

# Quantitative Credit Research

## Quarterly

Volume 2007-Q1

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Fundamental equity and credit analysts seek to interpret companies' financial statements in order to identify key areas of strength and weakness with a view to making informed judgments about future prospects. Over time individual analysts have adopted and adapted a myriad of measures to gauge opportunities and risks within their coverage universe. Lehman Brothers' CMetrics is a new financial framework aimed at improving the quality of financial analysis and valuations.



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## Base Correlation Mapping

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*The pricing of bespoke tranches in the base correlation framework requires mapping techniques to allow correlations calibrated in the liquid tranche market to be applied to bespoke portfolios. In this article we describe methods of mapping bespoke portfolios to standard indices and investigate their impact on pricing and risk. A useful quantitative test of the methods is to map one standard index to another and compare the prices with those observed in the market. We present the results of this analysis for mapping both the iTraxx S6 and CDX HY7 indices to CDX IG7 at the end of January 2007. We also compare the performance of the different methods in the pricing of a range of bespoke portfolios and discuss possible ways to price bespokes mapped to more than one index.*

### INTRODUCTION

The pricing of CDO tranches on bespoke portfolios depends crucially on our assumptions about the default correlations between the credits in the underlying collateral. The establishment of a liquid index tranche market means that it is now possible to obtain implied correlations for a range of standard portfolios from the observed market prices. In the current market standard approach, this is achieved by calibrating a one-factor Gaussian copula model with base correlation (BC) to the liquid indices [1]. Using mapping procedures, BCs can then be obtained for bespoke CDO tranches, allowing pricing and risk-management of these instruments. In this article, we describe a range of approaches that can be used to map bespoke portfolios to standard indices and investigate their impact on pricing and risk.

We start by defining what we mean by BC and then describe the various mapping methods that we consider in this article. A useful quantitative test of these methods is to map one standard index to another because in this case we can compare the prices and correlations with those observed or calibrated in the market. We present results from this analysis for the particular case of mapping the iTraxx S6 and CDX HY7 indices to CDX IG7 using market data from 31 January 2007. We also consider how the various mappings perform when the spread on a single-name in the iTraxx S6 portfolio widens dramatically, ultimately leading to a default. We then compare the methods for mapping a range of generic bespoke portfolios to CDX IG7. Here, judgments about the quality of the results are more subjective but we can make general observations about the range of prices produced, the relative behavior of the different methods and the various difficulties that can arise. Finally, we discuss two ways in which a bespoke portfolio can be mapped to more than one index and compare the results for a particular case.

### BASE CORRELATION

To value a tranche in the one-factor Gaussian copula framework, we need to know the correlations to apply to the underlying credits so that we can build the portfolio loss distribution for a range of times up to the maturity of the trade. These correlations may depend on time, and in the simplest implementation of the BC framework they are constant across all the credits in the portfolio. The phenomenon of correlation skew means that the correlation must depend on the position in the capital structure of the particular tranche being priced if the model is to match the observed market prices. Since any tranche can be written as a combination of a long and short position in two base tranches, we can write the correlation as a function of detachment point  $K$  and time  $T$ , i.e.  $\rho = \rho(K, T)$ . This BC surface gives the single correlation that should be used for all credits in the one-factor Gaussian copula model to compute the expected loss of a base tranche with detachment point  $K$  at time  $T$ .

For standard indices, the BC surface can be obtained by calibration to the liquid tranche market using a bootstrapping algorithm. For example, consider the case of the CDX IG index, for which liquid tranches trade at strikes of 3%, 7%, 10%, 15%, and 30%, and maturities of 5Y, 7Y, and 10Y. With an assumption about the level of initial correlations and a local method to interpolate in time, we can calibrate the BC at  $(K, T) = (3\%, 5Y)$  by matching the market price for this tranche. With this information the correlation at  $(K, T) = (7\%, 5Y)$  can be obtained so that we match the price of the 3-7% tranche. Proceeding up the capital structure we obtain the BC at all the standard strikes at the 5Y maturity. For the 7Y maturity, the correlation at  $(K, T) = (3\%, 7Y)$  is calculated by matching the market price for the 7Y equity tranche using the previously calibrated BCs for all times before 5Y. In this way, the BC surface can be obtained out to the 10Y maturity, and for a given strike all cash flows at a fixed time horizon are priced with the same correlation regardless of the maturity of the trade. The BC at non-standard maturities or strikes can be obtained by interpolation within the BC surface.

### MAPPING THE BASE CORRELATION SURFACE

Application of the BC model to tranches on bespoke portfolios requires a mapping rule to produce a BC surface for the bespoke portfolio at the strikes of interest. The general method is to associate a base tranche with detachment point  $K_B$  on the bespoke portfolio, with an equivalent base tranche on a standard portfolio with strike  $K_S^{Eq}$ . The correlation used to price the bespoke tranche is then taken to be the correlation at the equivalent standard strike, i.e.  $\rho_B(K_B, T) = \rho_S(K_S^{Eq}, T)$ . This procedure is used to generate the BCs for the bespoke portfolio at the standard maturities, and values at other times are obtained by interpolation as for the standard index.

Different mapping methods are distinguished by the way they define equivalence in this procedure. We will consider four examples in this article: No-Mapping (NM), At-The-Money (ATM), Probability Matching (PM), and Tranche-Loss-Proportion (TLP). These methods work by defining a quantity that measures the risk in a tranche and treating it as a market invariant. Calibration to the liquid indices tells us the correlation that should be used to price a particular level of risk and this value is therefore used to price bespoke tranches with the same risk. If a particular mapping rule is consistent with the market, then plots of the associated risk measure against correlation should coincide, independent of the particular portfolios we consider. We show an example of such a comparison later in this article, in Figure 4, for the PM and TLP mappings.

The mapping methods are defined in detail below, but we first consider what general characteristics a good method should have. Ideally, these would include as many as possible of the following criteria:

- It should be intuitive, in the sense that changes in the correlation should be easily attributable to changes in the market environment.
- It should have a plausible theoretical justification.
- It should be sensitive only to correlation and insensitive to all other drivers of tranche value, particularly to spread levels and spread dispersion.
- It should be stable with respect to small changes in the market environment.
- It should not introduce arbitrage in the bespoke where there is none in the index.
- It should be easy to implement and always give a solution.
- It should be able to map to a wide range of portfolios in terms of risk.
- It should reflect effects of sector or spread concentration in the bespoke portfolio.

Although none of the methods we discuss is entirely satisfactory in all these regards, we will see that some perform significantly better than others.

### No-Mapping (NM)

In the NM approach, the bespoke strike  $K_B$  and equivalent standard strike  $K_S^{Eq}$  are trivially related by

$$K_S^{Eq} = K_B.$$

Thus, in this case the invariant measure of risk is simply the tranche strike and the calibrated BC surface for the standard index is used directly to price bespokes. This approach can be considered a serious mapping rule only if one believes that the observed correlation skew should apply to all portfolios in the same sub-universe of credits, i.e. that the CDX IG skew describes all possible portfolios containing only US investment grade names, while the iTraxx skew applies to all possible portfolios containing only European investment grade names etc. In practice, we use this approach as a useful benchmark against which the other mapping methods can be measured. The difference in bespoke pricing between NM and other methods can be attributed purely to the different correlation assumptions made, as differences in the spread and dispersion of the credits between the bespoke and the index are included in the NM calculation.

### At-The-Money (ATM)

In the ATM mapping the bespoke and equivalent standard strikes are related by

$$\frac{K_S^{Eq}}{EPL_S} = \frac{K_B}{EPL_B},$$

where EPL is the expected portfolio loss. The rationale behind this approach is that the EPL sets the scale for the level of risk in the portfolio and the invariant measure of risk in a tranche is therefore the strike as a fraction of this expected loss. Tranches are generally equity-like or senior-like in their correlation sensitivity depending on the position of their strikes relative to the EPL. Thus, two tranches are considered equivalent if their strikes are in the same region of the capital structure of their respective portfolios, as measured by the EPL.

The ATM mapping has some theoretical justification if we consider mapping between two portfolios with similar composition. Suppose, for example, that the bespoke portfolio contains exactly the same credits as the reference portfolio but the contract specifies a fixed recovery rate that is a constant multiple of the value for the index (here we are assuming deterministic recovery rates for simplicity). In this case, the loss on the bespoke will be a constant multiple of the loss on the index in all possible states of the world. For concreteness, suppose that the recovery rate for the index is 40% while for the bespoke it is 0%. In this case, the losses on the bespoke will always be a factor of 10/6 of those on the index and a 10% tranche on the bespoke will experience the same relative losses as a 6% tranche on the index. This behavior may be captured by the BC model only if the correlation used to price the bespoke tranche is related to that for the index by the ATM formula. In the example given, the 10% strike on the bespoke should be priced with the same correlation as the 6% strike on the index. While this example is clearly artificial, an analogous argument may be expected to hold approximately if the bespoke portfolio has a similar composition to the index in terms of spread levels and dispersion.

A clear difficulty with the ATM method, however, is that the only information about the portfolios that is used in the mapping is the EPL, which is not even a correlation-dependent quantity. The method does not take spread dispersion into account, and two

portfolios with the same EPL but very different spread distributions will be priced with the same correlation, which is probably not reasonable.

From a practical point of view, although the numerical implementation of the ATM method is trivial, its application can be problematic. If the bespoke portfolio is much safer or much riskier than the index, then the standard equivalent strike  $K_S^{Eq}$  can be above the maximum standard strike or below the minimum standard strike, respectively. In both cases extrapolation is required, which can produce risk numbers or valuations that are sensitive to the precise mechanism chosen. This method can also generate arbitrage in the prices for the bespoke portfolio. We present results demonstrating this fact later in the article.

### Probability Matching (PM)

In the PM approach, the bespoke and equivalent standard strikes are related by

$$P(L_T^S \leq K_S^{Eq}, \rho(K_S^{Eq}, T)) = P(L_T^B \leq K_B, \rho(K_S^{Eq}, T)),$$

where  $L_T^S$  and  $L_T^B$  are, respectively, the cumulative loss on the standard and bespoke portfolios at maturity T. In words, two base tranches are priced with the same correlation in this approach if they have the same probability of being wiped out, which follows from the fact that  $P(L_T > K) = 1 - P(L_T \leq K)$ . The invariant measure of risk in this approach is therefore the probability that an investor loses his entire investment.

The PM method can be justified by noting that changing the correlation in a portfolio does not change the expected loss but rather redistributes losses around the capital structure. The effect of a change in correlation is therefore a change in the shape of the underlying loss distribution. The PM mapping method tries to capture this effect by directly comparing the loss distributions of two portfolios.

From a practical perspective, an immediate problem with this method occurs if the loss distributions are discrete, which happens, for example, if we are using deterministic recovery rates. In this case, we must smooth the cumulative loss distribution using an interpolation scheme, otherwise the equivalent strikes will be discontinuous functions of the market environment and risk calculations will not be stable. The method may not work well if the bespoke portfolio is much riskier than the index, as the equivalent strike may be below the lowest standard strike and we are sensitive to our extrapolation assumptions.

### Tranche Loss Proportion (TLP)

The final mapping method that we consider is the TLP approach, in which the bespoke and equivalent standard strikes are related by

$$\frac{ETL_S(K_S^{Eq}, \rho(K_S^{Eq}, T))}{EPL_S} = \frac{ETL_B(K_B, \rho(K_S^{Eq}, T))}{EPL_B}.$$

Here the expected-tranche-loss function (ETL) is defined by

$$ETL(K, \rho) = E[\min(L_T, K)],$$

and the measure for the expectation is determined by the correlation  $\rho$ . The market invariant risk measure in this approach is therefore the fraction of the total expected portfolio loss which resides in a given base tranche.

The rationale behind the TLP mapping is similar to that behind the PM approach. The correlation skew can be seen simply as a means of adjusting the loss distributions



implied by the one-factor Gaussian copula model to get the correct market prices. This is analogous to the volatility smile in the vanilla option market, where the wrong number is used in the wrong formula (the Black-Scholes equation) to get the right price. The TLP is a good proxy for the relative risk in a tranche so matching this quantity can be seen as a way of tracking the market-implied changes to the Gaussian copula prices.

### Bespoke Equivalent Strikes

The practical implementation of both the NM and ATM methods is trivial whereas the PM and TLP mappings require some numerical work. In principle, both these methods could be implemented by a root search procedure, where we guess a value for  $K_S^{Eq}$ , read off the corresponding correlation from the calibrated BC surface, calculate the mapping parameter for the standard and bespoke portfolios and iterate until the two values coincide.

In practice, an alternative procedure may be more convenient. This involves the concept of *bespoke* equivalent strikes  $K_B^{Eq}$ , which are simply strikes on the bespoke portfolio that are equivalent to the standard strikes in the sense defined by the mapping rule. Finding bespoke equivalent strikes is numerically simpler than finding standard equivalent strikes because the corresponding correlation is already known from the calibration of the index. Therefore, the bespoke loss distributions only have to be built once for each standard strike, which may be a considerable advantage if computations on the bespoke are very time-consuming relative to those on the index.

Of course, the bespoke strikes of interest in a given trade do not usually coincide with any of the equivalent strikes obtained by this procedure so interpolation in the bespoke BC surface is required after the mapping stage. A potential disadvantage of this approach is therefore that we require the mapping to be well-behaved for all (or most of) the standard strikes rather than just for one or two bespoke strikes. In addition, the method may in fact be slower than the alternative if there are a large number of standard strikes (e.g. if we are mapping from tranchelets) or if computations on the bespoke are not much more time-consuming than those on the index.

Although bespoke equivalent strikes may be more convenient for computation, the standard indices are ultimately the source of our correlation information and standard equivalent strikes are therefore more useful for developing intuition about mapping.

### MAPPING STANDARD INDICES

In general, quantitative tests of mapping methods are hard to find, as there is less transparency in the prices of bespoke tranches than there is for the liquid indices. One possibility, however, is to investigate how a mapping performs for two standard indices by treating one as a bespoke and mapping it to the other. We can then compare the prices obtained from the mapping with the correct values observed in the market.

In this section, we present the results of this analysis using market data from 31 January 2007. We treat iTraxx S6 and CDX HY7 as bespoke portfolios and map them to the CDX IG7 index. The market spreads for CDX IG7 that we use are shown in Figure 1. The market and mapped prices for the standard iTraxx tranches are shown in Figure 2 and the calibrated and implied correlation skews are shown in Figure 3.

**Figure 1. CDX IG7 tranche and swap quotes at close of business on 31 January 2007**

Term	Tranche	Upfront Or Spread	Swap
5Y	0-3%	20.09	31.37
	3-7%	64.3	
	7-10%	12.3	
	10-15%	4.7	
	15-30%	2.4	
7Y	0-3%	38.95	43.53
	3-7%	176.9	
	7-10%	34.9	
	10-15%	15.0	
	15-30%	6.1	
10Y	0-3%	50.51	55.81
	3-7%	425.9	
	7-10%	92.4	
	10-15%	42.2	
	15-30%	13.7	

Source: Lehman Brothers.

Note: The equity tranche is quoted as an upfront percentage for a fixed 500bp running spread, while the remaining tranches are quoted in terms of a pure running spread in bp. The swap level is a reference spread in bp.

**Figure 2. iTraxx S6 tranche prices at close of business on 31 January 2007**

Term	Tranche	Market	NM	ATM	PM	TLP
5Y	0-3%	10.53	10.83	9.58	9.74	10.35
	3-6%	42.2	38.5	36.0	43.2	42.9
	6-9%	12.3	7.2	6.4	11.1	10.3
	9-12%	5.6	2.5	1.0	4.4	4.7
	12-22%	2.2	0.8	0.0	2.3	1.9
7Y	0-3%	25.51	27.11	24.21	23.95	25.49
	3-6%	111.5	103.2	90.6	106.8	109.8
	6-9%	33.4	19.7	17.9	27.4	27.6
	9-12%	15.5	7.2	6.4	13.3	13.1
	12-22%	5.2	2.9	0.4	6.3	5.6
10Y	0-3%	40.38	43.02	40.74	39.92	41.48
	3-6%	325.4	317.9	269.9	280.1	302.7
	6-9%	85.5	68.1	54.0	68.7	73.3
	9-12%	39.0	23.3	30.4	40.5	35.9
	12-22%	13.9	11.3	7.3	16.6	16.2

Source: Lehman Brothers.

Note: The equity tranche is quoted as an upfront percentage for a fixed 500bp running spread, while the remaining tranches are quoted in terms of a pure running spread in bp. The Market column gives market prices while the others give the values implied by mapping to CDX IG7.

These results show that for the 5Y and 7Y case the TLP approach generally works best, followed by PM. The same is true for the 10Y term, although here TLP significantly overestimates the equity tranche price. Both PM and ATM are better for this tranche. The NM method significantly overestimates the price of the equity tranche at all maturities,

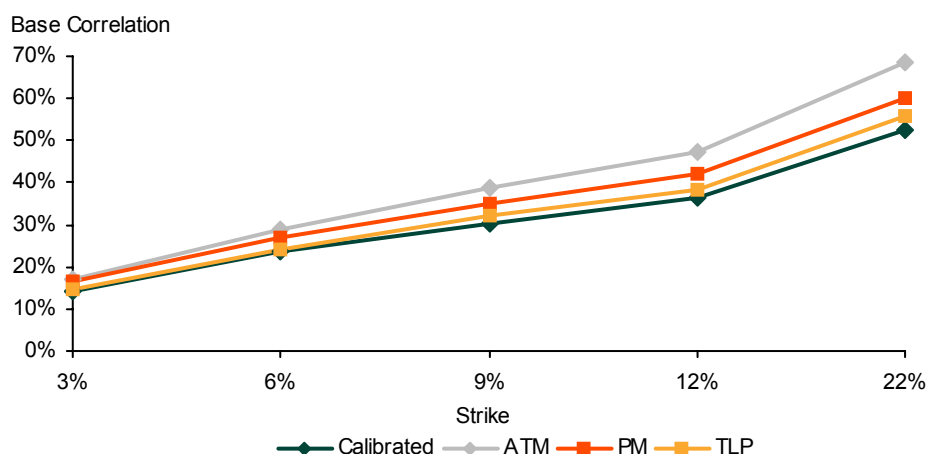


but otherwise it seems to work better than ATM which generally gives very poor results, especially for senior tranches.

A cut through the BC surface at the 5Y time horizon is shown in Figure 3. Here we plot the correlation skew calibrated to the iTraxx S6 market prices and the values implied by mapping to CDX IG7. Consistent with our observations on the tranche prices, we see that the skew obtained from the TLP mapping is closest to the calibrated curve, followed by PM and then ATM.

To check that our results are not restricted to the particular tight spread environment existing in the market at the end of January 2007, we repeated this analysis using data from 28 September 2006 and 30 October 2006 (see Appendix for details). On both dates, the results are qualitatively the same as those presented here and we conclude in general that the TLP mapping method performs best in a comparison of the CDX IG7 and iTraxx S6 indices, followed by PM and then ATM.

**Figure 3. iTraxx S6 5Y BC skew on 31 January 2007**

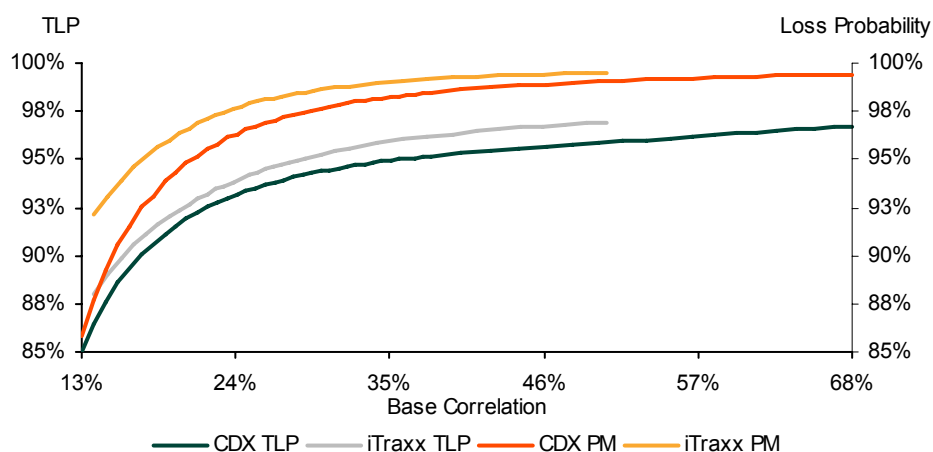


Source: Lehman Brothers.

Note: The lowest curve is calibrated from the market prices while the other curves are implied by mapping to the CDX IG7 index.

Figure 4 shows plots of TLP and cumulative loss probability against calibrated correlation for both CDX IG7 and iTraxx S6. As mentioned earlier, if the TLP mapping method worked perfectly then it would be an invariant between the portfolios at a fixed correlation and the two curves would coincide. Similarly, if the PM approach was correct, plots of cumulative loss probability against correlation for two portfolios would be identical. The Figure shows that neither the TLP nor the cumulative loss is an invariant between CDX IG7 and iTraxx S6 on 31 January 2007, although the TLP curves are close for values of correlation less than about 30%, corresponding to strikes below about 8%. The PM curves are quite far apart at low correlations but they are closer than the TLP curves at higher correlations (and hence strikes).

**Figure 4. CDX IG7 and iTraxx S6 5Y TLP vs BC (left axis and lower two curves) and cumulative loss probability vs BC (right axis and upper two curves) on 31 January 2007**



Source: Lehman Brothers.

Note: Corresponding curves should coincide if either TLP or cumulative loss is a mapping invariant.

CDX IG7 and iTraxx S6 are relatively similar portfolios in terms of their expected losses and average spread levels on 31 January 2007 (although the CDX index has significantly greater spread dispersion than iTraxx). A more extreme test of the methods is obtained by mapping CDX HY7 to CDX IG7 because in this case the spread levels are very different (the 5Y expected loss on HY7 is about 11.4% compared with about 1.6% for IG7). The results of this comparison for the liquid tranche prices of the high-yield index on 31 January 2007 are shown in Figure 5 while the calibrated and implied correlation skews are shown in Figure 6. Results for 28 September 2006 and 30 October 2006 are given in the Appendix.

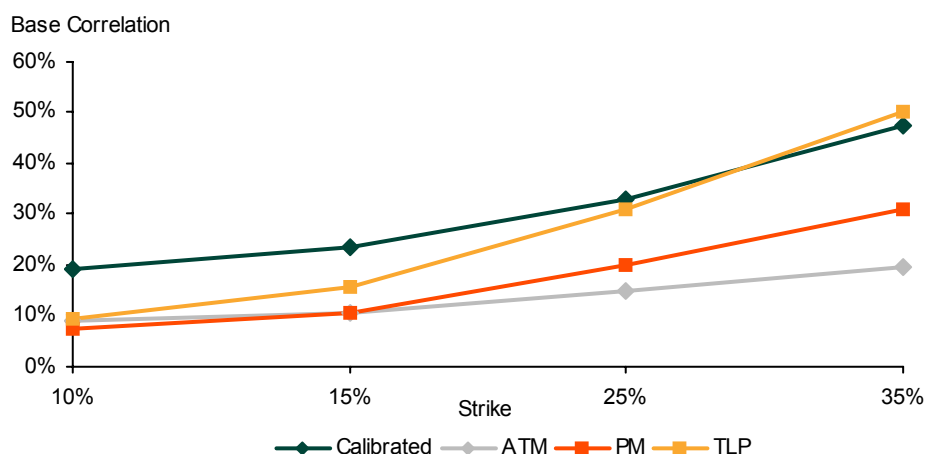
**Figure 5. CDX HY7 5Y tranche prices at close of business on 31 January 2007**

Term	Tranche	Market	NM	ATM	PM	TLP
5Y	0-10%	68.75	61.73	74.92	76.26	74.79
	10-15%	26.07	19.31	28.85	26.26	22.78
	15-25%	225.7	230.2	155.2	129.9	136.7
	25-35%	56.1	134.2	21.3	27.6	28.1

Source: Lehman Brothers.

Note: The first two tranches are quoted purely as an upfront percentage while the last two are quoted as a running spread in bp. The Market column gives market prices while the others give the values implied by mapping to CDX IG7.

All the mapping methods perform badly in this comparison, consistently putting too much risk in the equity tranche and too little risk in the senior part of the capital structure (NM is an exception). A possible explanation is that there is a limit to the amount a market participant would be willing to pay upfront for 5Y protection. The market therefore trades at lower levels for the high-yield equity tranches than that implied from the investment grade universe. The corresponding correlations are therefore higher than those predicted by mapping to CDX IG7, as shown in Figure 6. Since the expected portfolio loss is not a correlation-dependent quantity, the corollary of this is that the mapping methods put less risk in the senior tranches than is observed in the market.

**Figure 6. CDX HY7 5Y BC skew on 31 January 2007**

Source: Lehman Brothers.

Note: The upper curve is calibrated from the market prices while the other curves are implied by mapping to the CDX IG7 index.

## VALUE ON DEFAULT

One of our criteria for a good mapping method is stability with respect to small changes in the market environment. An important special case is the calculation of Value On Default (VOD), which is the change in the mark-to-market of a tranche position when a credit defaults. If the default is expected, the spread of the credit will be very wide (potentially thousands of bp), and there should be little difference in tranche valuations before and after the default. This will be true within the base correlation model only if the mapping method is continuous with respect to the default of a wide-spread name. Of the various methods considered in this article, this is the case only for the PM mapping, as we discuss below.

We can investigate theoretically how the mapping works for default of a high-spread name by considering the following two cases:

- A. A base tranche with detachment point  $K_A$  defined on a portfolio of  $N$  credits with one name trading at a very wide spread
- B. A base tranche with detachment point  $K_B = K_A - L_i$  defined on a portfolio of  $N-1$  credits, where  $L_i$  is the loss-given-default (lgd) of the high-spread name. The portfolio is the same as that in A except for the removal of the defaulted name.

Both portfolios are mapped to the same index and we consider instantaneous defaults so that all properties of the index are the same for the two mappings. Furthermore, we assume that the defaulting credit does not appear in the index. For simplicity, both the tranche detachment points and the lgd of the defaulting credit are given in absolute dollar amounts.

If the mapping method is continuous, the correlation for strike  $K_B$  on portfolio B should equal that for strike  $K_A$  on portfolio A, i.e., the equivalent standard strike should be the same for both cases. It is clear that this is true for the PM approach using the definition of the mapping invariant. If a name is certain to default, the portfolio loss distributions before and after this event are simply related by a translation equal to the lgd of the defaulting name. For example, the probability of zero loss after the default is equal to the previous probability of a loss equal to the lgd. To be precise, we have

$$P(L_T^A \leq K_A) = P(L_T^B \leq K_A - L_i) = P(L_T^B \leq K_B)$$

where  $L_T^A$  and  $L_T^B$  are the cumulative portfolio losses at the mapping maturity (e.g. 5Y) for portfolios A and B. The expression on the left of this equation is the quantity we map to the index before the default, while the expression on the right is the corresponding quantity after the default. The equality of the two expressions ensures continuity of the mapping through the default event under the PM methodology.

In contrast, neither the ATM nor the TLP approaches are continuous when a high-spread name defaults. This event reduces the absolute tranche strike and EPL by the same dollar amount, with the result that the ATM ratio  $\frac{K}{EPL}$  decreases for  $K < EPL$  and increases

for  $K > EPL$ . Thus, strikes below the bespoke EPL map to lower standard strikes after the default under ATM. In the usual case of an upward-sloping base correlation skew, these strikes will therefore be priced with a lower base correlation after default. The converse applies for strikes above the bespoke EPL. Only at a bespoke strike equal to the EPL is the mapping continuous in the event of default. For the case of a mezzanine tranche with attachment point below the EPL and detachment point above, the effect of the mapping will be to make the tranche safer after the default, over and above the effect coming from the removal of the high-spread name.

For TLP, the effect of the default is to reduce the absolute ETL for all surviving base tranches by the same dollar amount as the absolute EPL. Since the ratio of ETL to EPL does not exceed one, this means that the TLP decreases for all bespoke strikes and they map lower on the index, producing a discontinuous VOD. If the skew is upward-sloping, all bespoke strikes will be priced with a lower correlation after the default. The equity tranche will therefore become more risky, and its VOD, although non-zero, will have the correct sign. This is confirmed by our numerical calculations, discussed below. The same is not necessarily true for more senior tranches, however, as these depend on the slope of the base correlation skew as well as its absolute value.

We investigated the effect of a default numerically using the case of the iTraxx S6 portfolio mapped to CDX IG7 on 31 January 2007. We considered the change in the value of a 5Y, short-protection, 10MM USD position on the standard tranches of the iTraxx portfolio as the spread on a single name in that portfolio widened from its market value to 500bp, 5,000bp, 10,000bp, and finally to a level at which its survival probability for a single day was  $10^{-6}$ , i.e. a one-day default scenario. We compared these valuations with the case that the name had actually defaulted and was removed from the portfolio, with the tranche strikes adjusted accordingly.

Comparing the value after default with the base market we found that all the mapping methods gave negative VODs for all tranches, as one would expect for a short-protection position. The TLP and PM methods gave similar results for this case and also when the name defaulted from a spread of 500bp. However, as expected, only the PM approach gave VODs that remained negative as the name traded wider and were continuous at the point of default.

The results from ATM were generally reasonable only in the case of a sudden default of a low-spread name. For the one-day default scenario, the VOD for this method was large and positive for all tranches. Despite the fact that the equity tranche must cover the losses-on-default, a protection seller on this tranche benefits from a positive mark-to-market of about 56,000 USD from the default event under ATM. VOD was also discontinuous for the TLP mapping, with the one-day default scenario generating a change in mark-to-market of about -76,000 USD for the equity tranche. The fact that this quantity is negative is consistent with our discussion above and is a distinct improvement over ATM. The VODs for more senior tranches, however, were positive under TLP but significantly smaller than for ATM.

Based on this analysis, we conclude that the PM mapping works best for the calculation of VOD for distressed names. For investment grade names, however, there is little to distinguish the VODs from TLP and PM, and both give reasonable results.

## MAPPING BESPOKE PORTFOLIOS

In this section we discuss the results obtained from mapping a range of generic bespoke portfolios to the CDX IG7 index. Our analysis is necessarily more qualitative than before as we no longer have an absolute measure of correctness for the bespoke prices as we had for the standard indices. We consider six portfolios with low, medium and high spreads and either zero or substantial dispersion. All portfolios are priced in USD and contain 100 names trading with flat spread curves and a deterministic recovery rate of 40%. We will refer to these portfolios using the following names:

- Homogeneous 20bp: 100 names at 20bp.
- Homogeneous 40bp: 100 names at 40bp.
- Homogeneous 100bp: 100 names at 100bp.
- Dispersed 20bp: 50 names at 10bp and 50 names at 30bp.
- Dispersed 40bp: 50 names at 20bp and 50 names at 60bp.
- Dispersed 100bp: 50 names at 50bp and 50 names at 150bp.

The pricing results for a number of 5Y maturity tranches of the homogeneous portfolios are shown in Figure 7. A number of features of the data are of interest. First, we note that for the safe 20bp portfolio the ATM method performs very badly, putting hardly any risk in the 10-30% region and producing an arbitrage where the super senior 30-100% tranche pays a higher spread than more junior tranches. The same phenomenon is also seen for NM in this case, whereas both PM and TLP produce arbitrage-free quotes for these tranches. Overall, however, the differences between the prices generated by the various methods are smaller than we might have expected, especially for the two riskier portfolios.

Another feature of the data is that for portfolios that are riskier than the index (the 40bp and 100bp cases) the various mapping methods increase the risk in the junior part of the capital structure and decrease it in the senior, as compared with NM. This effect is clearly demonstrated in Figure 8, where we show how the protection PV is distributed across the capital structure for the 100bp portfolio. It is clear that all the methods increase the relative risk in the equity and junior mezzanine tranches at the expense of the senior tranches as compared with NM. The situation is reversed for the 20bp portfolio, which is safer than the index. Here both PM and TLP decrease the risk in the equity and increase it in more senior tranches compared with NM.

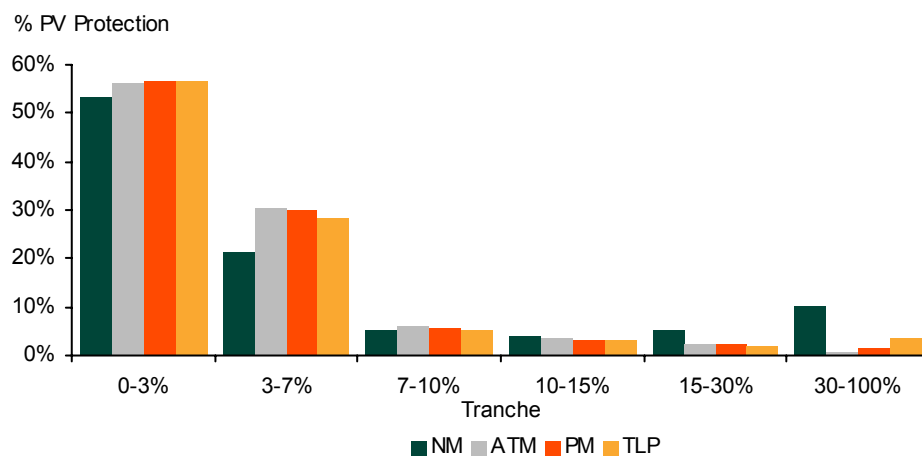
**Figure 7. 5Y tranche prices for bespoke portfolios mapped to the CDX IG7 index**

Strikes	Homogeneous 20bp				Homogeneous 40bp				Homogeneous 100bp			
	NM	ATM	PM	TLP	NM	ATM	PM	TLP	NM	ATM	PM	TLP
3%	7.47	5.68	6.06	6.96	28.91	30.00	29.82	30.27	63.84	68.48	69.01	69.03
7%	22.3	17.4	28.1	27.2	106.8	112.6	119.6	118.4	571.3	844.7	826.3	786.1
10%	2.7	0.2	6.0	6.3	22.9	22.5	25.2	23.0	176.2	203.4	187.1	180.6
15%	0.2	0.1	2.4	2.6	8.6	9.0	10.7	9.0	81.5	68.4	64.4	63.0
30%	0.0	0.1	2.0	1.2	3.9	3.9	4.2	2.8	35.1	16.1	16.1	13.2
100%	1.3	4.9	1.6	0.9	3.7	2.3	1.8	2.0	14.2	1.3	2.5	5.3

Source: Lehman Brothers.

Note: The equity tranche is quoted as an upfront percentage for a 500bp running spread while the other tranches are quoted as a pure running spread in bp.

**Figure 8. Tranche risk allocation (% PV Protection) for the homogeneous 100bp portfolio as implied by different mappings to CDX IG7.**



Source: Lehman Brothers.

Note % PV Protection is calculated as the ratio of the PVs of protection for the tranche and the portfolio.

Figure 9 shows pricing results from a similar analysis with the dispersed portfolios and many of the same comments apply here. As before, we see arbitrage in the quotes for the 20bp portfolio at senior strikes for both NM and ATM. In general, we see rather small changes in the bespoke correlations for junior tranches as we add dispersion to the portfolios and all the mapping methods are consistent with the fact that greater dispersion should increase equity tranche spreads.

**Figure 9. 5Y tranche prices for bespoke portfolios mapped to the CDX IG7 index**

Strikes	Dispersed 20bp				Dispersed 40bp				Dispersed 100bp			
	NM	ATM	PM	TLP	NM	ATM	PM	TLP	NM	ATM	PM	TLP
3%	7.59	5.87	6.19	7.01	29.26	30.29	30.12	30.46	64.54	68.95	69.63	69.62
7%	22.2	18.6	27.6	26.3	107.6	112.2	116.4	114.3	584.6	838.0	815.6	771.2
10%	3.0	0.3	5.7	6.0	23.4	22.4	24.1	21.9	180.1	195.1	176.4	171.3
15%	0.5	0.1	2.3	2.4	9.3	9.2	10.0	8.4	83.9	63.4	59.4	58.2
30%	0.4	0.1	1.8	1.3	4.6	4.1	3.9	2.9	36.4	14.0	14.4	12.1
100%	1.0	3.8	1.5	0.9	2.9	1.8	1.6	1.9	11.0	0.9	2.2	5.1

Source: Lehman Brothers.

Note: The equity tranche is quoted as an upfront percentage for a 500bp running spread while the other tranches are quoted as a pure running spread in bp.

## MAPPING BESPOKE PORTFOLIOS TO MULTIPLE INDICES

The dispersed 100bp portfolio, comprising 50 names at 50bp and 50 names at 150bp, is an example of a portfolio with clusters of names from two distinct market sectors, in this case investment grade and high yield. Intuitively, we expect that different correlations should be used for the 50bp names and the 150bp names, so it is not really sensible to price such a portfolio with a single flat correlation. Instead, we would like to use a correlation obtained from the high-yield market for the riskier names and a correlation from the investment grade market for the safer ones. The same issue arises if a portfolio contains clusters of names from different domiciles, e.g. 50% US names and 50% European names. In this case, we would like to map the US names to the CDX IG index and European names to the iTraxx index.

Of course, such portfolios really require a multi-factor model for an accurate representation of the risks involved. At a minimum, however, we should at least modify the mapping method for such portfolios. In this section, we consider two different ways of treating the dispersed 100bp portfolio which we call PV averaging and the barbell method. Both of these approaches are straightforward to implement and make use of the existing infrastructure developed for mapping to a single index. Although we restrict our discussion here to the case of mapping to two indices, both methods can be generalized in a straightforward manner.

- **PV Averaging:** We map the bespoke portfolio separately to both CDX IG7 and CDX HY7 and value the protection and premium legs. The final values for the bespoke portfolio are the weighted average of these results, where the weighting for each index is determined from the proportion of names in each cluster. In our example, we have a portfolio with 50% low and high spread names so we choose an equal weighting for the IG and HY portfolios.
- **Barbell mapping:** The second approach – the “barbell” method – also involves a separate mapping to the two indices as a first step. Subsequently, however, we assign the correlation from the IG mapping to the low-spread names and the correlation from the HY mapping to the high-spread names to produce a portfolio with heterogeneous correlations. A single calculation with these correlations gives the tranche prices.

Ideally, the barbell mapping would be calculated self-consistently so that heterogeneous correlations in the bespoke are used to calculate the equivalent standard strikes. In addition, the mapping to the two indices should be done simultaneously so that they are equivalent to each other as well as to the bespoke. This requires a more complex numerical algorithm, however, and in this article we restrict our discussion to the simpler approach outlined above.

We compare the prices obtained from these methods for the dispersed 100bp portfolio with those from a separate TLP mapping to each of the IG and HY indices (Figure 10). The first two columns show that the HY mapping generally gives higher correlations than the IG mapping in this case, with the result that the equity tranche is priced lower. Further up the capital structure the correlation from the HY mapping is both higher and flatter than that from the IG mapping so the senior tranches are priced at a greater spread.

Unsurprisingly, both the barbell and PV averaging methods give prices in between the extremes of the pure IG and pure HY results. Comparing the barbell case to the IG mapping, we see that the differences arise because we have given the riskier names a higher correlation, with the result that junior tranches are less risky and senior tranches are more risky. Alternatively, comparing the barbell results to the pure HY mapping, the differences arise because we have given the safer names a lower correlation, with the result that junior tranches are more risky and senior tranches are less risky.



**Figure 10 5Y tranche prices for the dispersed 100bp portfolio under various mapping assumptions**

Strikes	Correlation		Upfronts And Spreads			
	IG7	HY7	IG7	HY7	PV Average	Barbell
3%	8.20%	16.23%	69.62	61.84	65.73	64.20
7%	13.41%	21.59%	771.2	732.2	751.7	748.0
10%	18.74%	25.12%	171.3	257.9	214.2	233.7
15%	27.57%	30.62%	58.2	112.0	85.0	94.0
30%	53.77%	50.48%	12.1	25.0	18.5	19.5
100%	N/A	N/A	5.1	4.1	4.6	4.5

Source: Lehman Brothers.

Note: The equity tranche is quoted as an upfront percentage for a 500bp running spread while the other tranches are quoted as a pure running spread in bp. The first two columns give the 5Y correlation skew obtained by mapping purely to CDX IG7 or purely to CDX HY7 using the TLP method and the next two columns give the corresponding prices. The final columns give the results obtained for the PV averaging and barbell methods described in the text.

The barbell and PV averaging methods differ more substantially in the calculation of single-name deltas. Suppose for the barbell case that we map one of the 150bp names to the IG index instead of the HY index and one of the 50bp names to HY rather than IG. The PV averaging method is not sensitive to these changes and will give the same delta for all the 50bp names and all the 150bp names. Under the barbell mapping, however, the 150bp name mapped to IG will have a different delta compared with the remaining 150bp names mapped to HY, and similarly for the 50bp names.

This is demonstrated in Figure 11, which shows the single-name deltas for a 10MM USD protection leg on each tranche. The barbell results are intuitive in that if a name is mapped to HY, its delta is lower for the equity tranche and higher further up the capital structure than if it is mapped to IG. This is consistent with the fact that correlations mapped from the HY index are greater than those from the IG index for this portfolio. The delta from PV averaging usually falls between the two barbell results but the junior mezzanine tranche is a notable exception. A more detailed discussion of how single-name deltas vary over the capital structure and their dependence on spread and correlation levels is given in reference [2].

The fact that the barbell method uses heterogeneous correlations and can distinguish the different risks for names in different market sectors makes the barbell method more appealing as a mapping methodology than the PV averaging approach.

**Figure 11. Tranche deltas for the dispersed 100bp portfolio using TLP mapping with both PV averaging and the barbell method**

	50bp Name			150bp Name		
	PV Average	Barbell		PV Average	Barbell	
Tranche		IG	HY		IG	HY
0-3%	253.9	309.2	232.7	300.5	347.9	289.2
3-7%	378.7	362.0	350.5	390.5	365.7	372.0
7-10%	191.1	172.1	209.2	176.9	164.0	190.9
10-15%	91.8	85.1	108.3	78.4	76.7	88.3
15-30%	23.2	22.7	27.0	20.6	21.3	21.7
30-100%	7.4	7.4	7.2	2.3	2.3	2.3
0-100%	41.7	41.7	41.7	38.6	38.6	38.6

Source: Lehman Brothers.

Note: The values shown are the change in PV of a pure 5Y, 10MM USD protection leg on each tranche when one of the names in the portfolio is bumped by 1bp flat. For the barbell case, the columns marked IG or HY indicate that the perturbed name is mapped to the IG or HY index respectively. The delta for the PV averaging method is the same for both cases.

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## CONCLUSIONS

We have discussed a number of methods for obtaining BC surfaces for bespoke portfolios and tested them by mapping between standard indices and by mapping a range of generic bespoke portfolios to the CDX IG7 index. Our results for mapping iTraxx S6 to CDX IG7 show that the TLP method performs best in this case, followed by PM and then ATM. None of the methods performs satisfactorily for mapping CDX HY7 to CDX IG7, which is evidence that the high-yield and investment grade correlation markets are genuinely different from each other.

Of the various mapping methods we considered, we showed that only PM was continuous in the case of the default of a high-spread name. PM may therefore be preferable when a portfolio contains distressed credits. In the case of a sudden default of a name trading below about 500bp, however, there was little to distinguish the TLP and PM methods; both gave reasonable results. The ATM method generally performed poorly in this analysis.

For bespoke portfolios, we obtained sensible results from both TLP and PM. The ATM method, however, performed poorly, especially for mapping to low-risk portfolios, and could generate arbitrage in the quotes. We also described two approaches for treating bespokes mapped to more than one index, namely PV averaging and the barbell method. We argued that the barbell method gives more appealing results because it uses heterogeneous correlations and produces different single-name deltas for names in different market sectors.

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## REFERENCES

- [1] O’Kane and Livesey (2004), “Base Correlation Explained”, Lehman Brothers Fixed Income Research, *Quantitative Credit Research Quarterly*, November 2004, pp. 3-20.
- [2] Schloegl and Greenberg (2003), “Understanding Deltas of Synthetic CDO Tranches”, Lehman Brothers Fixed Income Research, *Quantitative Credit Research Quarterly*, November 2003, pp. 45-54.

## APPENDIX

This Appendix gives tranche prices and correlation skews for iTraxx S6 and CDX HY7 obtained directly from the market and via mapping to the CDX IG7 index using market data from close of business on 28 September 2006 and 30 October 2006. The analysis is the same as that presented in the main article for 31 January 2007. The results show that our earlier conclusions were not specific to the market environment of early 2007.

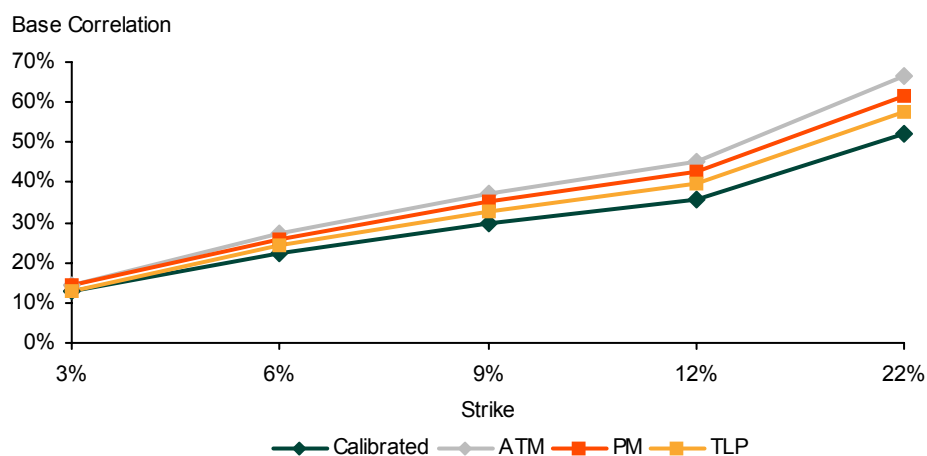
**Figure 12. iTraxx S6 tranche prices at close of business on 28 September 2006**

Term	Tranche	Market	NM	ATM	PM	TLP
5Y	0-3%	19.94	21.04	19.10	19.23	19.82
	3-6%	75.0	41.3	58.9	64.7	66.2
	6-9%	22.2	20.2	14.4	17.4	17.8
	9-12%	10.6	0.0	6.3	8.9	9.4
	12-22%	4.3	0.0	1.5	4.1	4.4
7Y	0-3%	37.37	39.31	37.12	36.94	37.71
	3-6%	190.0	161.6	179.6	187.4	189.9
	6-9%	54.8	53.7	44.8	49.0	49.2
	9-12%	26.7	0.0	21.2	23.8	23.7
	12-22%	8.9	0.0	5.6	8.4	8.9
10Y	0-3%	49.77	52.22	51.08	50.89	51.34
	3-6%	472.3	449.2	450.5	452.3	463.7
	6-9%	124.9	119.8	104.2	110.4	113.4
	9-12%	56.2	28.1	59.1	61.7	58.2
	12-22%	19.5	10.8	19.1	22.3	22.8

Source: Lehman Brothers.

Note: The equity tranche is quoted as an upfront percentage for a fixed 500bp running spread, while the remaining tranches are quoted in terms of a pure running spread in bp. The Market column gives market prices while the others give the values implied by mapping to CDX IG7.

**Figure 13. iTraxx S6 5Y BC skew on 28 September 2006**



Source: Lehman Brothers.

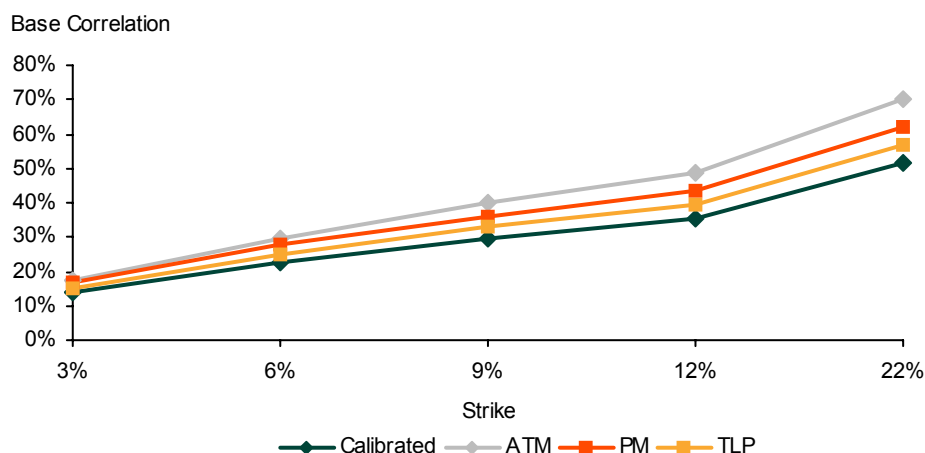
Note: The lowest curve is calibrated from the market prices while the other curves are implied by mapping to the CDX IG7 index.

**Figure 14. iTraxx S6 tranche prices at close of business on 30 October 2006**

Term	Tranche	Market	NM	ATM	PM	TLP
5Y	0-3%	12.29	12.74	11.03	11.27	11.87
	3-6%	54.7	45.7	42.6	49.1	50.1
	6-9%	13.4	9.4	8.5	13.3	13.5
	9-12%	5.6	3.6	1.5	5.2	6.0
	12-22%	2.4	1.1	0.0	2.5	2.5
7Y	0-3%	28.75	29.62	27.07	27.01	28.01
	3-6%	140.8	136.1	123.5	134.3	137.8
	6-9%	40.4	30.6	31.0	36.6	36.8
	9-12%	19.4	13.2	14.1	18.5	18.2
	12-22%	6.9	4.9	2.3	6.8	7.1
10Y	0-3%	43.48	44.76	43.21	42.95	43.66
	3-6%	375.1	377.2	335.6	341.8	356.7
	6-9%	102.7	90.0	78.8	86.7	88.4
	9-12%	41.6	35.0	48.4	52.6	47.9
	12-22%	12.7	15.8	12.9	18.2	18.6

Source: Lehman Brothers.

Note: The equity tranche is quoted as an upfront percentage for a fixed 500bp running spread, while the remaining tranches are quoted in terms of a pure running spread in bp. The Market column gives market prices while the others give the values implied by mapping to CDX IG7.

**Figure 15. iTraxx S6 5Y BC skew on 30 October 2006**

Source: Lehman Brothers.

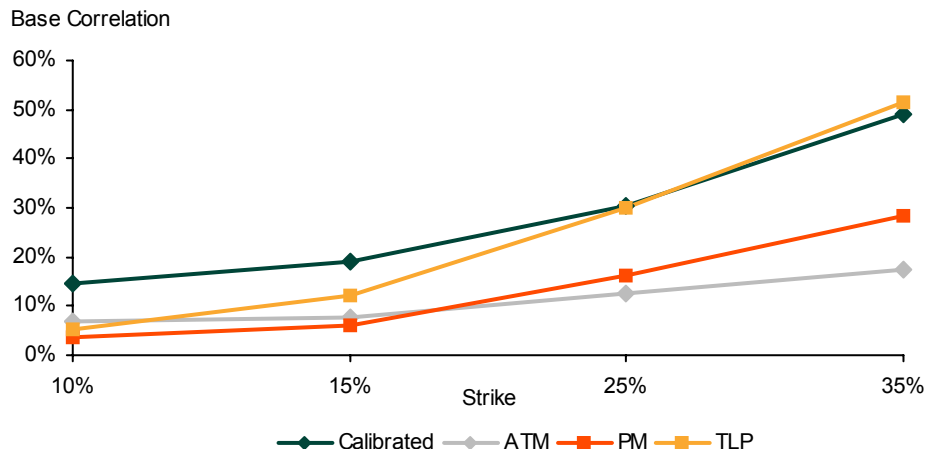
Note: The lowest curve is calibrated from market prices while the other curves are implied by mapping to the CDX IG7 index.

**Figure 16. CDX HY7 5Y tranche prices at close of business on 28 September 2006**

Term	Tranche	Market	NM	ATM	PM	TLP
5Y	0-10%	82.97	75.31	86.50	87.78	87.13
	10-15%	45.47	33.42	55.35	56.60	47.10
	15-25%	392.1	390.5	374.4	297.6	281.6
	25-35%	88.9	210.7	53.4	54.8	67.1

Source: Lehman Brothers.

Note: The first two tranches are quoted purely as an upfront percentage while the last two are quoted as a running spread in bp. The Market column gives market prices while the others give the values implied by mapping to CDX IG7.

**Figure 17. CDX HY7 5Y BC skew on 28 September 2006**

Source: Lehman Brothers.

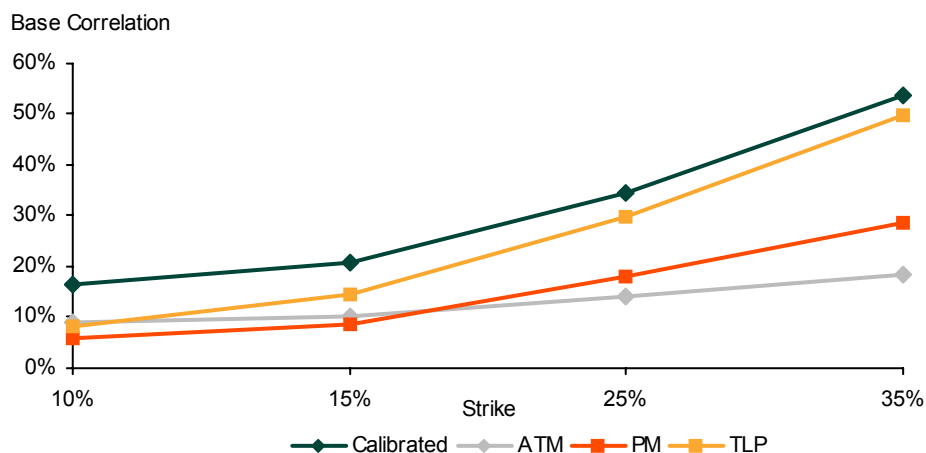
Note: The upper curve is calibrated from the market prices while the other curves are implied by mapping to the CDX IG7 index.

**Figure 18. CDX HY7 5Y prices at close of business on 30 October 2006**

Term	Tranche	Market	NM	ATM	PM	TLP
5Y	0-10%	78.38	70.51	82.47	84.14	82.89
	10-15%	37.22	27.69	44.39	43.64	36.99
	15-25%	294.0	321.8	289.8	232.5	235.9
	25-35%	70.0	179.7	42.6	46.4	49.5

Source: Lehman Brothers.

Note: The first two tranches are quoted purely as an upfront percentage while the last two are quoted as a running spread in bp. The Market column gives market prices while the others give the values implied by mapping to CDX IG7.

**Figure 19. CDX HY7 5Y BC skew on 30 October 2006**

Source: Lehman Brothers.

Note: The upper curve is calibrated from the market prices while the others are implied by mapping to the CDX IG7 index.

# Idiosyncratic Portfolio Risk in non-Normal Markets

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*We consider security-level return factor models with a heavy-tailed idiosyncratic component. We model the portfolio-level idiosyncratic component as a  $t$  distribution. The tail index, i.e. the degrees of freedom, of this distribution is accurately modeled as a function of two inputs. First, the risk-adjusted average of the single-security tail index: other things equal, portfolios of heavier-tailed securities give rise to heavier-tailed idiosyncratic terms. Second, the level of diversification in the portfolio: large and highly diversified portfolios of heavy-tailed securities give rise to quasi-normal idiosyncratic portfolio-level shocks. In order to suitably quantify diversification we introduce an entropy-based risk-adjusted measure.*

## 1. INTRODUCTION

Consider a market of  $N$  securities, whose returns are properly modeled by a suitable factor model:

$$R_n = f_n(\mathbf{X}) + \epsilon_n \quad (1)$$

where  $n = 1, \dots, N$ . In this expression  $\mathbf{X}$  is a  $K$ -dimensional vector of systematic factors that affect all the securities in the market;  $f_n$  is a security-specific pricing function; and  $\epsilon_n$  is an idiosyncratic risk independent across securities.

This formulation is very general. Among others, it includes standard APT-like linear factor models; more complex quadratic pricing functions such as the theta-delta-gamma-vega approximation; full repricing in terms of explicit factors. More details on the above and other models can be found in Meucci (2005). For a notable example in the industry see Dynkin *et al.* (2005).

Consider a generic portfolio in the market (1), as represented by the portfolio weights  $\mathbf{w}$ . Note that we do not assume that the weights sum to one: indeed, the portfolio  $\mathbf{w}$  can represent leveraged positions as well as allocations relative to a benchmark.

The total return  $R$  on the portfolio is the weighted average of the returns of the single securities. Therefore, the total return factors into the systematic component and the idiosyncratic component:  $R \equiv S + I$ , where  $S \equiv \sum_{n=1}^N w_n f_n(\mathbf{X})$  and the aggregate idiosyncratic term reads:

$$I \equiv \sum_{n=1}^N w_n \epsilon_n \quad (2)$$

If estimating and modeling the return of a single security is an arduous task, aggregating distributions at the portfolio level is an even harder problem.

For the systematic component one can make analytically tractable assumptions that hold true in approximation, see e.g. RiskMetrics (1996). Alternatively, results can be obtained via Monte Carlo simulations, because the number of common factors is typically much less than the number of securities involved. see Glasserman (2004). Hybrid approaches are also possible, see Albanese *et al.* (2004).

For the idiosyncratic component, the aggregation (2) of the potentially very large number of idiosyncratic shocks cannot be performed via Monte Carlo simulations in a quick and efficient way. Therefore, one needs to resort to approximate analytical results. Typically, the idiosyncratic shocks are modeled as normally distributed, where the mean is set to zero without loss of generality:

$$\epsilon_n \sim N(0, \psi_n^2) \quad (3)$$

see for instance Hamilton (1994) and Campbell *et al.* (1997). This way the portfolio-level aggregation of idiosyncratic risk is immediate. Indeed, under the normal assumption the idiosyncratic term at the portfolio level is also normal:

$$I \sim N\left(0, \sum_{n=1}^N w_n^2 \psi_n^2\right) \quad (4)$$

The normal assumption (3) is violated in several markets: most notably, the occurrence of extreme events induces heavy tails, see e.g. Rachev (2003). This is the case, for instance, in the credit world. Nevertheless, the normal assumption (4) becomes acceptable at the aggregate portfolio level when the number of securities is large and the portfolio is not concentrated in specific securities. Indeed, under these assumptions the central limit theorem dominates and (4) becomes a very good approximation.

However, portfolio managers monitor all sorts of positions, including those that are highly concentrated in specific securities. In such cases, the portfolio-level normal assumption is no longer valid. Hyung and DeVries (2005) discuss this issue in the asymptotic limit, namely for extreme events that extend to infinity.

Here we discuss a methodology to quickly and accurately compute the whole distribution of the portfolio, including the extreme tails, also for finite, non-asymptotic, tail levels. To achieve this, we model the aggregate idiosyncratic term as a  $t$  distribution. The tail parameter of this distribution is a function of the overall tail-thickness in the market and of the level of portfolio diversification: if diversification is high, the portfolio-level distribution of idiosyncratic risk is normal, as prescribed by the central limit theorem; if diversification is low and if the market is heavy tailed, the portfolio-level idiosyncratic risk displays heavy tails. In Section 2 we introduce the rationale behind the aggregate  $t$ -model, based on a set of necessary properties that need to be satisfied; in Section 3 we model the level of diversification in the portfolio in terms of the entropy of a suitable risk-adjusted distribution; in Section 4 we calibrate the parameters of the aggregate  $t$ -model based on the overall tail-thickness of the market and on the portfolio diversification; in Section 5 we present the performance of the model in an empirical study; in Section 6 we discuss directions for further research and we conclude.

## 2. AGGREGATION MODEL

First of all, we generalize the security-level normal assumption for the idiosyncratic risk (3) to a flexible parametric distribution that allows for heavy tails. In particular, we choose the Student  $t$  distribution:

$$\epsilon_n \sim \text{St}(\nu_n, \mu_n, \sigma_n^2). \quad (5)$$

In this expression the degrees of freedom  $\nu_n$  characterize the tail behavior of the idiosyncratic risk; the location parameter  $\mu_n$  can be set to zero without loss of generality; and  $\sigma_n^2$  represents the square dispersion parameter, which is proportional to the variance  $\psi_n^2 \equiv \sigma_n^2 \nu_n / (\nu_n - 2)$ . We assume  $\nu_n > 2$  in such a way that the variance is defined.



The exact distribution of the aggregate idiosyncratic term (2) under the assumption (5) cannot be computed either analytically or numerically in real time. Our plan is to approximate the exact aggregate distribution via a parsimonious parametric model. In order to implement the model, its parameters must be an analytical function of the set of market inputs  $(v_n, \mu_n, \sigma_n^2)$  as well as of the portfolio weights  $w_n$ . Furthermore, the aggregate model should satisfy the following properties:

- (i) The aggregate must be a symmetric and bell-shaped distribution.
- (ii) The expected value of the aggregate distribution must be null.
- (iii) The variance of the aggregate distribution must be the weighted average of the variances of the single securities.
- (iv) When the portfolio is concentrated in one position, the aggregate distribution must coincide with the security-level idiosyncratic term.
- (v) When the portfolio is extremely diversified, the aggregate distribution must be normal as in (4), in accordance with the central limit theorem.

Finally, suppose that we subdivide a given portfolio into a few sub-portfolios. The model for the direct aggregation (2) of all the idiosyncratic terms in the original portfolio must equal the two-step aggregation which first computes the idiosyncratic terms in the different sub-portfolios and then combines them into one single number. In other words:

- (vi) The aggregate model must be self-consistent.

We claim that for suitable parameters  $\tilde{\nu}$  and  $\tilde{\sigma}^2$  the  $t$  distribution:

$$I \sim \text{St}(\tilde{\nu}, 0, \tilde{\sigma}^2) \quad (6)$$

represents an adequate aggregate model. As we show in Section 4, the aggregate model (6) satisfies the above conditions (i)-(vi). However, a model that satisfies those conditions is not necessarily adequate. In order for a model to be adequate it must also accurately approximate the true aggregate distribution (2) in a very broad range of situations: we show this in Section 5.

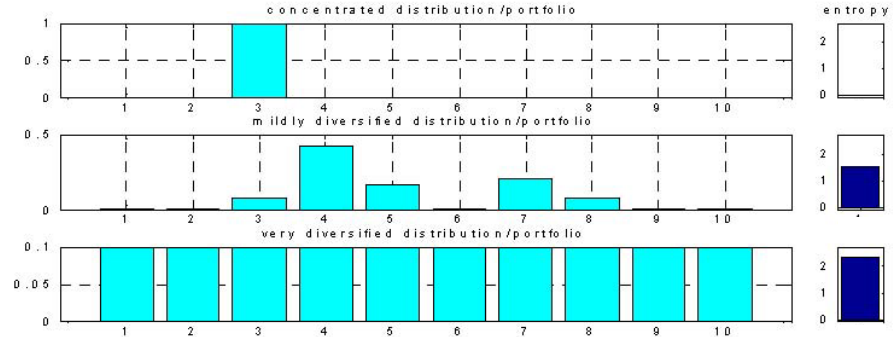
### 3. ENTROPY-BASED DIVERSIFICATION

Intuitively, the choice of the parameters depends on the portfolio diversification. In order to quantify this concept we introduce the risk-adjusted portfolio weights:

$$\tilde{w}_n \equiv \frac{\psi_n^2 w_n^2}{\sum_{m=1}^N \psi_m^2 w_m^2}, \quad (7)$$

where we used the fact that the idiosyncratic terms are independent.

Note that the risk-adjusted portfolio weights sum to one. Therefore, we can interpret them as a probability measure on the securities. We can easily establish a relationship between the diversification of the portfolio and the shape of the probability defined by the risk-adjusted portfolio weights (7) (Figure 1). When this probability density is close to uniform, i.e. each security is assigned an equal mass  $\tilde{w}_n \approx 1/N$ , the portfolio is highly diversified. When the probability density is concentrated, i.e. a specific security  $\hat{n}$  is such that  $\tilde{w}_{\hat{n}} \approx 1$ , so is the portfolio.

**Figure 1. Risk-adjusted portfolio weights as a probability measure**

Source: Lehman Brothers

From the above discussion it follows that we can measure diversification in terms of the dispersion of the probability defined by the risk-adjusted portfolio weights (7). The standard measure of dispersion for a probability is its entropy:

$$\mathcal{E} \equiv - \sum_{n=1}^N \tilde{w}_n \ln(\tilde{w}_n), \quad (8)$$

where the limit is considered when the weight is null. In Figure 1 we display the entropy for significant cases. Note that the entropy is never negative; it reaches its minimum value  $\underline{\mathcal{E}} \equiv 0$  when the probability mass is concentrated in the single  $\hat{n}$ -th position  $\tilde{w}_{\hat{n}} \equiv 1$ ; it increases with the dispersion of the probability; and it reaches its maximum value  $\bar{\mathcal{E}} \equiv \ln(N)$  when the probability density is uniform, i.e. each security is assigned an equal mass  $\tilde{w}_{\hat{n}} \equiv 1/N$ . Note that  $\bar{\mathcal{E}}$  grows to infinity as the number of securities in the portfolio increases: indeed, a larger market gives rise to more diversification opportunities. On the other hand, the logarithm grows extremely slowly: indeed, the marginal diversification effect of several new securities in a well-diversified market of a few dozen securities is minimal, see e.g. Luenberger (1998) and Meucci (2005).

#### 4. MODEL CALIBRATION

We can now proceed to calibrate the parameters  $\tilde{\nu}$  and  $\tilde{\sigma}$  of the model (6) according to the properties (i)-(vi) discussed in Section 2.

First of all, notice that (i) and (ii) are satisfied. In order to satisfy (iii), we impose that  $\tilde{\sigma}^2$  solve:

$$\frac{\tilde{\nu}}{\tilde{\nu} - 2} \tilde{\sigma}^2 \equiv \sum_{n=1}^N w_n^2 \psi_n^2. \quad (9)$$

The remaining parameter, namely the degrees of freedom  $\tilde{\nu}$ , determines the tail behavior of the portfolio-level idiosyncratic term. Therefore  $\tilde{\nu}$  must be a function of diversification, as represented by the entropy (8), and of the overall tail behavior of the securities (5) in the portfolio, as represented by the degrees of freedom  $\nu_n$ . Indeed, for a given level of diversification, a portfolio of heavy-tailed securities displays heavier tails than a portfolio of normal securities, whose distribution is normal. Therefore, we introduce the average<sup>1</sup> tail index  $\bar{\nu}$  defined as follows:

<sup>1</sup> We consider the inverse average instead of the arithmetic or geometric average because it performs better empirically, see Section 5.

$$\frac{1}{\bar{\nu}} \equiv \sum_{n=1}^N \frac{\tilde{w}_n}{\nu_n}. \quad (10)$$

In particular, in the null-entropy case of a portfolio concentrated in the single  $\hat{n}$ -th security, the average tail index is equal to that security's tail index  $\nu_{\hat{n}}$ . At the other extreme, in the maximum-entropy case of a diversified portfolio with equal risk-adjusted weights  $\tilde{w}_{\hat{n}} \equiv 1/N$ , the average tail index is properly biased toward its thick-tailed components.

To summarize, the portfolio-level tail index  $\tilde{\nu}$  is determined by  $\mathcal{E}$  and  $\bar{\nu}$ . According to property (iv) in Section 2 and the above remark,  $\tilde{\nu}$  must equal  $\bar{\nu}$  when the portfolio is concentrated in one single security, i.e. when the entropy is null. Furthermore, according to property (v)  $\tilde{\nu}$  must grow to infinity as the entropy  $\mathcal{E}$  increases.

The simplest functional form that satisfies these criteria reads:

$$\tilde{\nu} \equiv \bar{\nu} g(\mathcal{E}), \quad (11)$$

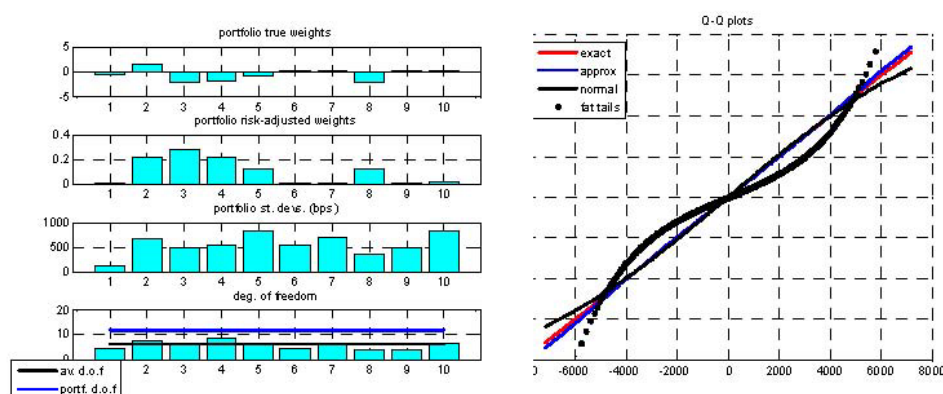
where  $g(0) \equiv 1$  and  $g$  grows to infinity with  $\mathcal{E}$ . Notice that the model defined by (6), (9) and (11) also satisfies the final self-consistency property (vi). Indeed, the aggregation process always “reads” directly on the “atoms”, i.e. the individual securities. In other words, given any two sub-portfolios  $A$  and  $B$ , then  $\tilde{\nu}_A \equiv \bar{\nu}_A g(\mathcal{E}_A)$  and  $\bar{\nu}_{Bg} \equiv \bar{\nu}_B g(\mathcal{E}_B)$ , which clearly holds true also for the special case of a one-security portfolio. To aggregate  $A$  and  $B$  one needs to consider all the securities in  $A$  and in  $B$  and therefore obtains unequivocally the result (11).

To calibrate the functional form of  $g$  in (11) we performed an extensive study along the lines of the empirical analysis discussed in Section 5. The function  $g(\mathcal{E}) \equiv 1 + 0.35\mathcal{E}^2$  proved to provide excellent fits to the true aggregate distribution of the portfolio-level idiosyncratic term (2) under very disparate assumptions on the portfolio and the market.

## 5. EMPIRICAL ANALYSIS

In this section we compare the aggregate model (6) with the true distribution (2), which we generate numerically by simulating  $10^6$  Monte Carlo scenarios for each idiosyncratic shock (5).

In Figure 2 we illustrate the prototype experiment. We consider a set of  $N$  securities,  $N \equiv 10$  in this case. We generate randomly long-short positions  $w_n$  that are independently and standard-normally distributed. We generate randomly the variances  $\psi_n$  of the  $t$ -distributed idiosyncratic shocks, uniformly over a range typical of the credit market. Finally, we generate randomly the degrees of freedom  $\nu_n$  of the  $t$ -distributed idiosyncratic shocks according to a Poisson distribution, shifted in such a way to guarantee that  $\nu_n > 2.5$ .

**Figure 2. Portfolio-level idiosyncratic risk model**

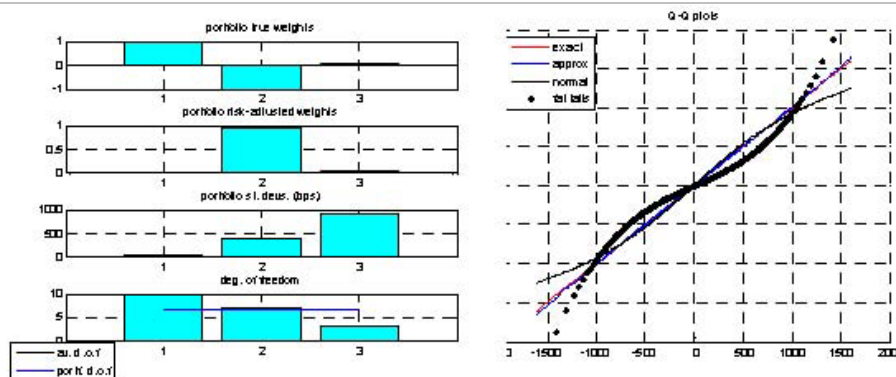
Source: Lehman Brothers

On the left-hand side in Figure 2 we display the weights  $w_n$ ; the standard deviations  $\sqrt{\psi_n}$ ; the degrees of freedom  $\nu_n$ ; and the risk-adjusted weights (7). In the plot for the degrees of freedom  $\nu_n$  we also superimpose the average tail index (10) and the portfolio tail index (11). On the right-hand side in Figure 2 we display the QQ plot of the true distribution against the approximation provided by the  $t$  model (6). To provide a comparative metric, we superimpose the QQ plot of the true distribution against the “perfect” model, i.e. the true distribution itself, which by definition is the  $\pi/4$  straight line through the origin. We also superimpose the QQ plot of the true distribution against the normal approximation (4). Finally, we superimpose the QQ plot of the true distribution against a moment-matching, very heavy-tailed distribution, namely the  $t$  distribution with 2.5 degrees of freedom.

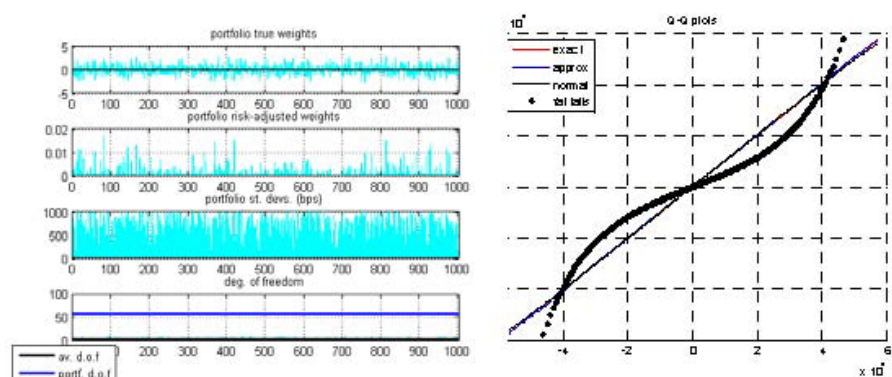
The QQ plots in Figure 2 show that the approximation provided in the above experiment by the  $t$  model (6) is excellent. To ascertain the general efficacy of the  $t$  model, we repeated the above experiment by randomizing also the number  $N$  of securities in a uniform range 1-1000. In all the experiments, the  $t$  model provides very accurate approximations of the true distribution. Below, we report a few experiments that we consider significant.

In Figure 3 we consider a prototype small credit portfolio. Three bonds of three different issuers in three different rating classes: a large long position in an AAA bond with duration of five years, standard deviation of 40bp and moderately heavy tails with 10 dof; a large short position in a high-yield bond with duration of five years, standard deviation of 390bp and heavy tails with 7 dof; and a small long position in a distressed bond which trades at price, standard deviation of 900bp and very heavy tails with 3 dof.

The QQ plots in Figure 3 show that the true distribution of the portfolio-level idiosyncratic risk is not close to normal but does not display extremely heavy tails. Instead, the true distribution is very well approximated by the  $t$  model (6) which in this case displays  $\tilde{\nu} \approx 8$  dof. Notice that the weighted average (10) of the dof is  $\bar{\nu} \approx 7$ . The 1 dof difference between the two numbers is due to the diversification effect induced by the portfolio entropy, see (11).

**Figure 3. Idiosyncratic risk model for a small credit portfolio**

Source: Lehman Brothers

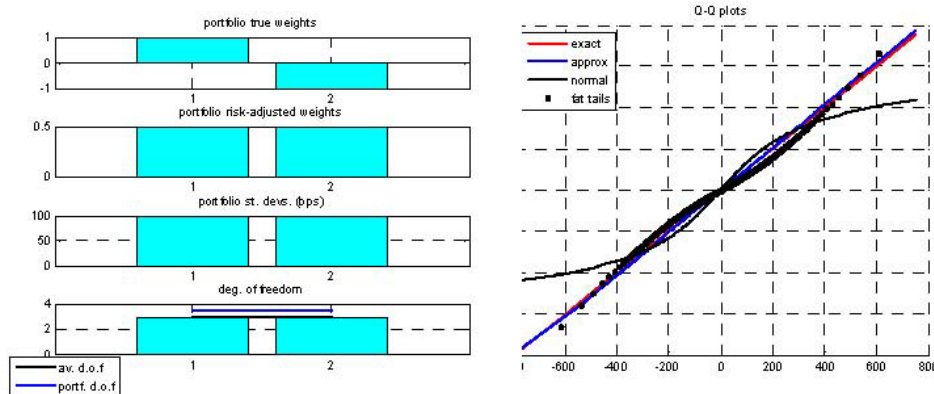
**Figure 4. Idiosyncratic risk model: large diversified portfolio**

Source: Lehman Brothers

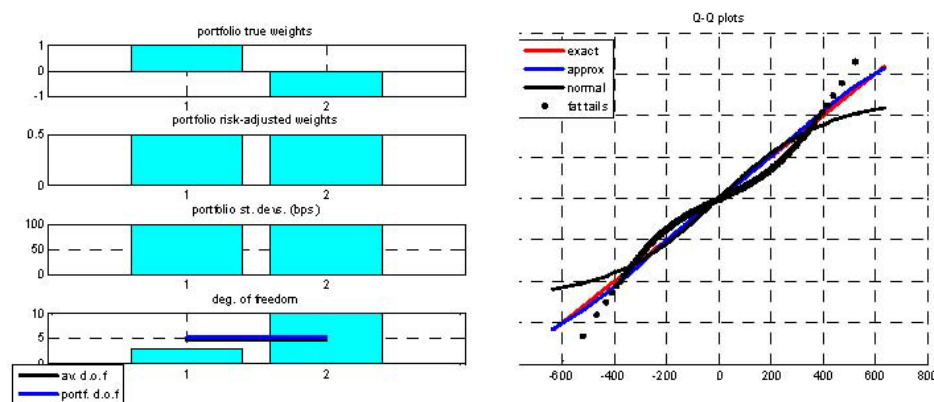
In Figure 4 we consider a prototype large diversified portfolio. As expected, the QQ plots in Figure 4 show that the true distribution of the portfolio-level idiosyncratic risk is practically normal. The true distribution is very well approximated by the  $t$  model (6) which in this case displays  $\tilde{\nu} \approx 60$  dof. Notice that the weighted average (10) of the dof  $\bar{\nu}$  is much lower: this difference is due to the large diversification effect induced by the portfolio entropy, see (11).

In Figure 5 we consider a long-short position of two securities both with heavy tails of  $\approx 3$  dof each. The resulting portfolio is mildly thinner tailed. Indeed, the weighted average (10) of the dof is  $\approx 3$ , but a small diversification effect appears in the portfolio tail index due to the non-null entropy. Indeed  $\tilde{\nu} \approx 4$  dof.

In Figure 6 we consider the same long-short position as above, but in a market with unevenly heavy tails of  $\approx 3$  dof and  $\approx 10$  dof respectively. Again, the aggregate model performs well. Notice that the inverse scheme (10) assigns more weight to the heavier-tailed security.

**Figure 5. Idiosyncratic risk model in a homogeneously thick-tailed market**

Source: Lehman Brothers

**Figure 6. Idiosyncratic risk model in an unevenly thick-tailed market**

Source: Lehman Brothers

## 6. CONCLUSIONS

We present a model for the distribution of the idiosyncratic risk of a portfolio when the security-level idiosyncratic shocks are heavy tailed. The proposed methodology relies on an entropy-based definition of portfolio diversification. Since none of the computations involved is numerical, the implementation of the proposed approach for portfolios of any size is straightforward.

The model applies to a large class of additive idiosyncratic models (1). The proposed methodology can also be extended easily to the situation where some idiosyncratic terms are correlated: this is the case for instance for same-issuer credit bonds. In this circumstance, the distribution of same-issuer bonds can be modeled as a multivariate  $t$ , in such a way that any sub-portfolio of same-issuer bonds becomes a  $t$ -distributed cluster independent of other clusters and thus it can be modeled as a single security as in (5). In future research we plan to relax the parametric  $t$  assumption at the security level, by including skewness and different tail behaviors.

**The author is grateful to Anthony Lazanas, Antonio Silva and Huarong Tang for their feedback.**

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# Trading Event Risk in Credit Markets using LEVER<sup>1</sup>

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*Releveraging events have recently become a significant source of risk in credit markets. The LEVER model and the LEVER Powertool on LehmanLive have been developed to assess this risk on a systematic basis. We present a new analysis of the LEVER model as an investment framework to identify and extract alpha. Our empirical analysis shows that trades based on the LEVER framework perform well historically and that their correlation with the market and other traditional credit trading strategies is low. This finding is useful for both portfolio managers with benchmark outperformance mandates and those with absolute-return mandates.*

## 1. INTRODUCTION

The risk of releveraging events such as LBOs and leveraged recapitalizations has been an important cause for concern among credit investors over the past two years. More specifically, 2006 saw a large number of big-ticket LBO transactions either being expected or actually going through. While this presents an opportunity for credit investors to generate outperformance using a strategy that is long protection in names that have a higher releveraging event risk, the impact of such events on credit spreads can be highly idiosyncratic.

Figure 1 presents 5-year CDS spread levels in the announcement month and in the six months before and after the announcement for the five largest LBO transactions announced in the US and Europe in 2006.

**Figure 1. Spread change of largest US and European LBOs in 2006**

Announcement date	Target	Spread <sup>1</sup> (bp)	Spread change		
			6M before annmt.	Annmt. month	6M after annmt.
US					
Nov	Equity Office Properties Trust	34	-3	-1	23
Jul	HCA Inc	435	309	282	-129
May	Kinder Morgan Inc	166	125	131	-38
Oct	Harrah's Entertainment Inc	241	191	127	-68
Nov	Clear Channel Commun Inc	271	179	-9	-74
Europe					
Feb	BAA PLC	85	64	54	-36
Jan	VNU NV	205	151	15	301
Oct	AWG PLC	25	3	0	-2
Mar	ITV PLC	86	-6	11	23
Mar	ProSiebenSat.1 Media AG	203	114	28	-27

Source: Lehman Brothers.

1. End of announcement month.

<sup>1</sup> The authors would like to thank Srivaths Balakrishnan, Vasant Naik and Marco Naldi for their helpful comments.

Clearly, releveraging events tend to be negative for credit spreads. However, not all the above names would have contributed equally to the outperformance of a 'perfect-foresight' strategy that was long protection on all these names. In addition, the fact that some of these names have wide spreads also implies that such a strategy would have been expensive in terms of carry.

Admittedly, the set of names in Figure 1 is not representative of the characteristics of LBO events in the long sample. Nevertheless the concerns mentioned above remain, and it is important to analyze whether a systematic attempt to capture risk premia embedded in credit spreads would be profitable.

Early last year, we launched our LEVER framework,<sup>2</sup> which helps quantify this risk and acts as a tool for investors to screen a large universe of names and identify those with high or low potential risk of such events.

While LEVER is a robust framework and has shown good empirical performance both in-sample and out-of-sample, it needs to be augmented in order to be directly used by credit investors in asset selection and portfolio construction. Indeed, as it stands the LEVER model is not a complete trading tool. One needs to know for instance whether it is necessary to short all the names with a high releveraging event risk (a high score) or whether a particular credit has enough excess spread to compensate for this risk.

With a view to addressing such issues we present an extensive empirical analysis of the performance of LEVER as a trading model in the investment grade credit market. More specifically, the primary goals of the current study are:

- To analyze and document the performance of trades on credits with high and low Firm LEVER-Scores<sup>3</sup> and to understand the time variation in the performance of these trades.
- To understand if it is useful to condition LEVER scores on the market valuation of bonds in trading releveraging risk.

Our analysis is that the LEVER framework by itself is a satisfactory predictor of bond performance – and that it shows an intuitive pattern of variation across different regimes. In addition, we find that by combining LEVER-Scores with spreads, it is possible to improve on the performance of the above trade. We also document the time variation of these trades.

On the basis of these findings, we propose a combination of two trading strategies. The first is a static trade that is intended to capture both the latent leveraging risk in the credit but also takes into account the risk premia that its bonds offer investors. The second trading strategy is a dynamic one that is attractive in regimes where the incidence of releveraging activity is more likely to be high. We find that the combination of the two strategies has performed well historically and that it has a low correlation both with the broad credit market and traditional credit trading strategies, such as that of the ESPRI model.

The rest of the article is organized as follows. In Section 2, we present a brief refresher of the LEVER framework. In Section 3 we present the performance of outright trades based on LEVER-Scores. In Section 4 we include spread levels to sharpen the information in

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<sup>2</sup> *Trinh et al (2006) 'Introducing LEVER: A Framework for Scoring LEVeraging Event Risk' Quantitative Credit Strategies January 9, 2006.*

<sup>3</sup> *In the rest of this article, we will refer to the Firm LEVER-Score as the LEVER-Score and the Macro LEVER-Score as such.*

the LEVER-Score. We examine the macro properties of these trades in Section 5 and present our conclusions in Section 6.

## 2. THE LEVER FRAMEWORK: A REFRESHER

*LEVER* is a quantitative framework for measuring the relative risk of releveraging events such as LBOs and leveraged recapitalizations. *LEVER* encapsulates key accounting and market information into two simple measures: the Firm *LEVER*-Score and the Macro *LEVER*-Score.

- The **Firm *LEVER*-Score** identifies companies that look potentially more attractive to financial sponsors. Scores range from 0 to 10, and companies that score above 7.5 are particularly at risk.
- The **Macro *LEVER*-Score** identifies market environments that are more amenable to LBOs.

In the following, we present a brief overview of the Firm and Macro *LEVER* Scores.

### The Firm *LEVER*-Score

The Firm *LEVER*-Score includes three broad categories of firm-level factors driving LBOs. The most attractive targets have below-market *valuations*, their *operations* generate adequate cash flows for servicing debt, and are likely to enjoy a smooth *execution* of the transaction. We list the variables used to compute these component scores and our hypothesis for the relative magnitude of these variables for LBO vs non-LBO names in Figure 2. (For example, our hypothesis is that potential LBO candidates would have a high book-to-market ratio.)

Figure 2. Components of the Firm-*LEVER* Score

	Valuation			Operation		Execution	
Variables	Book-to-Market Ratio	EV/EBITDA	Free Cash Flow Yield <sup>4</sup>	Growth of Capital Expenditure <sup>5</sup>	Cash Flow Variability <sup>6</sup>	Cash / Market Cap	Size of the Firm
Hypothesis	↑	↓	↑	↓	↓	↑	↓
Motivation	High B/M indicates cheap valuation	Reflects valuation vis-à-vis the earnings capacity	Indicates the ability to generate strong cash flows to service debt	Indicates operational commitments	Indicates the ability to service the debt raised	Indicative of liquidity	Smaller firms are more vulnerable

Source: Lehman Brothers.

### Constructing the Firm-*LEVER* Score

To construct the Firm *LEVER*-Score, we use the cross-sectional ranking of the normalized values of the variables listed in Figure 5. Each variable is divided by a normalizing factor which is the market-value weighted average of the particular variable. In the US and Europe, the average is computed over the entire universe or across the sector peer group only, depending on the variable.<sup>7</sup> Along each normalized variable, the firms in the universe are ranked. The Valuation, Operation and Execution scores for each firm are an average of the rankings corresponding to the underlying variables. The Firm *LEVER*-Score is then calculated as the average of the Valuation, Operation and Execution scores.

<sup>4</sup> The free cash flow yield is defined as the ratio of free cash flows to the market capitalization of the firm.

<sup>5</sup> We define the growth of capital expenditure as the year-on-year percentage change in the firm's capital expenditure.

<sup>6</sup> We define cash flow variability as the ratio of the two-year volatility of the firm's free cash flows to the debt of the firm.

<sup>7</sup> For the book-to-market ratio and EV/EBITDA multiple sector variations are taken into account. The rest of the variables are compared within the entire universe.

## The Macro *LEVER*-Score

The Macro *LEVER*-Score brings together the key factors that affect LBO activity.

### *a. Business cycle*

LBOs are more likely in expansions than in recessions. This is because revenue growth accelerates in periods of higher economic activity, making it easier for companies to take on additional debt. Several factors tell us which stage of the business cycle the economy is in, including GDP growth, changes in short-term interest rates and rate expectations.

### *b. Cost of capital*

The level of LBO activity is affected by the cost of capital of such transactions. This could be indicated by factors such as changes in the slope of the yield curve and credit spreads.

### *c. Characteristics of the universe*

Analysis of the broad universe of firms highlights the opportunities available to private equity firms and leveraged acquirers in general. Such factors as overall cash flow and dividend yields tend to be important signals of the broad attractiveness of the universe of firms.

### *d. LBO technicals*

An analysis of the data shows that the level of private equity raised in the previous year has a relatively high correlation with the number of LBOs. This could explain current high levels of LBO activity, as private equity firms are raising record amounts for their funds.

## 3. TRADING EVENT RISK USING THE FIRM *LEVER*-SCORE

We have documented before that the Firm *LEVER*-Score performs well in predicting the actual incidence of releveraging activity (Trinh, *et al* 2006). From the perspective of credit investors however, it is important also to analyze the performance of the Firm *LEVER*-Score as an indicator for a systematic trading strategy that buys credits with low scores and sells credits with high scores. This is because it is possible that the model may accurately identify a name as being a potential releveraging target, but credit spreads may already be completely pricing in this risk. In such a case, it would be of little use to buy credit protection on such a name. This reduces the utility of the model to credit investors.

### Structure of the tests

To address this concern, we perform the following exercise. We compute the Firm *LEVER*-Scores for all the firms in the combined universe of names that fall in the S&P 1500 Index and the Lehman US IG Corporate Index over the period 1990-2006.

We then divide the firms that fall in the Lehman IG Corporate Index (i.e. the names with bonds outstanding) into different rating and duration categories to remove any systematic bias arising from these differences between bonds. Within each rating-duration category we divide the bonds into three groups based on their Firm *LEVER*-Scores, as follows: the top 20%, middle 60% and bottom 20%. Based on this grouping, we go long the bonds of all names in the bottom 20% and short the bonds of those in the top 20% and hold the trade for three months.

This exercise is repeated every month.<sup>8</sup> In other words, in any given month there would be three portfolios outstanding. In order to compute the monthly returns of this trading strategy therefore, one needs to compute the average of the returns of the three overlapping portfolios. This back-testing methodology is very similar to that of the ESPRI model.<sup>9</sup>

### Performance of the unconditional LEVER long-short trade

In Figure 3, we present the performance of the above trading strategy for various rating categories. It is important to note that in Figure 3 and subsequent analyses of trading strategies, we assume zero transaction costs. We judge that this is a fair assumption in the context of a larger credit selection mechanism that also includes signals from other frameworks.

**Figure 3. Performance of long-short trades based on Firm LEVER-Scores**

		AA	A	BBB
<b>1990-2006</b>	Average Excess Returns (bp)	1	3	5
	Annualized Information Ratio	0.08	0.30	0.19
<b>1999-2006</b>	Average Excess Returns (bp)	3	6	9
	Annualized Information Ratio	0.21	0.45	0.25
<b>2004-2006</b>	Average Excess Returns (bp)	-0	7	16
	Annualized Information Ratio	-0.07	0.55	0.74

Source: Lehman Brothers.

Figure 3 presents the average excess returns of the long-short strategy and the annualized information ratio which is defined as the ratio of the average annual excess returns to the annual volatility of the strategy. In general, an annualized information ratio larger than 0.5 indicates a good trading strategy.<sup>10</sup>

We find that the trading strategy has a positive, albeit low, information ratio in the full sample for all investment-grade categories. However, we can see that in 2004-2006, when LBO activity was reasonably large, the trading strategy performs strongly.

This could be a sign that it is necessary to condition the trade based on the likelihood of the macro environment being conducive to releveraging events. In other words, risk premia for releveraging events may vary across time – and this time variation may be correlated with the variations in the macro attractiveness of the environment for such events.

### Conditioning the LEVER long-short trade

In order to reflect the macro behavior of releveraging risk premia, it would be valuable to condition the above trade on an indicator of the macro regime. The Macro LEVER-Score readily presents itself as one such indicator which ‘predicts’ the likelihood that the following period is one of high releveraging activity.

Investors could directly scale their trades using the Macro LEVER-Score as follows:

<sup>8</sup> While accounting data for US corporates is available on a quarterly basis – not all corporates follow the same reporting schedule. Therefore, it is likely that in every month some of the firms in the universe report their quarterly accounts, which alters the characteristics of the cross-section of firms each month. It is therefore possible to recompute the Firm LEVER-Scores for all issuers in the universe every month.

<sup>9</sup> Naik et al (2002) “Introducing Lehman Brothers ESPRI: A Credit Selection Model using Equity Returns as Spread Indicators” Quantitative Credit Research Quarterly January 31, 2002.

<sup>10</sup> The product of the annualized information ratio and the square root of the number of years in the sample is approximately equal to the t-statistic. In other words, given that our back-test uses 17 years of data, an information ratio of 0.58 is indicative of excess returns significantly different from zero at the 1% level.

$$\text{LEVER Trade} = 0.1 * \text{Macro Score} * (\text{Low Firm Score} - \text{High Firm Score})$$

In other words, this mechanism would increase the exposure to the leveraging event risk trade in periods that are more likely to be conducive to such events and scale it down in periods that are less conducive.

Figure 4 presents the performance of the conditional LEVER long-short trade.

**Figure 4. Performance of conditional long-short trades based on Firm LEVER-Scores**

		AA	A	BBB
<b>1990-2006</b>	Average Excess Returns (bp)	0	2	6
	Annualized Information Ratio	0.03	0.34	0.39
<b>1999-2006</b>	Average Excess Returns (bp)	1	5	12
	Annualized Information Ratio	0.18	0.50	0.54
<b>2004-2006</b>	Average Excess Returns (bp)	-0	5	13
	Annualized Information Ratio	-0.07	0.54	0.78

Source: Lehman Brothers.

It is clear from Figure 4 that conditioning the trade based on the macro environment improves its performance. The excess returns of this trade have a correlation of -40% with that of the US IG Corporate Index, which is an attractive feature for both investors with benchmark outperformance mandates and those with absolute return mandates.

#### 4. USING SPREAD LEVELS AND LEVER SCORES IN EVENT RISK TRADES

From the previous results, we see that the performance increases as we go down the rating spectrum and implicitly trade higher spread names. The trades described above do not involve any assessment of the likely magnitude of risk premia priced into the bonds of different issuers. Adjusting for variations in these risk premia should enhance the performance of these trades. In this section, we carry out such an analysis.

##### Conditioning LEVER-Scores on the level of spreads

In order to extract and trade releveraging risk premia we therefore introduce an additional sorting based on the option adjusted spreads (OAS) of individual bonds. Among issuers with similar Firm LEVER-Scores, higher spreads could be indicative of a higher degree of releveraging risk premia priced in. As a result, as opposed to buying all names with low Firm LEVER-Scores, it would be more prudent to only buy those with low LEVER-Scores but high spread levels.

To implement this, we sort each category of LEVER-Scores (as described in Section 2) into three equal-sized buckets based on level of OAS. This gives rise to nine portfolios of issuers. The four corner portfolios have interesting economic properties, as shown in Figure 5.

**Figure 5. Properties of the corner portfolios**

Variables	High Spread	Low Spread
High LEVER-Score	Cheap Bonds; High Event Risk: <i>Defensive Short</i>	Rich Bonds; High Event Risk: <i>Core Short</i>
Low LEVER-Score	Cheap Bonds; Low Event Risk: <i>Core Long</i>	Rich Bonds; Low Event Risk: <i>Defensive Long</i>

Source: Lehman Brothers.

The economic intuition about the corner portfolios is very similar to that of the ESPRI model (Naik et al, 2002). Bonds with low LEVER-Scores and high spreads are attractive core longs both from a valuation standpoint and from an event-risk perspective. Similarly bonds with high LEVER-Scores and tight spreads are attractive core shorts.

In addition, bonds whose issuers have low LEVER-Scores are attractive longs. However, if these bonds are rich to their peers, they would outperform only when market conditions are volatile and there is a flight to quality. In effect this portfolio would be good as a defensive long. A similar argument can be made about the High Spread High LEVER-Score portfolio, whereby it can be thought of as a defensive short. One would therefore put on the defensive trades only when the market is deteriorating and risk aversion is high; in normal market conditions, we would implement only the core trades.

### Empirical behavior of the corner portfolios

Figure 6 documents the performance (average excess returns per month in bp and annualized information ratio) of the four corner portfolios in the full sample. As before, we perform the two-way sorting (based on Firm LEVER-Scores and OAS) within rating-duration buckets. However, we report the averages across duration buckets in the interest of simplicity.

**Figure 6. Performance of corner portfolios: full sample**

Rating Category		LL	LH	HH	HL
AA	Average Excess Returns (bp)	-6	10	11	-10
	Annualized Information Ratio	-0.80	1.17	0.85	-1.19
A	Average Excess Returns (bp)	-4	9	5	-8
	Annualized Information Ratio	-0.34	1.14	0.30	-1.17
BBB	Average Excess Returns (bp)	-9	6	-9	-7
	Annualized Information Ratio	-0.54	0.24	-0.16	-0.47

LL – Low LEVER-Score Low Spread

LH – Low LEVER-Score High Spread

HH – High LEVER-Score High Spread

HL – High LEVER-Score Low Spread

Source: Lehman Brothers.

In the full sample, we find that firms with low LEVER-Scores and wide spreads outperform, on average, while firms with high LEVER-Scores and tight spreads underperform. This is in line with the idea that firms with high releveraging event risk that has not yet been priced into bond spreads are attractive shorts, while firms with low scores and wide spreads are attractive longs.

When we compare firms with low LEVER-Scores and tight spreads (LL) with firms that have high LEVER-Scores and wide spreads (HH) in the full sample, we observe a pattern that seems counter-intuitive. In other words, we find the HH portfolio to outperform (except in the case of the BBB universe) and the LL portfolio to underperform. Thus, it is important to analyze the sub-sample performance of this portfolio. However, it is likely that this diagonal exhibits more intuitive properties in some sub-samples. We explore this in the following sections.



### Trading strategies based on the corner portfolios

We can create two long-short ‘event-risk’ trades based on the corner portfolios, as follows:

*Trade 1: Long LH (Low LEVER-Score, High Spread); Short HL (High LEVER-Score, Low Spread)*

This strategy involves going short names with tight spreads and high LEVER-Scores, while going long names with wide spreads and low LEVER-Scores. As described above, this strategy would be attractive as a core ‘event-risk’ trade. However, being a carry trade this trade would underperform in periods of high market volatility (Figure 7).

**Figure 7. Performance of LEVER Trade 1 in sub-samples**

		HL-LH
<b>1990-2006</b>	Average Excess Returns (bp)	16
	Annualized Information Ratio	1.04
<b>1999-2006</b>	Average Excess Returns (bp)	15
	Annualized Information Ratio	0.78
<b>2004-2006</b>	Average Excess Returns (bp)	10
	Annualized Information Ratio	1.59

Source: Lehman Brothers.

*Trade 2: Long LL (Low LEVER-Score, Low Spread); Short HH (High LEVER-Score, High Spread)*

This strategy involves going short names with high LEVER-Scores and wide spreads and going long names with low LEVER-Scores and tight spreads. As this trade is likely to have a negative carry, it would be attractive only in periods of heightened volatility and flight to quality.

We investigate the empirical properties of these trades in Figure 8. For ease of exposition, we report the properties of the two trades across different rating and duration buckets.

**Figure 8. Performance of LEVER Trade 2 in sub-samples**

		LL-HH
<b>1990-2006</b>	Average Excess Returns (bp)	-9
	Annualized Information Ratio	-0.30
<b>1999-2006</b>	Average Excess Returns (bp)	-2
	Annualized Information Ratio	-0.04
<b>2004-2006</b>	Average Excess Returns (bp)	9
	Annualized Information Ratio	0.43

Source: Lehman Brothers.

The profile of the two trades is in line with the performance of the corner portfolios in Figure 7. We find that the LH-HL trade is a consistent outperformer and that it significantly improves on the performance of the simple LEVER trade seen in Section 3.

### Understanding the LL-HH trade

It seems the LL-HH trade underperforms in 1990-98, is in line with our hypothesis that the trade would underperform in periods that are favorable to carry trades in general. However, we find that it outperforms in the 2004-2006 which was one of heightened releveraging event risk.

From the above, it appears that there are two drivers of the performance of the LL-HH trade:

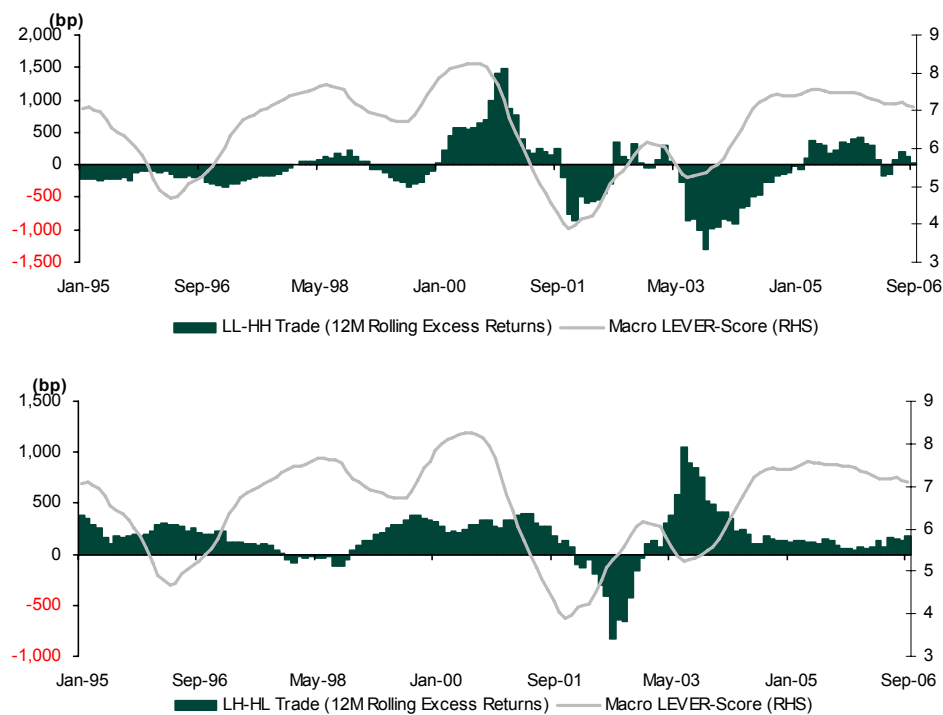
- The stage of the credit cycle: The LL-HH trade being a negative carry trade would perform well in volatile market conditions
- Leveraging event risk: While the HL-LH trade performs consistently in all periods, the LL-HH trade appears to outperform in periods that are supportive of releveraging events in general. We examine this hypothesis in the next section.

## 5. MACRO PROPERTIES OF THE LEVER TRADING STRATEGY

It is likely that the two trading strategies in Section 4 have different macro properties over time. These can be useful in improving the properties of the overall trade arising from these signals.

We can see in Figure 9 that the LL-HH trade has a significant positive relationship with the Macro LEVER-Score, while the LH-HL trade has no significant dependency on it.

**Figure 9. LEVER trades and the macro environment**



Source: Lehman Brothers.

To quantify this dependency, we regress the monthly returns of both the above trades on the monthly Macro LEVER-Score (Figure 10).

**Figure 10. Dependency of trades on Macro LEVER-Score**

	LH-HL	LL-HH
Constant	33.1	-80.0
t-stat	2.50	-3.13
Slope	-2.9	<b>12.0</b>
t-stat	-1.33	<b>2.88</b>

Source: Lehman Brothers.

In summary, we find the following:

- The standard LEVER trading strategy LH-HL outperforms across regimes because it has a positive carry that enables it to enhance the degree of releveraging risk premium it extracts.
- The performance of the LL-HH trade is dependent on the macro environment – i.e. it outperforms only in periods of heightened releveraging activity, such as the current one.

### Combining the two trading strategies

In order therefore to optimally align our portfolio to the macro environment, we need to predict the degree of releveraging activity in the following period. The LEVER model readily allows us to do this, through the Macro LEVER-Score, which can also be used as the weight allocated to the LL-HH trade. The investor's portfolio would be following:

$$(LH-HL) \text{ Trade} + w * (LL-HH) \text{ Trade}$$

where  $w$  is defined as  $0.1 * \text{Macro LEVER-Score}$ .

In other words, the portfolio consists of two components which directly reflect the macro behavior discussed above:

Component 1: The *Static* LEVER Trade which is long the LH portfolio and short the HL portfolio.

Component 2: The *Dynamic* LEVER Trade which is long the LL portfolio and short the HH portfolio. This part of the trade is scaled up in periods of high releveraging event risk.

### Performance of the combined trading strategy

In Figure 11 we present the performance of the combined trade in the three rating categories both in the full sample and in the sub-samples.

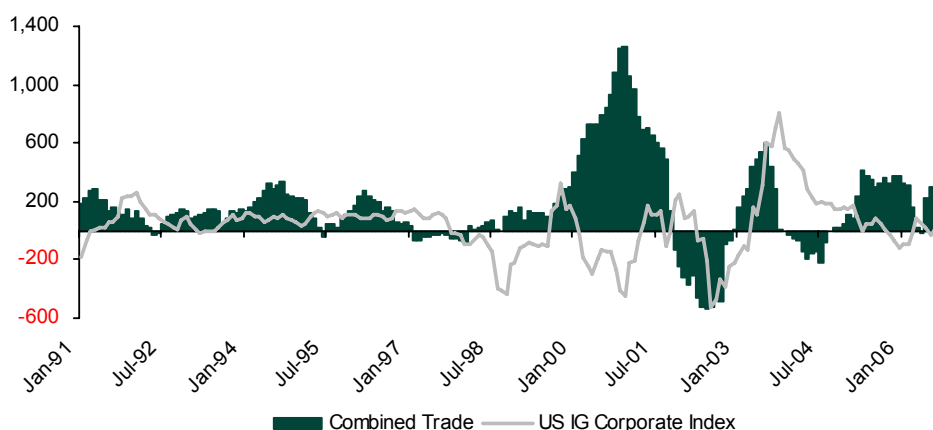
**Figure 11. Performance of combined trading strategy**

		<b>AA</b>	<b>A</b>	<b>BBB</b>	<b>Overall</b>
<b>1990-2006</b>	Average Excess Returns (bp)	8	14	22	14
	Annualized IR	0.51	0.73	0.55	0.90
	Hit Ratio	56%	58%	53%	59%
	Skew	1.18	4.07	2.02	1.73
<b>1999-2006</b>	Average Excess Returns (bp)	8	18	34	20
	Annualized IR	0.44	0.69	0.62	0.92
<b>2004-2006</b>	Average Excess Returns (bp)	3	18	33	18
	Annualized IR	0.35	0.56	0.90	1.12

Source: Lehman Brothers.

Figure 11 shows that the trade exhibits strong performance, and that it improves on the standard trade by means of a more balanced profile across sub-samples.

To enhance our understanding, Figure 12 shows rolling 12-month cumulative returns for the combined trading strategy across all rating categories and for the US IG Corporate Index.

**Figure 12. Rolling 12 month cumulative returns of combined trading strategy (bp)**

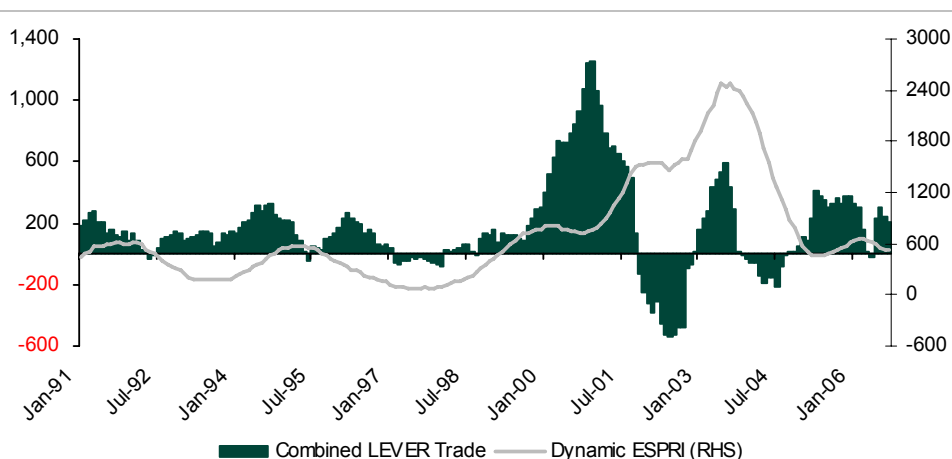
Source: Lehman Brothers.

The combined trade has a correlation of -20% with the excess returns with the Lehman US IG Corporate Index in the full sample and exhibits a stable performance profile.

### Comparison of the combined LEVER trade with the ESPRI model

It is also interesting to analyze the comparative performance of the combined LEVER trade with that of a model such as ESPRI – which also in part attempts to capture the risk-premia embedded in wide spread vs tight spread names.

In Figure 13 we present a comparison of the performance of the Dynamic ESPRI strategy for BBB rated long duration bonds and that of the combined LEVER trade. The in-sample correlation of the two trades is -1%, which is attractive, as it would be valuable to add the LEVER signals to a trading strategy that already includes signals from the ESPRI model.

**Figure 13. Rolling 12 month cumulative returns of combined trading strategy (bp)**

Source: Lehman Brothers.

## 7. CONCLUSION

We have analyzed the performance of the LEVER model as an investment framework to identify and extract risk premia. Our empirical analysis shows that trades based on the LEVER framework perform well historically and that their correlation with the market and other traditional credit trading strategies, such as that of the ESPRI model, is low. This finding is useful for both portfolio managers with benchmark outperformance mandates and those with absolute return mandates.

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# Introducing Lehman Brothers' CMetrics Framework<sup>1</sup>

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## INTRODUCTION

Fundamental equity and credit analysts seek to interpret companies' financial statements in order to identify key areas of strengths and weaknesses with a view to making informed judgments about future prospects. Over time individual analysts have adopted and adapted a myriad of measures to gauge opportunities and risks within their coverage universe. The result has often been a seemingly endless number of financial ratios that cannot be easily compared across sectors and sometimes even within the same sector. Lehman Brothers' CMetrics is a new financial framework aimed at improving the quality of financial analysis and valuations. In particular, CMetrics provides:

- Concise, comparable and consistent financial ratios linked to Enterprise Value
- Adjusted metrics to enable cross company, cross industry comparisons
- An integrated framework that analyzes independently the three key management activities:
  - Operating the core business
  - Financing the enterprise
  - Investing in non-core business activities
- A broad coverage of U.S. public companies
- On-line tools for Company and Industry level financial analysis

While many investors focus on earnings per share, academic and practitioner research has established a link between recurring operating return (Return on Invested Capital or "ROIC") and long-term intrinsic value. The CMetrics Framework recognizes this relationship and offers ROIC-based performance metrics that are linked to operating performance, as well as financing and investing performance measures, so that users can evaluate how the results of management decisions and various aspects of performance drive firm value. As a result, the entire CMetrics framework is value-relevant. The Section entitled "Enterprise Valuation and Performance Measurement" discusses this in more detail.

CMetrics makes adjustments to the financial statements to enable cross comparison of companies and industries. The framework makes adjustments in order to control for differences in financial reporting, recognize unrecognized assets and liabilities, and reflect the underlying economics of the business and industry into the financial analysis and valuation of the firm. The section entitled "Adjustments" describes these adjustments in a greater detail.

<sup>1</sup> The authors would like to acknowledge Meredith Adler, Margery Cunningham, Mathew Rothman, Sergey Vasethsov, Ann Gillin Lefever, Jack Malvey, Elmer Huh, and S.R. Rajan for their helpful comments and suggestions.

## ACCESS

CMetrics can be accessed on LehmanLive, keyword CMetrics. Additional information on using CMetrics is found by clicking on the CMetrics User Guide.

## OVERVIEW

The aim of the management of a company is to provide maximum return for its equity holders. Even well-known recent cases of accounting scandals and fraud were primarily driven by a desire on the part of management to keep stock prices and returns from falling. While short-term market returns can be influenced by many factors, often outside the control of management, the long-term success or failure of a company is tied to the strategic operating decisions that influence the firm's earnings and cash flows over time.

**Figure 1. Firm Value and Managerial Decisions**

	Recurring	One-Time
<b>Operating</b>	<ul style="list-style-type: none"> <li>• Products &amp; Markets</li> <li>• Cap Ex and R&amp;D/Advertising</li> <li>• Credit terms</li> <li>• Operational improvements</li> <li>• HR &amp; benefits policies</li> </ul>	<ul style="list-style-type: none"> <li>• Restructuring programs, exiting markets</li> <li>• Asset sales</li> <li>• Changes in accounting policies</li> </ul>
<b>Financing</b>	<ul style="list-style-type: none"> <li>• Capital structure/leverage</li> <li>• Debt instruments</li> <li>• Near debt/hybrid capital</li> <li>• Changes in performance of pension assets</li> </ul>	<ul style="list-style-type: none"> <li>• Gains/losses on debt retirement</li> <li>• Changes in assumptions of pension assets/liabilities</li> </ul>
<b>Investing</b>	<ul style="list-style-type: none"> <li>• Investment decisions</li> <li>• Performance of investments</li> </ul>	<ul style="list-style-type: none"> <li>• Reclassification of investment assets (non-trading to trading)</li> </ul>

Source: Lehman Brothers Analysis.

Figure 1 provides examples of managerial decisions classified in the operating, financing and non-operating (or investing) categories that affect firm financial performance. It also provides examples of “recurring” decisions (decisions that are part of the normal day-to-day running of the firm) and “one-time” decisions (decisions that happen with less frequency and represent a departure from the normal course of business). Financial analysts focus significant attention on understanding how the recurring operating items (the shaded items) affect performance because the long-term value of a firm is driven by recurring operations.

The aim of fundamental historical financial analysis is to gauge the impact of these past decisions on the future prospects of the firm. Performance measures such as Return on Equity (ROE) or Earnings per Share (EPS) are helpful in assessing the overall success of the management team in improving the financial return of equity holders. They are less useful in diagnosing the reason for the change in performance because they do not routinely exclude one-time items or decompose performance into the core aspects of management: (1) operation of the business, (2) financing of the enterprise, and (3) other

non-operational investments<sup>2</sup>. The CMetrics framework addresses these concerns by decomposing company financial results into recurring vs. non-recurring items as well as distinguishing between operating, financial and non-operating investing performance.

CMetrics aims to provide a more robust framework for financial analysis with value-relevant and consistently measured financial ratios that can be readily and appropriately compared to those of their industry peers and with companies in other sectors. These metrics are made comparable by controlling for differences due to use of different accounting methods in financial reporting, reflecting unrecognized liabilities, and making the financial statement reflect the underlying economics of the business or industry.. Importantly, the measures are part of an integrated system so that investors can drill down from the financial ratios to the performance measures of various aspects of the business such as trend in inventories, receivables, fixed assets, and capital structure decisions. Users can compare these ratios across with those of individual industry competitors, with the industry or sub-industry grouping as a whole, or with non-industry peers to uncover the reasons for the improvement/deterioration in performance and gain insight about future prospects.

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<sup>2</sup> *This framework is consistent with proposals made by the Joint Project of the International Accounting Standards Board (IASB) and Financial Accounting Standards Board (FASB) on Financial Statement Presentations to improve the usefulness of financial reports.*



## THE CMETRICS FRAMEWORK

The CMetrics framework summarizes firm performance into three categories: performance, market and credit risk, and valuation. Figure 2 presents the full list of CMetrics ratios.

**Figure 2. CMetrics Ratios**

### Key Performance Metrics

Adjusted EPS  
 Sales Growth (from previous qtr)  
 ROE  
     Return on Invested Capital (ROIC)  
         NOPAT Margin  
             EBITDA Margin  
             Depreciation Margin  
             R&D Margin  
             COGS Margin  
             Other SG&A Margin  
     Capital Intensity  
         Working Capital Turnover  
         AR Days  
         AP Days  
         Inventory Days  
         PPE Margin  
     Financing Return  
         Debt to Equity Ratio  
         Financing Spread  
     Non-Operating Return  
         Investment Ratio  
         Investment Spread  
 Non-recurring Income (Expenses) to Sales

### Additional Market & Credit Risk Metrics

Beta  
 WACC  
 Interest Coverage Ratio  
 Cash Position  
 Operating Cash Flow Discrepancy  
 Free Cash Flow to Sales

### Key Valuation Metrics

P/E multiple  
 EV/EBITDA  
 EV/IC  
 EV/FCF

*Source: Lehman Brothers CMetrics version 1.0.*

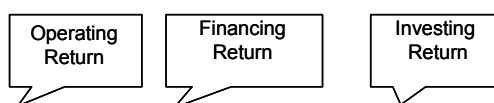
These metrics provide users with a comprehensive set of measures for analyzing and valuing non-financial companies. Each one of these metrics meets certain criteria. First, the metrics have to be value relevant—a clear relationship between the metric and value must exist. Second, the metrics must be meaningful across industries and time periods. Therefore industry measures, such as growth in subscriber base for wireless telecom, or same-store sales growth for retail are not provided. Instead, CMetrics focuses on metrics such as revenue growth rate, which are comparable across sectors.

To enable better understanding of these metrics, CMetrics uses a modified version of the Du Pont ROE decomposition formula.

**Figure 3. Decomposition of ROE**

$$\text{ROE} = \frac{\text{After-tax Operating Income} - \text{Interest Expense} + \text{After-tax Non-Operating Income}}{\text{Equity}}$$

Expressing interest expense and after tax non-operating income as a rate times debt and non-operating assets, respectively, defining Invested Capital (IC) as debt plus equity less non-operating assets (or financial assets) and multiplying equation 1.1 by IC/IC, equation (1) is derived.



$$(1) \quad \text{ROE} = \text{ROIC} + (D/E) * (\text{ROIC} - i_d) - (FA/E) * (\text{ROIC} - i_a)$$

Where *D*: Debt

*E*: Equity

*ROIC*: Return on Invested Capital

*FA*: Financial Assets

*i<sub>d</sub>*: after-tax interest cost (expressed as a rate of return)

*i<sub>a</sub>*: return on financial assets (expressed as a rate of return)

*Du Pont Formula, Lehman Analysis.*

ROE is defined as earnings after payment of all operating expenses, taxes and interest payments (including preferred dividends) divided by end of period book value of common equity. It includes all interest and other non-operating earnings received by the firm and can be decomposed into operating, financing and non-operating investing return as shown in Figure 3.

Equity ownership provides a levered return to investors. By financing a portion of their activities with debt, companies can increase the return to equity holders. This is because the equity holders receive the average earnings generated on the capital they invested in operations plus the earnings in excess of interest paid on capital contributed by debt investors. In addition, public companies often make investments outside their core operations (for example Nestlé's investment in L'Oreal). This increases the value of the firm so long as non-operating investment return exceeds the return on investments in core operations. Both financing return and equity return are generated by different types of management decisions and may be affected differently by economic factors. Therefore, in order to analyse the impact of past decisions on current results and future prospects, it is critical to separate ROE into these three components.

As summarized in equation (1), the factors that drive ROE are:

- (1) operating return on capital employed in the core business;
- (2) leverage and the firm's ability to finance itself at a rate which is below its operating return; and
- (3) the portion of equity invested in non-operating assets and the amount by which the returns from non-operations exceed those of operations.

We explain these three components of the equation below.

The Return on Invested Capital (ROIC) is net operating income after-tax (NOPAT) divided by debt and equity capital invested in the operations of the firm (Invested Capital)<sup>3</sup>. This is the profit earned by the operations of the firm on its invested capital.

The second term in equation (1) is the amount of return to equity holders from leverage; that is using debt to finance the enterprise. The firm increases its return to equity investors by taking on debt so long as the return on the firm's operations is greater than the cost of the debt assumed. In other words, more debt can be used to support the operation (and increase the average return to equity holders) if the spread between ROIC and the cost of debt is positive. Firms with relatively lower leverage present an opportunity for improving equity returns by using additional debt.

The third term in equation (1) is the amount of ROE that can be attributed to the firm's investments in other areas or "non-operating" assets. Companies increase their ROE when returns from non-operating assets are higher than returns from operating assets. This is difficult to do on a sustainable basis in light of the fact that investment performance is generally outside the control of management. Therefore, a company with a high percentage of ROE stemming from non-operating investments should be examined carefully for restructuring opportunities or looked at from the perspective of whether the business model is changing. Companies that hold significant amount of cash and marketable securities relative to their equity also need to be examined closely to make sure that the interest income generated by these assets exceeds that of the operating return so as to not destroy shareholder value.

The next section emphasises the importance of correctly understanding the significance of the firm's operating performance or its ROIC.

## ENTERPRISE VALUE AND PERFORMANCE MEASUREMENT

The value of an asset is equivalent to the aggregate value of the claims on that asset. The value of the entire business (the Enterprise Value or EV) determines the value of the claims on its assets. Thus the value of a company, which is the combined value of its tangible and intangible assets, is equal to the sum of the value of its debt and its equity. Further, assuming efficient markets, the EV equals the present value of the expected future income when adequately adjusting for the risk embedded in these earnings.

Assuming that value is equivalent to the present value of expected future cash flows (the classic Discounted Cash Flow or "DCF" model), and that a company's cash flows grow at a constant rate, several authors<sup>4</sup> have shown that Enterprise Value is a function of growth, ROIC and the company's cost of capital as shown in equation (2) below.

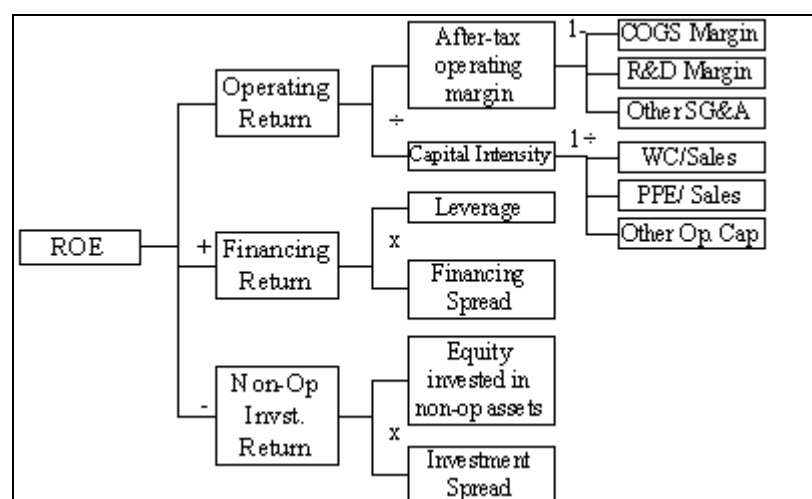
$$(2) \quad \text{Value} = \text{ROIC} * \text{IC} * (1 - (g/\text{ROIC})) / (\text{WACC} - g)$$

<sup>3</sup> Invested Capital includes all interest-bearing debt and debt like claims on assets plus all equity and equity like claims in excess of non-operating assets. See Section "CMetrics Invested Capital" for further discussion of the financial line-items that are included in the Invested Capital calculations.

<sup>4</sup> Copeland and Weston, and Koller, et al.

In practice, market values for companies may differ from DCF estimates for many reasons that exceed the ability of a stylized model to capture. However, academic and Wall Street research has shown that over time market returns are correlated with fundamental ratios of growth, return and risk<sup>5</sup>. For this reason, CMetrics reports ROIC as its primary measure of operating performance and an indicator of future value. An analysis of ROIC by itself, however, is not informative about the reason for a change. For this, a DuPont analysis decomposition of ROIC is performed. ROIC is a function of operating margin (the amount by which the enterprise's operating revenues exceed the operating costs) and capital turnover (the amount of invested or operating capital used by the business) relative to the size of the business. In addition, each of these metrics can be further decomposed into useful operating statistics, as shown in Figure 4, below.

**Figure 4. Decomposition of ROE and ROIC**



Source: Lehman Brothers Analysis.

Figure 4 details how ROIC is decomposed into the CMetrics operating drivers. Figure 4 in conjunction with equation (2) provides a valuation framework for analyzing how changes in operational drivers such as margin or working capital intensity affect ROIC and enterprise and equity valuations. In theory, these measures can be decomposed into finer and finer measures of performance. CMetrics stops at this level because further decompositions cannot be meaningfully done across sectors; moreover, the data is not available consistently across our coverage universe.

Figure 5 summarizes the ratios that are presented in CMetrics. The table contains the formula for computing each ratio, what the ratio measures, and how to interpret the observed values of these ratios. Additional information is also available in the CMetrics Glossary provided in the appendix.

<sup>5</sup> See for example Nissim and Penman (2001) and Fairfield and Yohn (2001).

Figure 5. CMetrics at a glance...

Performance Measure	Definition	What it measures	Watch out for
EPS	<u>Earnings Before Non Recurrings</u> Common shares outstanding	Earnings available per equity share	Significant difference from proforma EPS, diluted EPS
Sales Growth	$\left[ \frac{\text{Sales}_t}{\text{Sales}_{t-1}} - 1 \right] * 100$	Rate of growth in demand for company's products / service	Acquisitions, divestitures, sustainability Sales growth exceeding industry norms may indicate aggressive accounting policies
ROE	<u>Earnings Before Extraordinary</u> Shareholders Equity	Equity holders book return	Examine leverage if ratio is high relative to peers
ROIC	<u>NOPAT</u> Invested Capital	Profitability before financing expenses	ROIC lower than WACC indicates value destruction ROIC out of line with the industry would warrant further investigation
NOPAT Margin	<u>NOPAT</u> Net Revenues	After tax profitability of operations	Declining ratio could mean greater competition or cost inefficiencies Rising ratio and rising prepaid expenses could indicate inflated earnings
EBITDA Margin	<u>EBITDA</u> Net revenues	Profitability before financing and investing expenses	Declining ratio could mean greater competition or cost inefficiencies Rising ratio and rising prepaid expenses could indicate inflated earnings
Depreciation Margin	<u>Depreciation</u> Net revenues	Provision for diminution in value of fixed assets as % of net revenues	Low ratio as compared to peers and a high capex / depreciation ratio could indicate insufficient provision for future capital expenditure
R&D Margin	<u>R&amp;D Expense</u> Net revenues	Amount invested in R&D as % of net revenues	Declining ratio with declining EBITDA margin could indicate limited growth prospects Declining ratio with rising capitalized R&D could indicate inflated earnings
COGS Margin	<u>COGS (Excl Depreciation)</u> Net revenues	Pricing power and efficiency of manufacturing	Rising ratio could mean greater competition or cost inefficiencies Declining COGS and rising prepaid expenses could indicate inflated earnings
Other SG&A Margin	<u>SG&amp;A</u> Net revenues	Efficiency of selling and administrative functions	Declining ratio with declining EBITDA margin could indicate limited growth prospects or netting of one time gains
Capital Turnover	<u>Invested capital</u> Net Revenue	Efficiency of capital utilization and whether revenue comes from core operations or additional investments	High ratio relative to peers could indicate inefficient utilization of capital or insufficient scale
Working Capital Turnover	<u>Working capital</u> Net revenue	Efficiency of working capital management	High ratio relative to peers could indicate inefficient working capital management
AR Days	<u>Trade Receivables * # of Days</u> Net revenue	Days of credit extended to customers	High ratio relative to peers may indicate channel stuffing or failure to write of bad debts
AP Days	<u>Trade Payables * # of Days</u> Net Revenues	Days of credit obtained from suppliers	Low ratio relative to peers combined with low profitability could indicate tightening credit
Inventory Days	<u>Total Inventories* # of Days</u> Net revenues	Estimated days of sales for which inventory has been produced but is yet to be sold	Rising ratio as compared to trend or peers could indicate falling demand or failure to write of obsolete inventory
PPE Margin	<u>NPPE</u> Net revenues	Efficiency of utilization of fixed assets	Low ratio relative to peers could indicate insufficient investments or insufficient provision for depreciation
Financing Return	Leverage * Financing spread	ROE attributable to financing decisions	Examine sustainability if contribution to ROE is significant (especially in increasing interest rate scenarios)

Performance Measure	Definition	What it measures	Watch out for
Leverage Ratio	<u>Book Debt</u> Book Equity	The amount of debt for each dollar of equity	High leverage with high volatility in cash flows could result in future defaults
Financing Spread	ROIC – After tax cost of debt	Excess of ROIC over after tax cost of debt	Financing Spread less than ROIC may indicate financial distress
Non-Operating Return	Investment Ratio * Investment Spread	ROE attributable to non operating income	Examine sustainability if contribution to earnings is high
Investment ratio	<u>Non Operating Assets</u> Book Equity	Amount of assets deployed in non operating assets as a % of total equity	High ratio could mean restructuring opportunity
Investment Spread	Non Operating Return – ROIC	Excess of non-operating return over ROIC	Investment Spread lesser than ROIC could indicate inefficient deployment of funds
Non recurring Income (Expenses) to Sales	<u>Non Recurring Income (Expense)</u> Net Revenues	Amount of non recurring items as a % of net revenues	Operating expenses incorrectly classified as non recurring Creation of cookie jar reserves
<b>Additional Market &amp; Credit Measures</b>			
Beta		Sensitivity of a stock's returns to the returns of market index (S&P 500)	Beta's in excess of 1 indicate stock's higher risk relative to the market
WACC	After Tax cost of debt * Proportion of debt + Cost of Equity * Proportion of equity	Expected cost of financing the company's operations at current market rates	WACC greater than ROIC indicates economic loss and probable low future earnings
Coverage Ratio	<u>EBITDA</u> Interest Expense	Number of times the cash from operations can cover interest payments	Low ratio could indicate difficulty in meeting financial obligations
Cash Position	<u>Cash &amp; Equivalents</u> Total Current Assets	Indicates extent of liquid resources to meet obligations	Very low ratio relative to peers may indicate possible bankruptcy
Op. Cash flow discrepancy	(Cash From Ops – (Earnings before non recurrings, depr)/abs( Earnings before non recurrings, dep)	Amount of gross cash flow invested in non capex balance sheet items as a proportion of earnings	Low ratio relative to trend / peers could indicate inflated earnings
Free Cash Flow (FCF) to Sales	<u>FCF</u> Net Revenues	Proportion of revenues yielding cash after adjusting for capital expenditure	Low ratio relative to trend/ peers not explained by large capital expenditure may indicate inflated earnings High ratio relative to peers / trend could indicate insufficient investments
<b>Key Valuation Metrics</b>			
P/E multiple	<u>Common Equity Price</u> EPS	Valuation of a common share relative to earnings per share over the last 12 months	Acquisitions Firms with declining growth rate and high PE ratio relative to peers could be overvalued
EV/ EBITDA	<u>Market value of equity + debt</u> EBITDA	Valuation of company relative to cash earnings over the last 12 months	Acquisitions
EV / IC	<u>Market value of equity + debt</u> Invested Capital	Valuation of company relative to the capital invested	Acquisitions
EV / FCF	<u>Market value of equity + debt</u> Free Cash Flow	Valuation of company relative to FCF over the last 12 months	Acquisitions

Source: Lehman Brothers Analysis.

## CMETRICS INVESTED CAPITAL

The CMetrics framework categorizes all assets and liabilities on the balance sheet as operating, investing or non-operating investing. Figure 6 presents a “typical” U.S. GAAP balance sheet and illustrates how assets are classified.

CMetrics classifies preferred equity and minority interests as debt because they represent claims on the firm’s assets that are not common equity. In addition, CMetrics also includes pension liabilities and other long-term liabilities in debt because these generally represent financing provided by workers or customers. We treat deferred tax liabilities as equity components because these are generally non-interest bearing and are likely never to be repaid.

**Figure 6. CMetrics Classification of Balance Sheet Items**



Source: Lehman Brothers Analysis.

Non-operating assets include all long-term investments as well as cash and marketable securities. In some cases, long-term investments may be operational in nature (for example Coca-Cola's investment in some of its bottlers). In general these investments are not part of the day-to-day operations of the firm and are not under the direct control of management. Therefore, we treat all such investments as non-operating.

The treatment of cash as non-operational is more controversial. It is clear that some cash is required in order to fund current operations. However, many companies have significant investments in cash. According to a recent *New York Times* article, U.S. public companies hold stockpiles of cash to repay all their debt and still have additional money left over.<sup>1</sup> Because of the very high levels of cash held by companies it is hard to argue that this cash is necessary to fund current operations. For this reason, CMetrics treats all cash as a non-operational investment asset until the cash is used to purchase productive assets.

In a similar manner, CMetrics treats each income statement line item as operating, financing or non-operating investment income. Line items are allocated to these categories so as to be consistent with the treatment of the underlying assets that generate the income. For example, because cash is included in non-operating investment assets, interest income earned on that cash is included in non-operating income. Similarly, costs that are associated with the financing of assets (for example the implied interest expense on non-capitalized leases) are reclassified from operating expenses to interest expense.

## ADJUSTMENTS

The CMetrics Framework includes seven standard adjustments to each company's financials where appropriate. The adjustments were developed in order to improve comparability between companies and between industry sectors. Adjustments were designed to enable the user to control for differences in accounting standards between firms, to compare the financial statements of companies over time in a consistent manner and to recognize off-balance sheet asset and liabilities that affect company performance. In making these adjustments the guiding principle of CMetrics is to adjust financial statements to better reflect the underlying economics of the business<sup>2</sup>.

When choosing which adjustments to make and how to make them, we have been mindful of the following requirements:

- *Meaningfulness/Relevance*: Adjustments are only made if the failure to make such adjustments decreases the user's ability to interpret the financial statements of the company.
- *Consistency*: Adjustments are only made if they can be made reliably for all companies that would be affected.
- *Simplicity and Economic Rigor*: The adjustments must be simple to explain, have easy interpretation and be consistent with the underlying economic conditions of the firm.

CMetrics adjustments are designed to restate the income statement and balance sheet of the company as they would appear if the company followed the adjustment for financial reporting purposes. All adjustments that affect net income have an offsetting adjustment to equity as well as the appropriate adjustments to asset and/or liability accounts. All

<sup>1</sup> Hulbert, Mark. "Behind Those Stockpiles of Corporate Cash", *New York Times*, October 22, 2006.

<sup>2</sup> Recognizing that financial analysis is an art and that in some cases it may be appropriate to consider results before the impact of the adjustments, CMetrics allows users the flexibility to turn on or off some or all of the adjustments.



adjustments are tax-effected to reflect the after-tax impact of the adjustment on equity and tax liabilities.

It should be noted that financial statement analysis, especially the adjustment of financials to improve meaning and comparability is an art, not a science. In all cases, the adjustments have been designed to be as simple and transparent as possible. Also because of data limitations, some adjustments have been simplified or approximated.

The seven standard adjustments are listed below:

- Last In First Out (“LIFO”) inventories restated as First In First Out (“FIFO”)
- Adjust financial statements to reflect stock-based compensation if options were not expensed in the financial statements
- Capitalization of off-balance sheet leases
- Capitalization of R&D expenditures
- Capitalization of Advertising expenditures
- Pension and Other Post Retirement (“OPEB”) financing expenses reclassified from operating to financing (interest) expense
- Pension liabilities restated to reflect full funded status.

The remainder of this section provides details of these adjustments and examples on how these adjustments could have a significant impact on the operating performance of some of the companies. Although we believe it is important to make these adjustments when conducting a historical financial analysis, CMetrics gives the user the flexibility to apply the adjustments or not.

### LIFO/FIFO

For companies that follow the LIFO inventory policy, inventory values are lower, and cost of sales is higher than companies that follow FIFO or Weighted Average policies. These differences are more pronounced when commodity prices are rising and/or when inventories are rising, making it difficult to properly assess the financial health of companies. To control for this difference, inventories are restated at the level they would attain if FIFO were used, and COGS are likewise restated to the amount that would be recognized under FIFO.

Figure 7 presents an example of the LIFO/FIFO adjustment for the chemicals industry for the fourth quarter of 2005, a period of rising prices and significant changes in inventories. While the adjustment has little effect on the median ROIC, which increases from 2.19% before adjustment to 2.35% afterwards, the adjustment changes the relative ranking of Engelhard Corp. and Olin Corp. Before adjustment Engelhard Corp. has a ROIC of 3.0% and an industry ranking of 3, but after adjustment its ROIC becomes 2.6% while its ranking changes to 5. Similarly, Olin Corp. has a pre-adjustment ROIC of 2.3% and an industry rank of 5. After adjustment from LIFO to FIFO, its ROIC increases to 3.3% and the ranking becomes 2.

Figure 7. LIFO/FIFO Example

2005 CQ4	Sales 2005 (USD mn)	ROIC		Rank		Delta in ROIC
		Before Adj. (%)	After Adj. (%)	Before Adj.	After Adj.	
HUNTSMAN CORP	12,961.6	5.1	5.4	1	1	0.38
PPG INDUSTRIES INC	10,201.0	3.1	3.1	2	3	-
<b>ENGELHARD CORP</b>	<b>4,597.0</b>	<b>3.0</b>	<b>2.6</b>	<b>3</b>	<b>5</b>	<b>(0.35)</b>
DOW CHEMICAL	46,307.0	2.8	2.9	4	4	0.08
<b>OLIN CORP</b>	<b>2,357.7</b>	<b>2.3</b>	<b>3.3</b>	<b>5</b>	<b>2</b>	<b>0.97</b>
EASTMAN CHEMICAL	7,059.0	2.2	2.4	6	6	0.16
HERCULES INC	2,068.8	1.9	1.6	7	8	-0.31
CABOT CORP	2,125.0	1.7	1.6	8	7	-0.03
FMC CORP	2,150.2	1.2	1.1	9	9	-0.15
DU PONT	27,516.0	0.5	0.7	10	10	0.14
SOLUTIA INC	2,825.0	(1.6)	(1.0)	11	11	0.57
<b>Median</b>		<b>2.19</b>	<b>2.35</b>			

Source: CMetrics v1.0, Lehman Brothers Analysis; data as of January 2, 2007.

### Operating Leases

Operating leases are rental contracts in which assets are rented by a firm for a non-cancellable period of time, but for which no asset ownership is recognized by the lessee. This arrangement is in contrast to capital leases in which beneficial ownership is deemed to be with the lessee and the value of the assets are recognized on the lessee's balance sheet. Companies in several industries including transportation and retailing frequently arrange financing with asset owners in such a way as to avoid capital lease recognition, thereby improving their ROIC. However, because the assets are non-cancellable and represent real future commitments on the part of the company, from an economic perspective they represent capital invested in operations. In order to make comparisons between companies that acquire assets through operating leases and those that do not, CMetrics adjusts the financial statements to recognize the value of non-cancellable operating leases in the financial statements. On the balance sheet the capitalized value of the leases are added to net PPE and to Long-Term Debt. On the income statement, the implied interest component of the lease payment is reclassified as an interest expense. The capitalized value of operating leases is derived from the discounted value of future lease payments necessary to sustain current operations and the useful life of the assets.

For simplicity, CMetrics assumes that all operating leases have a term of 15 years. Future lease payments are discounted at an interest rate that reflects the company's cost of obtaining long-term secured financing.

The operating lease adjustment is particularly important for companies in the transportation, retail, and automotive industries. Ignoring operating leases can lead to very different rankings and implied valuation of companies. For example, Figure 8 below includes before adjustment and after adjustment data for the restaurant industry.

Prior to adjustment, Jack in the Box Inc's ranking in the industry is 7 with a ROIC of 3.1%. After adjusting for its operating lease commitments, its ROIC falls by almost one-third to 2.0%, making its relative ranking in the industry fall by 3 positions. We also notice an almost 50% drop in ROICs of CKE Restaurants and Domino's. Overall, the median ROIC of the group decreases from 3.1% to 2.5% after we adjust for operating lease commitments.

Figure 8. Operating Lease Example

2005 CQ4	Sales 2005 (USD mn)	ROIC		Rank		Delta in ROIC
		Before Adj. (%)	After Adj. (%)	Before Adj.	After Adj.	
CKE RESTAURANTS	1,519.9	25.6	13.4	1	1	(12.2)
DOMINO'S PIZZA INC	1,511.6	18.1	9.0	2	2	(9.2)
STARBUCKS CORP	6,369.3	9.3	4.3	3	3	(5.0)
YUM BRANDS INC	9,349.0	5.8	3.7	4	4	(2.1)
CHEESECAKE FACTORY INC	1,177.6	3.7	3.1	5	5	(0.5)
MCDONALD'S CORP	20,460.2	3.2	2.5	6	6	(0.7)
<b>JACK IN THE BOX INC</b>	<b>2,507.2</b>	<b>3.1</b>	<b>2.0</b>	<b>7</b>	<b>10</b>	<b>(1.0)</b>
<b>DARDEN RESTAURANTS</b>	<b>5,278.1</b>	<b>2.8</b>	<b>2.4</b>	<b>8</b>	<b>7</b>	<b>(0.4)</b>
BRINKER INTL INC	3,912.9	2.7	2.0	9	9	(0.6)
OSI RESTAURANT PARTNERS INC	3,601.7	2.5	2.1	10	8	(0.4)
WENDY'S INTERNATIONAL INC	3,766.7	2.1	1.7	11	12	(0.4)
RUBY TUESDAY INC	1,110.3	1.9	1.8	12	11	(0.2)
<b>Median</b>		<b>3.1</b>	<b>2.5</b>			

Source: CMetrics v1.0, Lehman Brothers Analysis; data as of January 2, 2007.

### Capitalizing Research & Development

When comparing companies across industries it is important to consider the use of intangible assets created by expenditures in research and development (R&D) and advertising. Current accounting rules require that most of these expenditures be expensed in the period in which they are incurred even if from an economic perspective they have an impact on future profits. This rule creates several problems in comparing the financial statements of competitors in the same industry. For example, consider the case of a pharmaceutical company that makes investments in R&D and brings to market a blockbuster new heart medication. During the period in which investigations into the new treatment are being performed, the company's financial performance will be lower and it will have lower invested capital because equity is reduced by the amount of R&D. After the drug is launched, the firm will have higher profits and invested capital. Compare this company to another that acquires the rights to a similar blockbuster drug either through the purchase of a license or by acquisition. This company would have an intangible asset equal to the value of the rights to exploit the R&D and lower profits as a result of charges for license fees and/or amortization.

Current accounting rules regarding R&D also make it difficult to compare the returns to invested capital across industries. R&D is an investment in the core business and just as important (if not more so) than capital expenditures for companies in technology-driven sectors such as pharmaceuticals, biotechnology and semiconductors. However, the invested capital of these companies will be considerably lower than that of traditional manufacturing companies that have large investments in property, plant and equipment (PPE) but relatively modest investments in R&D. When comparing ROIC between R&D intensive industries and non-R&D intensive industries, the R&D intensive industries will generally have higher ROIC and will not be reflective of the accounting return on all funds invested in the business.

In order to adjust for this difference which is purely a result of accounting conventions, CMetrics adjusts the financial statements of a companies that conduct R&D to capitalize and amortize R&D expenditures through the financial statements assuming a useful life of five years. Net PPE is increased by the amount of unamortized R&D outstanding in the quarter. On the income statement, R&D expense is replaced by the amount of the amortization of the R&D asset for the quarter.

Ignoring differences in the level of R&D investments can lead to incorrect assessments of company performance. Figure 9 below presents an example.

Figure 9 accentuates the impact of capitalizing R&D expenses. Within the semiconductor industry, we notice that Broadcom is ranked 1 in terms of ROIC before adjustment of capitalized R&D. Its ROIC is 14.5% pre-adjustment which becomes less than half at 6.0% post adjustment. Similarly, for Intel, ROIC changes from 11.0% to 7.5%. Most importantly, we notice that these companies' relative rankings change – Intel becomes the industry leader, while Broadcom is pushed to the No. 2 position.

**Figure 9. Capitalized R&D Example**

2005 CQ4	Sales 2005 (USD mn)	ROIC		Rank		Delta in ROIC
		Before Adj. (%)	After Adj. (%)	Before Adj.	After Adj.	
<b>BROADCOM CORP</b>	<b>2,670.8</b>	<b>14.5</b>	<b>6.0</b>	<b>1</b>	<b>2</b>	<b>(8.5)</b>
ANALOG DEVICES	2,388.8	11.3	5.3	2	5	(6.0)
<b>INTEL CORP</b>	<b>38,826.0</b>	<b>11.0</b>	<b>7.5</b>	<b>3</b>	<b>1</b>	<b>(3.5)</b>
NATIONAL SEMICONDUCTOR	1,913.1	10.1	4.9	4	7	(5.1)
XILINX INC	1,573.2	9.0	5.5	5	4	(3.5)
TEXAS INSTRUMENTS INC	13,392.0	8.4	5.5	6	3	(2.9)
ADVANCED MICRO DEVICES	5,847.6	6.9	5.0	7	6	(1.9)
FREESCALE SEMICONDUCTOR	5,843.0	6.2	4.1	8	8	(2.1)
LSI LOGIC CORP	1,919.3	3.1	0.9	9	10	(2.3)
AGERE SYSTEMS	1,676.0	2.1	(1.8)	10	12	(3.9)
MICRON TECHNOLOGY	4,880.2	1.1	1.0	11	9	(0.1)
SPANSION INC	2,002.8	(2.0)	0.1	12	11	2.2
<b>Median</b>		<b>7.7</b>	<b>5.0</b>			

Source: CMetrics v1.0, Lehman Brothers Analysis; data as of January 2, 2007.

### Capitalize Advertising Expenditures

Advertising expenditures are similar to R&D in that they are used to build brand awareness and can drive significant future revenues. The fact that some brands live on and remain well known long after they are no longer used (e.g. Pan Am) and are often reintroduced (e.g. Breck) after being abandoned indicates the role of advertising in building intangible assets that drive future revenues. As with R&D, failing to adjust for differences in the level of advertising between firms makes it difficult to assess the profitability of companies accurately. Accordingly, CMetrics adjusts the financial statements of companies that report advertising expenses by capitalizing and amortizing advertising expenses over an assumed useful life of three years.

**Figure 10. Capitalized Advertising Expenditures Example**

2005 CQ4	Sales 2005 (USD mn)	ROIC		Rank		Delta in ROIC
		Before Adj. (%)	After Adj. (%)	Before Adj.	After Adj.	
<b>REVLON INC -CL A</b>	<b>1,332.3</b>	<b>15.8</b>	<b>8.9</b>	<b>1</b>	<b>2</b>	<b>(6.9)</b>
<b>AVON PRODUCTS</b>	<b>8,149.6</b>	<b>10.9</b>	<b>10.0</b>	<b>2</b>	<b>1</b>	<b>(0.9)</b>
LAUDER ESTEE COS	6,336.3	8.0	3.9	3	7	(4.1)
HERBALIFE LTD	1,566.8	7.2	7.2	4	3	-
COLGATE-PALMOLIVE CO	11,396.9	6.9	6.1	5	4	(0.8)
ENERGIZER HOLDINGS INC	2,989.8	6.1	5.0	6	5	(1.2)
CLOROX CO/DE	4,388.0	4.2	3.3	7	9	(0.8)
NU SKIN ENTERPRISES	1,180.9	4.2	4.2	7	6	-
KIMBERLY-CLARK CORP	15,902.6	4.0	3.9	9	8	(0.2)
NBTY INC	1,737.2	2.5	2.6	10	10	0.0
PROCTER & GAMBLE CO	56,741.0	2.5	2.5	11	11	(0.0)
SPECTRUM BRANDS INC	2,359.4	1.1	1.1	12	12	0.0
<b>Median</b>		<b>5.1</b>	<b>4.0</b>			

Source: CMetrics v1.0, Lehman Brothers Analysis; data as of January 2, 2007.

Figure 10, presents ROIC before and after the Capitalized Advertising Expenditure adjustment for companies in the consumer packaged goods industry. Avon, ranked 2 within the industry, has a pre-adjustment ROIC of 10.9%. Its ROIC changes marginally to 10.0% after this adjustment. However, the impact of this adjustment is much larger on industry leader Revlon, whose ROIC changes to 8.9% from 15.8%. This also pushes Revlon's ranking to No.2 behind that of Avon.

### Stock-Based Compensation

SFAS 123R, which is effective for companies not filing as small businesses for fiscal years beginning after December 15, 2005, requires that companies compute costs associated with stock option grants and recognize these costs over the life of the contract. Prior to SFAS 123R, companies could choose to recognize this expense in their income statement or as an adjustment to comprehensive income. Therefore, when comparing 2006 results with prior period results, or when comparing companies that expensed options with those that did not, it is necessary to adjust financial statements. CMetrics adjusts the financial statements of companies prior to the adoption of SFAS 123R to include the implied option expense for the quarter as an operating expense.

Figure 11 highlights the importance of controlling for differences in accounting treatments between firms. Prior to adjustment, Broadcom's ROIC is 14.5% (second highest in the industry) and more than twice the industry median. After adjusting for the stock-based compensation, Broadcom's ROIC falls by more than two-thirds to 4.3%, and its relative ranking falls to 4 – behind that of Nvidia, AMD and Freescale.

Figure 11. Stock-Based Compensation Example

2005 CQ4	Sales 2005 (USD mn)	ROIC		Rank		Delta in ROIC
		Before Adj. (%)	After Adj. (%)	Before Adj.	After Adj.	
NVIDIA CORP	2,010.0	18.5	12.9	1	1	(5.6)
<b>BROADCOM CORP</b>	<b>2,670.8</b>	<b>14.5</b>	<b>4.3</b>	<b>2</b>	<b>5</b>	<b>(10.3)</b>
TEXAS INSTRUMENTS INC	13,392.0	8.4	8.4	3	2	-
<b>AMD</b>	<b>5,847.6</b>	<b>6.9</b>	<b>6.4</b>	<b>4</b>	<b>3</b>	<b>(0.5)</b>
FREESCALE SEMICONDUCTOR INC	5,843.0	6.2	5.1	5	4	(1.1)
LSI LOGIC CORP	1,919.3	3.1	2.3	6	6	(0.9)
MICRON TECHNOLOGY INC	4,880.2	1.1	1.1	7	7	-
FAIRCHILD SEMICONDUCTOR INTL	1,425.1	(0.1)	(0.0)	8	8	0.0
<b>Median</b>		<b>6.6</b>	<b>4.7</b>			

Source: CMetrics v1.0, Lehman Brothers Analysis; data as of January 2, 2007.

### Pension and Other Post-Employment Benefit Adjustments

Pension and Other Post-Employment Benefits (OPEBs) present challenges for investors seeking to consider the financial performance and unrecognized liabilities of companies. Prior to the adoption of SFAS 158, pension and OPEB liabilities<sup>3</sup> were not always fully recognized in the financial statements. Instead, liabilities related to the adoption of the accounting standard or changes in plans, as well as gains and losses on pension plan assets are recognized over three years. In addition, in computing the operating expenses related to pension and OPEBs, the costs of financing unfunded liabilities and the offsetting returns from plan assets, both of which are funding items, are included in pension costs, frequently resulting in very low (or negative) pension and OPEB costs. Because pension and OPEB costs are part of operating costs, this treatment has the effect of including in operating expenses costs and income that are financing in nature. In recent years, poor stock market performance over the early years of the decade has led many companies to have large financing costs and/or amortized losses included in their pension expense.

Because of the complications involved in accounting for defined benefit plans, it is difficult to assess the true liabilities incurred by firms or to make meaningful comparisons with companies that do not provide traditional defined-benefit pension plans. In order to better make these comparisons, CMetrics makes several adjustments to account for these differences. First, CMetrics reclassifies the costs associated with pension and OPEB interest costs and actual change in plan asset values as financial expenses/income. In addition, operating expenses are restated to include only the pension and OPEB service cost. Second, CMetrics reclassifies the recognized pension assets, liabilities, and minimum pension liabilities so that the net liability recognized is recognized as a single number and is reclassified as long-term debt. Further, the amount of the unrecognized pension liability (the difference between the funding status and the net amount recognized in the financial statements) is recognized in the financial statements. Figures 12 and 13 illustrate the adjustments for Delphi Corporation.

Delphi's service cost, the cost associated with current employees' 2005 activities, is \$326 million. This number compares with the recognized expense of \$668 million. The additional \$340 million represents current and prior losses on plan assets, as well as financing costs. In this case, CMetrics restates pension expense at the Service Cost (\$326 million) rather than the recognized pension expense of \$668 million. CMetrics adds to net interest expense of -\$294 million (\$789 million interest expense less \$1,083 million

<sup>3</sup> SFAS 158, which was issued in September 2006, is effective for fiscal years ending after December 15, 2006.

return on plan assets). Figure 12 highlights how large pension liabilities are for some companies, and how current treatment over- or understates operating expenses.

**Figure 12. Delphi Corporation: Components of Periodic Pension Benefits**

in U.S. \$Million	2005	Description
Service Cost	326	Operating Current Period
Interest Cost	789	} Net Financing Cost
Expected Return on Plan Assets	-848	
Special Termination Benefits	15	Operating Non Current
Amort of Transition Amount	1	Operating Non Current
Amort of Prior Service Costs	143	Operating Non Current
Amort of Actuarial Losses	242	Financing Cost, Non Current
<b>Net Pension Benefit Expense</b>	<b>668</b>	
Note: Actual Return on Plan Assets	1083	

Source: Delphi Corporation Annual Report, 2005, Lehman Brothers Analysis; data as of January 2, 2007.

**Figure 13. Delphi Corporation: Funded Status and Unrecognized Liabilities**

U.S. \$Million	2005	Description
Fair Value of Plan Assets	10511	
<b>Projected Benefit Obligation</b>	<b>15070</b>	
Underfunded Status	-4559	Liability to Employees
Unamortized Actuarial Loss	4281	
Unrecognized Transition Obligation	7	
<b>Unamortized Prior Service Cost</b>	<b>903</b>	
Net Amt Recognized in Bal Sheet	632	Net Amount Recognized
Balance Sheet Accounts	2005	
LT Prepaid Benefit Cost (Other LT Assets)	110	Asset
Pension Liability (Other Liabilities)	-3880	Liability
Intangible Pension Asset (Intangibles)	889	Asset
<b>Acc. Other Comp. Income</b>	<b>3513</b>	<b>Deduction from Equity</b>
Net Amount Recognized	632	
Net Adj. to Equity & Deferred Tax Liab.	-1678	Add'l Amt Recog by Cmetrics

Source: Delphi Corporation Annual Report, 2005, Lehman Brothers Analysis; data as of January 2, 2007.

Figure 13 provides data on the funded status and the recognized pension liabilities of Delphi Corporation. As of December 2005, the Delphi pension plans had projected obligations in excess of fair value of plan assets of \$4,559 million. Of this, \$5.2 billion are unrecognized in the financial statements; hence Delphi has net pension assets of \$632 million. CMetrics recognizes the full underfunded status as the pension liability and restates the balance sheet accounts, subtracting the asset amounts and the comprehensive income amount (associated with the Minimum Pension Liability) from the pension liability in other liabilities, reclassifying this amount from other liabilities to debt and adding to the unrecognized portion of the pension adjustment. The net effect on Delphi's equity is a decrease of \$1.678 billion. The impact on capital employed is a deduction in capital of approximately \$1 billion, due to the reclassification of the pension assets as reductions in the recognized pension liability.

Reviewing Figure 14, it is clear that pension and OPEB liabilities, as currently accounted for, have a depressing impact on operating returns. The median ROIC of Automotive components industry changes from 1.6% to 2.4% after this adjustment. We also notice that the relative ranking of Delphi and ArvinMeritor changes. While ROIC of Arvinmeritor changes to 1.9%, there is a much larger impact on the ROIC of Delphi which changes from -0.02% to 2.3% post OPEB and Pension adjustments.

In addition to the standard adjustments CMetrics reclassifies all non-recurring charges, such as restructuring charges, gain on sale of assets, or gains from the retirement of debt, as one-time charges and removes them from operating expenses. These charges are removed because true one-time charges do not reflect the ongoing results of the business and are not indicative of future performance. In addition, restructuring charges, and other reserves, have been used by companies historically to smooth earnings. By removing these items from the analysis, the user gets a better picture of the recurring earnings of the firm.

**Figure 14. Pension and Other Post Employment Benefits Example**

		ROIC (%)				Rank			
		Before Adj.	After Adj. for Pensions	After Adj. for OPEBs	After Adj.s for OPEBs and Pensions	Before Adj.	After A dj.s for Pensions	After Adj. for OPEBs	After Adj. for OPEBs and Pensions
2005 CQ4	Sales 2005 (USD mn)								
LEAR CORP	17,089.2	4.9	5.2	5.2	5.5	1	1	1	1
BORGWARNER INC	4,293.8	2.5	2.6	2.7	2.9	2	3	2	3
AUTOLIV INC	6,204.9	2.4	2.4	2.4	2.4	3	4	3	4
TRW AUTOMOTIVE HOLDINGS CORP	12,643.0	2.2	3.3	2.2	3.3	4	2	4	2
<b>ARVINMERITOR INC</b>	<b>8,903.0</b>	<b>1.0</b>	<b>1.5</b>	<b>1.4</b>	<b>1.9</b>	<b>5</b>	<b>5</b>	<b>6</b>	<b>6</b>
<b>DELPHI CORP</b>	<b>26,947.0</b>	<b>(0.0)</b>	<b>0.7</b>	<b>1.5</b>	<b>2.3</b>	<b>6</b>	<b>6</b>	<b>5</b>	<b>5</b>
VISTEON CORP	16,976.0	(3.4)	(2.5)	(1.6)	(0.6)	7	7	7	7
DANA CORP	8,626.0	(93.8)	(105.7)	(93.0)	(104.9)	8	8	8	8
<b>Median</b>		<b>1.6</b>	<b>2.0</b>	<b>1.8</b>	<b>2.4</b>				

Source: CMetrics v1.0, Lehman Brothers Analysis; data as of January 2, 2007.

## TOOLS AND FEATURES

CMetrics includes a number of features to aid in portfolio review and analysis.

### Peer Group Analytics

CMetrics allows the user to analyze up to four companies or industries at a time. The user can also select pre-defined sector, industry and sub-industry peer groups. These peer groups are based on the S&P published Global Industrial Classification (GICs) schema.

In all cases, when peer group analysis is computed, the peer group operating metrics are computed as a weighted average (where the weight is the denominator of the metric). For WACC, beta and the valuation multiples the industry metric is the market value weighted average.

### Relative Performance Flags

Every company observation in CMetrics is color coded, based upon its position relative to the industry. If a company observation for a particular metric is within the middle half of the observations for that quarter in the industry group, the observed company metric appears as black. If a company observation is within the bottom quarter or top quarter of observed values than the number is coded as red or green depending on whether an



extreme high or low value for the metric is enterprise value increasing (good) or not (bad). Figure 15 summarizes the meaning of the color-coded flags within CMetrics.

**Figure 15. Performance Flags**

<b>Key Performance</b>	<b>Above Industry</b>	<b>Below Industry</b>
EPS	Not Meaningful	Not Meaningful
Sales Growth	Good	Bad
ROE	Good	Bad
ROIC	Good	Bad
NOPAT Margin	Good	Bad
Depreciation Margin	Bad	Good
R&D Margin	Bad	Good
COGS Margin	Bad	Good
Other SG&A Margin	Bad	Good
Capital Turnover	Bad	Good
Working Capital Turnover	Bad	Good
AR Days	Bad	Good
AP Days	Good	Bad
Inventory Days	Bad	Good
PPE Margin	Bad	Good
Financing Return	Good	Bad
Leverage Ratio	Good	Bad
Financing Spread	Good	Bad
Non-Operating Return	Bad	Good
Investment Ratio	Bad	Good
Investment Spread	Bad	Good
Non-Recurring Income (expenses) to sales	Not Meaningful	Not Meaningful
<b>Additional Market &amp; Credit Risk Measures</b>		
Beta	Bad	Good
WACC	Bad	Good
Coverage Ratio	Good	Bad
Cash Position	Good	Bad
Cashflow Discrepancy	Bad	Good
<b>Key Valuation Metrics</b>		
P/E multiple	Good	Bad
EV/EBITDA	Good	Bad
EV/IC	Good	Bad
EV/FCF	Good	Bad

Source: CMetrics v1.0.

### Trend Flags

CMetrics contains trend line flags for the current value of each metric. An up-arrow (↑) indicates the current value of the ratio is higher than the average of the ratio from four quarters and eight quarters prior<sup>4</sup>. A down-arrow (↓) indicates the opposite.

### Graphics Capabilities

CMetrics contains custom charts to analyze the data. CMetrics provides two standard charts. The Trend Analysis plots the selected metric for the four companies and/or industry selected. All of the CMetrics Key Performance and Additional Market and Credit Risk Measures can be plotted. As in POINT and the Time Series Plotter, a custom data tool on LehmanLive, the user can zoom in and out of the graph to get a closer view of the desired time period. The Two Metrics Time trend chart plots any two metrics over time to allow users to understand trend and correlation between metrics for one company/industry at a time. In addition, users can download data series into Microsoft Excel to create additional graphs and analysis.

### User Control of Adjustments

CMetrics places control of the adjustments with the user. A user can select all, one or none of the adjustments depending on the purpose of the analysis. However, because it is not meaningful to compare companies across sectors without adjustment, the default set up within CMetrics is to activate all adjustments.

## COVERAGE AND DATA SOURCES

CMetrics provides consistent standardized metrics on a quarterly basis from our database of over 3,000 companies. Beta coverage is limited to U.S. companies (excluding financial institutions, insurance, and real estate companies) that have been included in the Russell 3000 index over the past five years. CMetrics ratios are constructed from quarterly data with historical data history that goes back to the first quarter of 2001. The CMetrics database is updated nightly during earnings announcement season. Outside of earnings announcement season, the database is updated weekly.

<sup>4</sup> If the observed metric at a point in time,  $t$ , (expressed as  $metric_t$ ) is less than  $(1/2) * (metric_{t-4} + metric_{t-8})$  than the trend is considered to be decreasing and a ↓ appears. In this formula,  $t$  is the current quarter, and  $t-4$  and  $t-8$  reflects the result for this quarter 1 year and 2 years prior.

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## APPENDIX: LEHMAN CMETRICS FINANCIAL ANALYSIS FRAMEWORK

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### Performance Metrics

The CMetrics framework decomposes Return on Equity (ROE), the primary measure of performance, into the three key aspects of firm performance: operating performance, financing performance, and return on non-operating investments. By separating and decomposing overall performance the framework allows users to identify how managements' operating, financing, and non-operating investments decisions influence overall performance. Importantly, decompositions into operating statistics, such as AR days and expense ratios can be useful in assessing the sustainability of current earnings levels.

In addition, two measures of overall performance, Sales Growth and Earnings per Share (EPS)), are also presented.

#### *Overall Performance Measures*

**ROE** is defined as earnings before extraordinary and discontinued operations divided by shareholders equity. In the CMetrics Framework, ROE is also measured before all non-recurring items (e.g. restructuring charges, gains on sale of assets, etc.). Earnings before extraordinary and discontinued operations and non-recurring items measures the income from normal business operations after all operating and financing charges; it is the profit available to pay dividends to shareholders and includes profits associated with all aspects of firm performance (operations, financing, and non-operating investments). ROE therefore is the profit margin of the firm's equity investors as a class.

**Sales Growth** is computed as the quarter-on-quarter growth in Net Revenues. Equation 2 above shows that growth in cash flows (of which sales growth is a large component) is a key factor in value.

**EPS** is the per share profits that may be compared to share price to measure the relative value of a security. CMetrics presents the GAAP-compliant EPS, which includes all non-recurring charges that are excluded from our other metrics. EPS can only be compared overtime with care because stock splits and share buybacks will affect this number. EPS should not be compared to those of other firms, even within the same industry.

**Non-Recurring Income (Expenses) to Sales** is the ratio of non-recurring income and/or expenses as a percentage of sales. Companies that have an unusual number of "non-recurring" items to sales compared to their peers, especially if the company frequently declares such charges, should be examined closely for signs of aggressive accounting practices.

#### *Performance Measures: Operating Return*

**ROIC** is net operating profits after cash taxes (NOPAT) divided by invested capital (IC). Operating profits exclude all interest charges and non-operating income and expenses (including interest income), and all non-recurring items. NOPAT is the profits of the enterprise (excluding non-operating investments) before payment to debt or equity capital providers. IC is book value of the total capital invested in the operations of the firm, namely the debt and debt-like claim on assets and equity and equity-like claim on assets less investments in non-operating assets and non-interest bearing operating liabilities. Importantly, IC includes all book intangibles including goodwill, because these intangibles generally represents investments made by the firm in acquiring intangibles and represent a use of investors' cash. ROIC is the profit margin of the firm's

debt and equity investors as a class; it measures the efficiency of the organization in exploiting its capital.

ROIC is particularly useful in comparing performance across industries, especially when examined in excess of the company's cost of capital. Also, as seen in equation 2, ROIC is a key driver of firm value.

While ROIC is useful in assessing overall operating performance, it is less useful in identifying the reasons for that performance. However, using a variant on the du Pont analysis, ROIC is decomposed into performance statistics related to operating margins and capital intensity.

#### *Operating Return: Margin*

**EBITDA Margin** is earnings before interest, taxes, and depreciation and amortization divided by net revenues. EBITDA is computed before non-recurring items. EBITDA Margin is only a rough approximation of cash flows from operations as a percentage of sales. EBITDA Margin will differ from free cash flow margin by the amount of investment made in working capital and other assets and by the amount of releases from long-term liabilities. These items must be examined in detail when examining the cash flow of the business.

**COGS Margin** is cost of goods sold divided by net revenues. COGS is computed as company-reported Cost of Goods Sold (or Cost of Sales) less depreciation charges. COGS Margin measures the costs of producing or acquiring goods and services for sale as a percentage of sales. Changes in COGS margin should be examined closely for sustainability.

**R&D to Sales**, which is computed as Research and Development expenses (as reported) divided by Net Revenues, is the percentage of Net Revenues invested in the development of new products and services. Declines in R&D to sales ratio, especially in a stable or declining EBITDA margin environment, may indicate that future growth prospects for this firm are limited or that management has reduced funding future projects to meet near term profit targets.

**SG&A to Sales** is the ratio of non-R&D Selling, General and Administrative Costs (SG&A) to sales. This ratio (often called the expense ratio) measures the efficiency of a company's selling and administrative functions. Comparing a company's SG&A to sales with its peers is useful assessing the overall efficiency of the operations and in identifying areas of potential margin improvements from cost cutting measures.

#### *Operating Return: Capital Turnover*

**Capital Intensity** is defined as Invested Capital (IC) divided by Net Revenue. It measures the amount of capital required in the core business operations to produce \$1 of revenues. Because IC includes working capital and other long term assets, as well as fixed assets (such as machinery and equipment) it is useful in assessing the efficiency of a firms' ability to collect on its receivables as well as the degree of asset intensity of the business.

While capital turnover differs substantially across industries, a company that has capital turnover that is significantly lower than the industry is more likely to have a higher return on capital. A review of capital intensity and its decomposition can provide information to help diagnose the reason for and provide additional insights into the sustainability of current performance. The CMetrics framework provides 5 additional measures of capital intensity: Working Capital to Sales (WC/Sales), Account Receivables Days (AR Days), Accounts Payable Days (AP Days), Inventory Days, and Fixed Asset Intensity (FA Intensity).

**WC/Sales** is computed as total working capital divided by net revenues; where working capital is computed as total non-cash current assets less total current liabilities, excluding debt included in current liabilities. Working Capital is the funds tied up in current operations less the short-term, operating non-interest bearing liabilities that partially finance them. Working Capital may rise because receivables and/or inventories rise (as is likely at the beginning of a recession when sales begin to lag and non-collectible receivables rise) or payables fall (as happens if, in response to perceived increase in the likelihood of non-payment, suppliers do not extend or reduce credit terms). To understand the reason for a rise or fall in Working Capital, the CMetrics framework provides data on three key components of WC/Sales: AR Days, AP Days and Inventory Days.

**AR Days** is the estimated number of days of sales that is not yet collected. *AR Days* that exceed those of competitors may indicate aggressive accounting practices such as failure to write off bad-debt or channel stuffing. Increases in AR Days may also indicate declines in demand so that more attractive financing terms may be required to induce sales.

**AP Days** is the estimated number of days of sales that is not yet paid to creditors. AP Days that exceed those of competitors by a large margin may indicate cash flow problems. Such rise in payables may also indicate problems to bond holders, as these claims are superior to those of the bondholders in the case of default.

**Inventory Days** is the estimated number of days of sales that have been produced (or acquired) that have not been sold at the end of the period. Growth in Inventory Days generally indicates that the company's sales are falling due to decreases in demand. When Inventory Days are high relative to the industry or historic firm levels, especially while COGS margin is stable or falling, the company may be overproducing in order to reduce its per unit costs.

**Fixed Asset Intensity** is the ratio of Property, Plant and Equipment, net of depreciation (NPPE) to Net Revenues. Fixed Asset Intensity measures the amount of long term production assets the firm uses to produce 1 dollar of revenues. Fixed Asset Intensity varies substantially by industry and should be compared across sectors with care. Within a sector, differences in Fixed Asset Intensity can indicate that the company may lack the scale to fully utilize its fixed costs. Accordingly high Fixed Asset Intensity coupled with high growth can indicate that firm profits should increase above historic levels if sales growth continues. Fixed Asset Intensity that is low relative to peers should be reviewed with care, as this may indicate aggressive depreciation policies or lack of investment in property, plant and equipment.

#### *Financing Return*

**Financing Return** is the amount of ROE that is due to the capital structure and financing decisions previously made by the firm. Financing Return that is low relative to its industry peers indicates that opportunities exist to improve overall equity returns by better exploiting the capital structure. However, while it is clear that capital structure affects value, the issue of what is the optimal capital structure of a firm is extremely complex and should be analyzed in much more detail.

CMetrics also presents the two main components of Financing Return: leverage and financing spread. **Leverage** is computed as book debt divided by book common equity.

Leverage is positively related to the firms financing return, however, a company that has experienced increases in leverage, or one that is more highly levered than its peers, are

also more likely to have problems making debt payments should revenues and cash flows decline.

**Financing Spread** is computed as ROIC less the after tax cost of debt incurred by the firm. A large financing spread increases the return from financing; however when comparing firms with high financing spreads it is important to consider whether or not the spread will continue as debt comes due and must be refinanced at higher rates.

#### *Non-operating Investment Return*

**Non-operating Investment Return** is the amount of ROE that results from investments in non-operating investments. It is computed as the ratio of non-operating assets (at book value) to book equity times the spread between non-operating returns and ROIC. Non-operating investments include cash and marketable securities, as well as investments in joint ventures and other unconsolidated subsidiaries, net of minority interests in the company's operations. Non-operating return is the financial statement non-operating income less minority interest expense divided by non-operating financial assets multiplied by 1 minus the cash tax rate.

### **Additional Market and Credit Risk Metrics**

**Beta** is the commonly used measure of the sensitivity of a stock's return to the market return. Betas are computed using 60 months of return data for each firm. No beta is computed unless a 60 month data history exists. The return on the S&P 500 was used as the market return. Beta is a measure of systematic stock market risk. Firms with high betas generally have more variable cash flows and higher operating risk.

**Weighted Average Cost of Capital (WACC)** is the expected cost of financing the company's operations at current market rates, assuming the current capital structure. Because IC is equivalent to the debt and equity invested in the operations of the firm, companies with WACC that is greater than ROIC are making an economic loss on their economic capital and should be expected to have lower future returns.

**Coverage Ratio** is the ratio of EBITDA to interest expense. It is a rough approximation of the number of times by which cash from operations can pay (or "cover") interest expense. Companies with coverage ratios higher than industry peers will, conditional on similar cash flow volatility, have a lower probability of default. Many debt covenants, especially for companies with lower debt ratings, require that the coverage ratio stay above a certain number.

**Cash Position** is the ratio of cash and equivalents to total current assets. Cash Position measures the cash a company has on hand. Cash Position that is low relative to peers, especially when coupled with low cash flows from operations, is associated with a higher likelihood of bankruptcy.

**Cash Flow Discrepancy** is the ratio of the difference between cash flows from operations and Earnings before Extraordinary Items before depreciation and amortization and other non-cash charges divided by the absolute value of cash flow from operations. Cash Flow Variance that is low relative to its peers, or relative to its historical levels is an indicator that the firms accounting may be aggressive in recognizing revenues early or expenses late. Such firms should be further examined for material weaknesses.

**Free Cash Flow to Sales** is the ratio of Free Cash Flow (FCF) to Net Revenues. It measures the cash provided by operations, in excess of capital expenditure, as a percentage of Net Revenues. FCF represents the cash flows derived from the business operations after capital expenditures. Declines in FCF/Sales, especially those not

explainable by large increases in capital expenditures, should be monitored closely as an indicator of the future health of the business.

#### *Valuation Metrics*

***Price to Earnings Ratio*** is the common equity price divided by earnings per share over the last 12 months. P/E is a common measure of market pricing and is frequently used to determine whether a company is trading high or low for its industry. PE may not be a good multiple to make comparisons when companies have significantly different capital structures.

***Enterprise Value to EBITDA*** is the ratio of the market value of the company's equity plus debt divided by EBITDA over the last 12 months.

***Enterprise Value to Invested Capital*** is the ratio of the market value of the company's equity plus debt divided by IC. It is the ratio of market value to book value of invested capital.

***Enterprise Value to Free Cash Flows*** is the ratio of market value of the company's equity plus debt divided by Free Cash Flows over the last 12 months.

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