10% Barrier			30% Barrier			50% Barrier		
	1 year	3 Years	5 Years	1 year	3 Years	5 Years	1 year	3 Years	5 Years
Gini coefficient	91.97%	83.98%	80.88%	82.79%	75.34%	69.86%	73.47%	63.08%	57.53%

Table 14: rank ordering of Categories

As can be seen the level of performance is very good, confirming that the proposed EDS classification is adequate.

Surprisingly, Categories keep on having a relatively good level of performance for 60% and 70% barriers, as can be seen in table 15.

EDS Categories	60% Barrier			70% Barrier		
	1 year	3 Years	5 Years	1 year	3 Years	5 Years
Gini coefficient	64.21%	54.85%	50.89%	54.70%	47.46%	44.42%

Table 15: looking at 60% and 70% barriers

6. Stability of EDS Categories over time

6.1 Taking into account the impact of the relative level of equity markets

From the table above, we consider the mean probabilities of Event per EDS Category, per time horizon and barrier level. We have coloured in yellow what would correspond to an investment grade level (table 16)⁴¹. Typical EDS transactions entail an initial barrier level of 30%. In this respect, we can see that only Categories I and II would correspond to an investment grade level. With a 50% barrier no EDS Category can be considered as investment grade.

Barrier	10%				30%				50%		
Category / year	1	3	5		1	3	5		1	3	5
I	0.002%	0.054%	0.257%	I	0.059%	0.679%	1.664%	I	0.818%	4.058%	7.080%
II	0.007%	0.153%	0.570%	II	0.165%	1.465%	3.164%	II	1.707%	7.186%	11.440%
III	0.028%	0.426%	1.233%	III	0.462%	3.113%	5.894%	III	3.458%	12.215%	17.741%
IV	0.159%	1.451%	3.162%	IV	1.619%	7.588%	12.146%	IV	7.980%	21.931%	28.440%
V	1.725%	7.309%	10.419%	V	8.527%	21.900%	27.377%	V	22.563%	41.081%	46.301%

yellow corresponds to investment grade quality

Table 16: IG / NIG

This suggests that the initial value of the equity and the general market current and expected conditions at origination of an EDS are very important. Typically an EDS with a 30% barrier written at the climax of equity markets would quickly translate into an EDS with a 40 / 50% barrier following a period of downturn. In an opposite way, an EDS with a 30% barrier written just after an equity shock could translate into an EDS with a 10 / 20% barrier as soon as the market recovers. For this reason, paying attention to the factor corresponding to the ratio of the S&P 500 index, compared with its highest level over the past ten years is critical. It informs on the impact of the equity market cycle on the risk of EDSs.

In addition to this systematic component of risk accounted for by the use of a generic equity index, there may also well exist an idiosyncratic shock on a given company that would impact all directly related EDSs. Apart from an unexpected shock coming from the lack of transparent information (e.g. undisclosed accounting irregularities, etc.), some of the structural weaknesses of such a company at risk should however already be, to some extent, embedded in its rating and in its equity volatility. This should prevent such EDSs from being allocated to the best EDS Categories.

6.2 Measuring the stability of the Category of an EDS during its life

Being able to assess the risk of an EDS on a regular basis is particularly important for the surveillance of CDO transactions including these new instruments.

We know that the downgrade of a company for which a CDS is included in a CDO can have an impact on the rating of some of the tranches.

In the case of EDSs, two elements matter: the Category in which the EDS stands and the “marked to market” barrier level. The reason for this is that cumulative EEPs are not Category specific, but are derived from this combination of Category and Barrier level. We need to review the drivers for the change in the risk assessment on an EDS.

⁴¹ Based on Standard & Poor’s CreditPro®

A Category downgrade will mainly come from:

- a change in the rating of the underlying company associated with the EDS,
- a jump in its equity volatility that is not anticipated by the scoring models,
- a significant move of the S&P 500 index.

An increase in the Barrier level will come from an equity price that has gone below the price at origination of the EDS.

Instead of one downgrade trigger like in the CDS world, we now have in the EDS world at least 4 triggers. This explains why more EDS cumulative EEPs volatility could be expected, relative to credit rating migrations.

The initial EDS Category at the origination of the CDO will typically give a robust view on the equity event risk in the pool likely to affect the stability of a CDO in a hold to maturity perspective⁴². From a fair value perspective generated thanks to regular updates in ratings and Categories, EDSs may well introduce some volatility increase to the migration of CDO tranches.

6.3 Measuring the stability of the risk assessment of different 5-year EDSs over time, for a given company

We now ask ourselves the following question: how informative is a 5-year EDS on a company positioned in one of the five Categories at the beginning of this year on the risk Category of a new 5-year EDS to be originated a year later?

In other words, we calculate in table 17 below the average one-year EDS based stability matrix over a period of 18 years from 1980 to 1998

One year stability matrix					
	I	II	III	IV	V
I	61%	30%	7%	1%	0%
II	18%	46%	28%	7%	1%
III	4%	21%	46%	26%	3%
IV	0%	3%	21%	48%	27%
V	0%	0%	1%	19%	80%

Table 17: 1-year stability matrix (there is no specific column for events, as events are included in V)

This stability matrix is not comparable with the transition matrices computed in the credit universe. Again an EDS risk estimate is an issue assessment where as a rating is an issuer assessment. We are trying to compare here the risk for two subsequent and distinct 5-year instruments rather than looking at the evolution of the risk Category for a single facility / counterparty, irrespective of its maturity / investment horizon.

We can observe that the likelihood, for two instruments considered with a 1-year lag, to remain in the same risk Category is quite low (diagonal). The volatility of these changes in EDS Category remains however rather limited over short periods of time: they are usually kept within +/- one

⁴² We would like to point out that price movements within the bands of average equity market noise should not lead to immediate updates in the absolute risk (event probabilities) as this level of uncertainty is captured in the calibration of the Categories. Only significant and persistent changes in the price and distance to the barrier should cause an update of this nature.

Category⁴³. We are not surprised by this low stability phenomenon, given the relatively high level of equity market volatility over one year.

From this one-year stability matrix let us try to infer the five-year stability matrix by computing the power five of the one-year matrix⁴⁴. Consequences look much more dramatic as for example 10% of companies for which the current 5-year EDS is in Category I today will give a Category V new 5-year EDS in 5 years time.

Power 5 of the 1 year stability matrix					
	I	II	III	IV	V
I	23%	27%	24%	16%	10%
II	19%	27%	28%	21%	16%
III	12%	18%	23%	23%	25%
IV	6%	11%	18%	26%	40%
V	2%	5%	13%	27%	53%

Table 18

We are now testing this theoretical matrix looking at the data themselves. What we observe is an even higher level of instability than predicted.

	No. of observations		No. companies classified ONLY in each Category		
		% of obs.			% of comps.
I	1,752	15%	I	12	0.70%
II	2,305	19%	II	18	1.10%
			I or II	82	5.00%
III	2,568	21%	III	58	3.60%
IV	2,535	21%	IV	69	4.20%
V	2,922	24%	V	394	24.20%
			other combinations	994	61.20%
Total	12,082	100%	Total	1627	100.00%

Table 19

We can observe in table 19 a confirmation of the above statement as only 0.7% of companies remain in Category I during the full period of observation in our sample and only 6.80% of companies remain in the I and II categories during the same period. This period corresponds to an average of 3.4 cohorts (3.4 successive years of observations)

6.4 Some key differences between CDSs and EDSs

EDSs, like CDSs seem to be reasonably well qualified by a “through the cycle” classification. In the case of a CDS, it is the rating, in the case of an EDS, it can be the EDS Categories described above.

The main difference between these two products is that EDSs appear to be really sensitive to volatility jumps of the stock and to changes in “marked to market” barrier levels. Equity prices

⁴³ For instance the likelihood of a new EDS to remain in the Category II, (i.e. the previous EDS on the same name initially was in Category II a year before), is only 46%, but 92% within one notch up and down.

⁴⁴ This assumes a time homogeneous Markov process that is probably not true given equity cycles.

matters only indirectly to ratings / CDSs. For EDSs on the contrary, equity prices can cause discontinuities in the risk assessment of the instrument. An important factor to the risk of an EDS is indeed related to some additional systematic risk: the cyclicity of equity markets and more precisely the likelihood of downturns / shock in the equity markets. The 5-year stability matrix exhibited above stands as a good illustration of such risk.

7. Comparison between EDS prices and the Category based risk assessment

In this section we analyse European companies for which we have received a database of daily 30% EDS prices at origination, covering the period going from 2 June 2003 to 15 December 2004. We have selected 4 dates: 30 June 2003, 31 December 2003, 30 June 2004 and 31 December 2004. We have retained 42 Investment Grade companies in the Euro and GBP zones for which we have both the corresponding EDS Category and the market price⁴⁵. We display the main findings in table 20 and in figures 21, 22, 23, 24.

The results are somewhat surprising, as prices do not always seem to be monotonically increasing with Categories. This is especially true in December 2004. Though we recognize that the sample on which we have worked may not be sufficiently large to infer definitive conclusions, we also tend to think that liquidity on EDS markets is limited and varying.

In addition, one of the reasons for the dislocation between EDS prices and risk Categories could be that we are only looking at investment grade companies. In this segment, volatility is indeed the main driver to Category differentiation. For Categories, the volatility factor taken into account is based on one-year historical monthly equity returns, where as EDS prices are often underpinned by implied volatilities in conjunction with local volatility models. Implied volatilities can be much shorter term looking than historical volatilities. In the present case, as volatility has been decreasing steadily in markets over the last years, historical volatility is still “remembering” of higher volatility levels, where as implied volatilities are not. As a consequence, we can see that as per December 2004, the price differentiation per Category has diminished substantially, while the general level of EDS prices seems to have gone down accordingly. Because we want to provide a risk assessment of EDS risk at a 5-year horizon, we believe that the past history of volatility is informative to indicate potential volatility jumps in the future. In our scoring exercises we have tested, during the risk factor selection process, the 1, the 3 and the 5-year historical volatilities. This testing revealed that the 1-year volatility is the most relevant risk factor. We therefore feel quite comfortable with relying on it for the assessment of EDS Categories.

⁴⁵ Regarding the December 31st information, the spread data corresponds to the last date in our database, which was the 15th of December.

Date	Category	Mean	Median	StDev	Number of Obs.
30-Jun-03	I	0	0	0	0
30-Jun-03	II	144	144	1	2
30-Jun-03	III	217	200	141	6
30-Jun-03	IV	165	132	135	16
30-Jun-03	V	243	285	117	18
31-Dec-03	I	0	0	0	0
31-Dec-03	II	61	77	37	4
31-Dec-03	III	114	99	69	10
31-Dec-03	IV	148	141	82	16
31-Dec-03	V	144	167	93	12
30-Jun-04	I	86	99	54	4
30-Jun-04	II	161	141	57	6
30-Jun-04	III	159	150	55	12
30-Jun-04	IV	99	51	77	11
30-Jun-04	V	175	196	121	9
31-Dec-04	I	98	98	16	3
31-Dec-04	II	132	126	52	13
31-Dec-04	III	80	81	53	12
31-Dec-04	IV	152	147	58	7
31-Dec-04	V	123	123	102	7

Table 20: summarised prices per EDS Risk Category

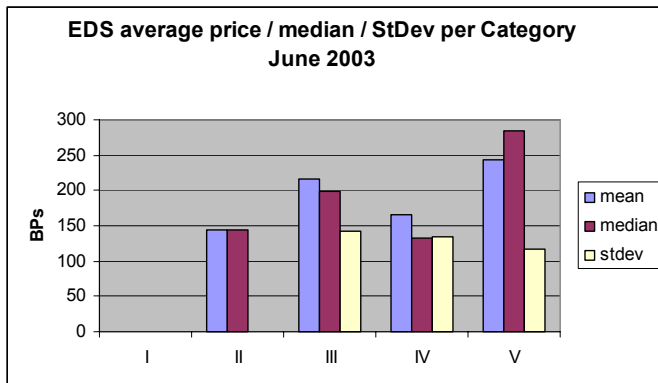


Figure 21: EDS prices per Category as per June 2003

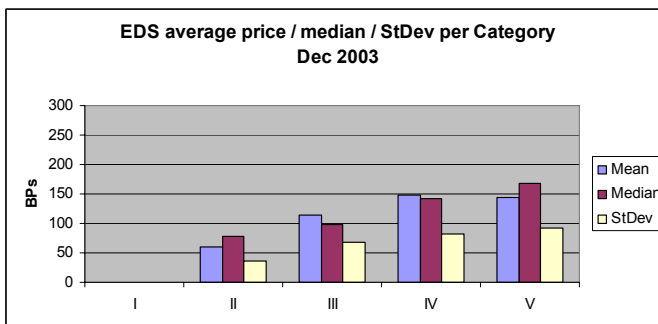


Figure 22: EDS prices per Category as per December 2003

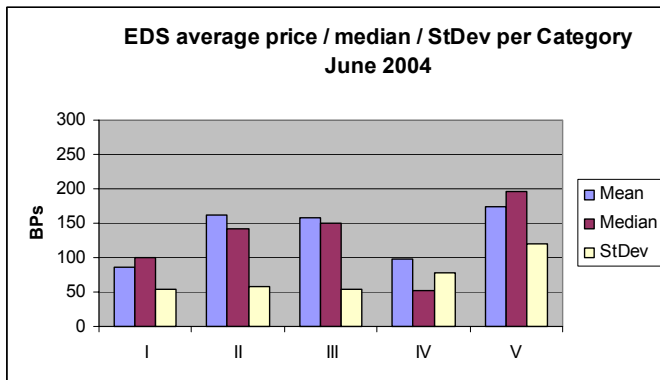


Figure 23: EDS prices per Category as per June 2004

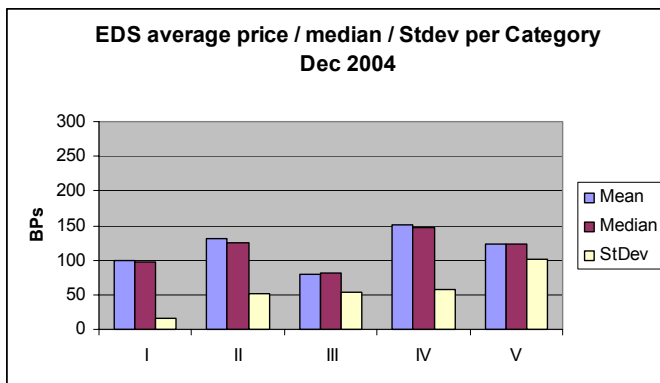


Figure 24: EDS prices per Category as per June 2004

8. Conclusions and further research

EDSs are complex products, depending on three types of drivers: credit information, equity information and the general evolution of equity markets. In addition to this, EDSs integrate a “memory” component characterised by the barrier level today, which is derived from the barrier level at origination. In this paper, we have focused on characterising EDS risk with two indicators, i.e. the one to five Categories and the barrier level at the time risk is measured. This analysis could lead both practitioners and academics to integrate these parameters as two layers of jump in the pricing and in risk management techniques.

In order to be able to review more complex strategies, such as CDS – EDS carry trades or CDOs including short and long CDS and EDS positions, we now need to analyse the behaviour of EDS at a multivariate level. Jobst and de Servigny (2005) is offering an analytical framework for this purpose.

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Appendix 1
Factors considered

Description of factors	
<i>1</i>	Simple arithmetic 1 year return
<i>2</i>	Simple arithmetic 3 year return
<i>3</i>	1 year return – S&P500 1 year return
<i>4</i>	3 year return – S&P500 3 year return
<i>5</i>	1 year return – previous year's 1 year return
<i>6</i>	3 year return – previous year's 3 year return
<i>7</i>	1 year volatility
<i>8</i>	3 year (annualised) volatility
<i>9</i>	1 year vol – previous year's 1 year volatility
<i>10</i>	3 year vol – previous year's 3 year volatility
<i>11</i>	Skew of 1 year return distribution (based on monthly returns)
<i>12</i>	3 year skew
<i>13</i>	Kurtosis of 1 year return distribution (based on monthly returns)
<i>14</i>	3 year kurtosis
<i>15</i>	Credit rating in form AAA, AA, A etc. Includes D and SD for default. It is transformed in a dummy variable ranging from 1 to 18
<i>16</i>	The market capitalisation, in millions \$, of the most actively traded issue of the company
<i>17</i>	Total Liabilities (= current liabilities + long-term debt) / Total Assets (= current assets + net property, plant + ...)
<i>18</i>	Total Debt (= Total long-term debt (i.e. due in more than one year) + Debt in current liabilities (i.e. short term debt + long-term debt due in current year)) / Shareholders equity
<i>19</i>	Total Assets / total liabilities
<i>20</i>	Income Before Extraordinary Items available for common (i.e. less preferred dividend requirements) / Common Equity * 100
<i>21</i>	Income or loss reported in millions of dollars
<i>22</i>	Income – previous years income
<i>23</i>	Current price / 12-months moving earnings per share
<i>24</i>	Current price / (12-month income before extraordinary items / common shares outstanding)
<i>25</i>	Market Value / Common Equity
<i>26</i>	Cash dividends per share over last year / close price
<i>27</i>	Ratio of current S&P 500 on max over 10 years of S&P 500

Appendix 2
Brief summary of scoring techniques

Box 1: Simple linear logit model

A linear logit model directly generates a probability of default (in this case a probability of equity event). It can be represented as:

$$PD(x) = \frac{1}{1 + \exp\left(-\left[\beta_0 + \sum_{i=1}^K \beta_i x_i\right]\right)}$$

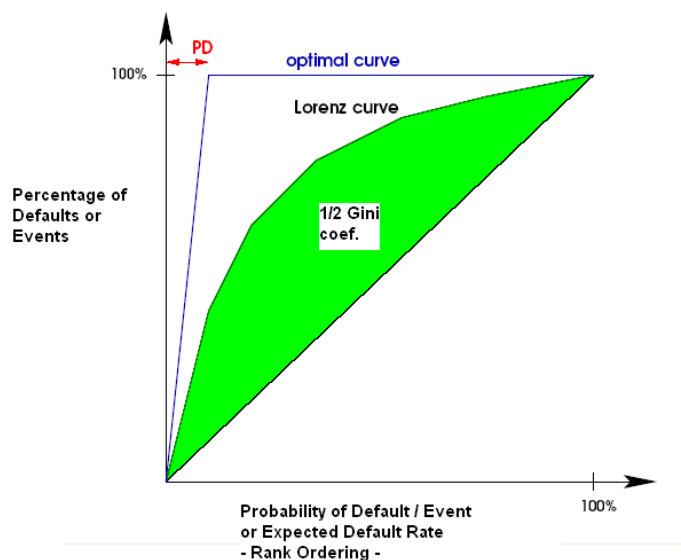
Where company / EDS x is characterised by x_i that are the values for K selected predictive factors. The β_i 's, estimated by maximum likelihood techniques, are the K parameters that indicate the sensitivity of the PD to each of these factors.

Box 2: Gini Coefficient (Gini)

The Gini / Lorenz curve, measures the quality of the rank ordering of a model. A very good model should identify all defaults or Events with the higher PDs / EEPs.

In the graph below, the X axis corresponds to the PDs / EEPs or Ratings / Categories ranked from highest percentages to lowest. The Y axis reports the cumulative observed default / event rate corresponding to the observations ranked from highest score to lowest on the x axis.

The Gini Coefficient represents two times the green surface under the Gini / Lorenz curve. Gini coefficients are sample dependent. In general, in the Credit universe, Gini coefficients are positioned in the 50% to 90% interval. Results are usually measured out-of-sample. When the size of the dataset is sufficiently large, which is the case in this paper, out-of-sample and in-sample performance results converge. Gini Coefficients are sample dependant.



Box 3: Geometric Mean Probability (GMP)

The GMP is calculated as follows:

$$GMP = \exp \left[\frac{1}{N} \sum_{i=1}^N (y_i \log(p(x_i)) + (1 - y_i) \log(1 - p(x_i))) \right]$$

The GMP is a maximum likelihood indication that measures the quality of fit and calibration to a prior: the default status of the companies included in the modelling database. The GMP is essentially the log-likelihood that has been transformed to be bounded by zero and one. A model with a GMP of one would be a perfect model. In the credit universe, the expected level of performance is typically above 75%.