European Credit Research
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Learning Curves – Curve Trading Using Model Signals

Analysing the Effectiveness of Our 5y/10y Curve Trading Model, Which Works Surprisingly Well

INVESTMENT STRATEGIES: NO. 37

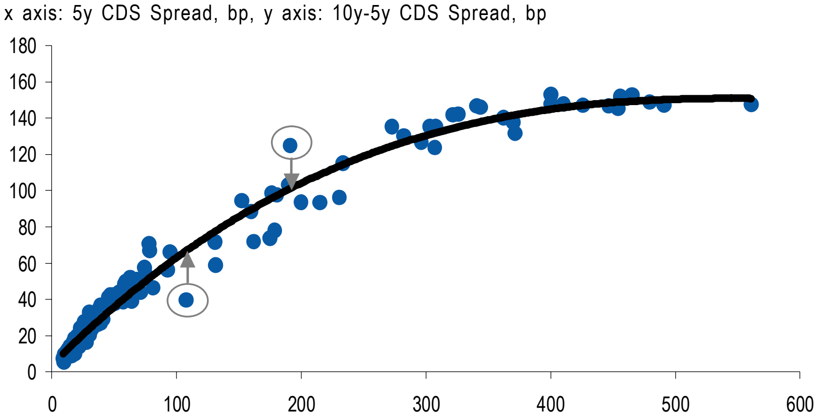
- **In this note we analyse our model for predicting the steepness of single name CDS curves and test the effectiveness of its predictions.** The model we analyse uses the 5y point to predict where the 5y/10y curve should be for each company and can be used to spot outliers (see Figure 1).

- **We found this simple model works surprisingly well.** As illustrated in Figure 1, the curves furthest above the 5y versus 10y-5y aggregate credit curve tend to flatten in subsequent months, and curves furthest below the aggregate curve tend to subsequently steepen. The model predicts profitable curve movements correctly 70% of the time for the CDS furthest from the curve.

- **Backtesting the model's trade predictions produced an average unfunded annual return on notional of 1.23% (123bp), a prediction success rate of 70% and an Information Ratio of 0.95** using data from October 2000 to the present.

- **We introduce a new weighting scheme for curve trades: 'Market Weighting'** which weights curve trades to neutralise for the *directionality* of curves. We find this produces superior trading results.

Figure 1: Single Name CDS 5y/10y Aggregate Curve
x axis: 5y CDS Spread, bp, y axis: 10y-5y CDS Spread, bp



Source: JPMorgan

We would like to thank James Maynard for his contribution to this research note.

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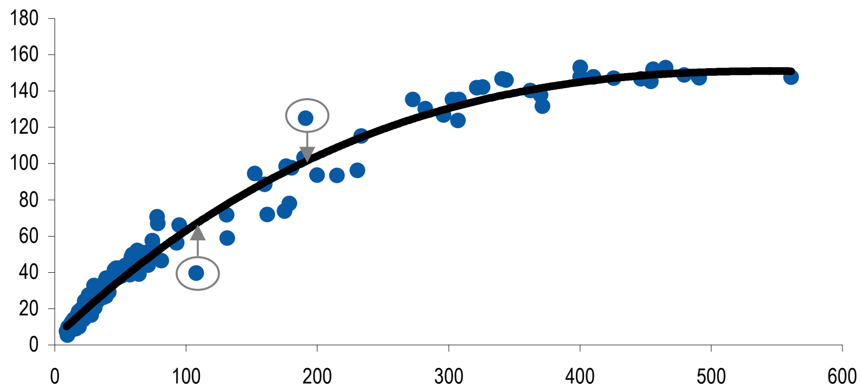
1. Overview

In Credit, the 5y Spread is a Good Indicator of the 10y-5y Curve Steepness – We Test if it Works to Spot Future Moves
If we plot the 5y CDS spread on single name CDS against the 10y-5y curve there is a clear relationship (Figure 2) – on a given day, 5y spread levels are a good explanation of 10y-5y curves (the regression has a high R^2, typically > 90%). We plot this 'model' every day in our analytics packages. We fit an 'aggregate' regression line through the points, which tells us *on aggregate* what 10y-5y curve we observe for a given 5y spread. For example, for a name trading at 70bp at the 5y point, the 10y-5y curve may be on aggregate 50bp, according to the regression best-fit line for that period[1].

We analyse whether the divergence of a single name from the aggregate curve is likely to revert, in which case we could construct a trading rule to exploit this trend. If the model is useful and the aggregate curve does indicate where the curve 'should' be, we will be able to take advantage of the corrective movement to come. For example, we could put curve flattening trades on any CDS which the model shows are too steep relative to the curve and therefore should flatten.

Figure 2: Single Name CDS 5y/10y Aggregate Curve
x axis: 5y CDS Spread, bp, y axis: 10y-5y CDS Spread, bp



Source: JPMorgan

We are surprised to find this model works remarkably well as a predictive tool and trading rule.

[1] See previous research notes introducing this model: *The Curve of DJ TRAC-X Europe* (J Due, 12th Jan 04)*, Revisiting Credit Maturity Curves* (J Due, 22nd Nov 04) and *Cubic Splines and Credit Curves J Due, 4th May 05).*

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Key Conclusions

- **Names that are steep to the aggregate curve flatten, those which are flat steepen (both in absolute terms and relative to the model).**
  On average a company whose 10y-5y CDS curve trades below the 10y-5y *aggregate* curve will move 'up' (steepen) closer to the curve and a CDS above the curve will move 'down' (flatten) towards the curve. This indicates that the aggregate curve shows how steep a CDS curve 'should' be, and points away from the curve indicate a mis-pricing by the market which will be corrected in the following few weeks or months. Historically (since 2000), the model was successful (gave profitable trade predictions) 70% of the time when trading the 10 steepest and 10 flattest CDS each month.

- **Trading this signal has produced profitable trading strategies (since 2000).**
  Testing the predictions of the model from October 2000 showed consistent success. The model's predictions had a success rate of 70% (in giving profitable trade predictions) and this level of success was fairly constant throughout the 7 year period. Earlier years experienced much more volatile profits, however, due to a generally more volatile environment. The strategy produces an Information Ratio of 0.95 over the full period using base-case parameters and produced a % Return on Notional of 1.23% (123bp) unfunded (see explanation later). Even when we take costs into account, the strategy is consistently profitable.

- **The model is stronger for Investment grade than for High Yield**
  We find that our aggregate curve model is better at producing profitable trades and predicting curve movements for investment grade CDS curves than for high yield, where (in high yield) more idiosyncratic factors account for curve movements.

- **The relationship is much stronger for points further away from the curve – the movement of points close to the curve is negligible.**
  If a company's 10y-5y CDS curve lies very close to the aggregate 10y-5y curve, then any movement caused by a potential re-pricing by the market is small. If a point lies further away from the curve, however, the effect of market re-pricing is much more significant.

- **Despite this relationship, single name CDS generally stay consistently above or below the curve.**
  Even though spreads do tend to move *towards* the aggregate curve, they also stay consistently above or below the curve, i.e. if a CDS lies above the curve, then it will, on average, stay above the curve. The curve acts as an attractor but does not pull names all the way to it, only closer to it. Hence the aggregate curve is not a definitive measure of where spreads should be or how steep or flat a CDS is trading, but is more an indication of whether a point is trading *relatively* steeply or flat for points further away from the curve.

- **We introduce a new method of weighting curve trades - 'Market Weighting' - which takes into account the directionality of curves.**
  Curves are directional over a short horizon – investment grade curves tend to be steeper at higher spread levels – and the aggregate shape of the curve tells us about that directionality. We find that accounting for this directionality by 'Market Weighting' trades improves trading profits. We hope to use this curve weighting scheme in future analysis.

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The key results are explained in the main part of this note and the appendices provide a more technical and thorough analysis, as well as the list of names our model currently suggests are too flat or too steep (Appendix III). The Conclusion and Explanation section gives a rationale for why this model works and what that tells us about credit derivative curve pricing.

We start with an analysis of whether our model curve predicts future single name curve moves in general, before looking at how this performed as a trading strategy.

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2. The Aggregate Curve Steepness is an 'Attractor' for Single Name Steepness

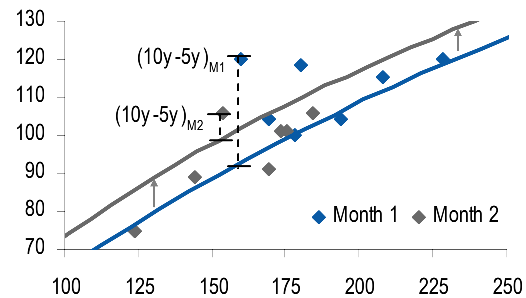
Curves that are steep to our 'aggregate' model curve flatten in subsequent periods, while flat curves steepen. So the aggregate curve acts as an attractor for single name curves.

We can simply see whether curves generally flatten towards the aggregate curve over a period by plotting the single name curve distance from the aggregate curve at a given time. In Figure 3, the vertical distance between a point and the aggregate curve is illustrated for two different months. We can then see how this distance changes for steep or flat names over a period (10y-5y, Month 2 in Figure 3).

We plot a history of the monthly change for each single name curve steepness relative to the aggregate curve in Figure 4, where the x-axis shows the distance from the aggregate curve (single name 10y-5y curve *minus* model aggregate 10y-5y curve) in month 1 and the y-axis shows this distance from this curve again in the next month. We have done this for every month since 2000 for every name that has been in iTraxx (Main and Xover). Using a linear regression we see a line with intercept approximately zero and gradient of 0.8. This means that the aggregate curve is acting as an attractor as the gradient of the regression line is less than 1 (0.8); in other words, steep curves to the model subsequently become (0.8 times) less steep and flat curves subsequently become (0.8 times) less flat. As highlighted in the chart, a name trading 40bp steep to the model in month 1 subsequently is seen to trade only 32bp steep to the model in the next month. This indicates that points are generally flattening or steepening according to whether they are above or below the credit curve respectively[2].

Figure 3: Plot of Single Name CDS Curve Relative to Aggregate Curve

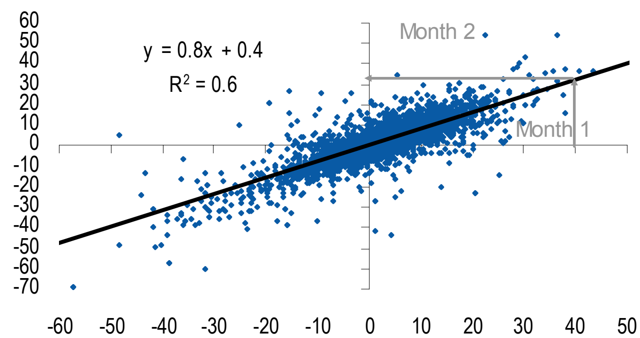
x-axis: 5y spreads (for single names), bp; y-axis: 10y-5y spreads (for single names, bp



Source: JPMorgan

Figure 4: Distance from Aggregate Curve Over Two Periods

x axis: Distance from aggregate curve in Month 1, bp; y axis: Distance from aggregate curve in Month 2, bp. HG and HY names together.



Source: JPMorgan

[2] The R^2 of 0.6 shows that whilst this was a reasonable overall indication of where points were likely to move, it only explained about 60% of the actual movement observed.

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These results held for testing both the investment grade and high yield curves. We found it has a stronger R^2 of 0.7 for investment grade compared to 0.5 for high yield names. This simple result shows that we can expect a single name curve that is steep to our model to subsequently flatten and a flat name to the model to subsequently steepen. The question is whether this finding is strong enough to form the basis of a systematic trading strategy and we now turn to a rules-based strategy based on our model. We begin (in the grey box) with a brief outline of the base-case assumptions (parameters) of the trading strategy that we adopt.

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3. Trading Strategy Back-testing

Back-testing a curve trading strategy for the curve outliers based on our model produced successful results over the past seven years, throughout the cycle.

Trading Strategy Methodology: Base Case Parameters

We use the model to calculate the aggregate curve (i.e. aggregate 10y-5y curve for each 5y spread level) each month and find the ten CDS furthest above and below the aggregate curve. We test trading more / fewer than 10 names in the Appendices. We put flatteners on the ten CDS furthest above the curve each month (the steepest) and steepeners on the ten CDS furthest below the aggregate curve (the flattest). This produces a market-neutral trading strategy which profits from correct predictions from the model. We hold the trades for four months and then we unwind to calculate the profit (again the 4-month holding period is stress-tested in the Appendices). These trades are CDS-based and are unfunded. We tested with both trading at Mid and including Bid / Offer spreads.

We are focused on whether our model produces profitable trades due to curve movements, so our base-case is to exclude Time (Carry + Slide) from our P+L. In Section 3.iii we show what effect time value has as well.

We found the best framework to highlight the 'steepness' and 'flatness' of a single name CDS in order to put on curve trades was:

- Using a cubic regression line of best fit (R-Squared model) to calculate the 5y versus 10y-5y aggregate credit curve.
- Measuring relative steepness by calculating the *actual* spread difference of the 10y-5y from the average curve (as opposed to a *ratio* difference).
- Analysing whether curve moves can produce profitable trades by using 'market-weighted' curve trades.

Appendix I shows the results for alternative strategies and Appendix II focuses on the different choices of curve trade weighting strategies.

Trading strategies over the 7-year testing period (October 2000 – September 2007) used all CDS which have ever been in the relevant iTraxx index to create the aggregate curve and for trades.

All trades were put on with €1m notional on the 10y leg (the size is unimportant) and sized given the relevant weighting strategy in the 5y leg.

Back-testing Results

Back-testing Results

i. Overall Results

ii. Results Through Time

iii. Flatteners versus Steepeners

iv. High Yield Curve Results

v. Factoring in Costs

We now look at our back-testing results, starting with the overall results and then analysing different aspects of these.

i. Overall Results

Putting on a monthly portfolio of steepeners and flatteners on the high grade CDS furthest below and above the aggregate curve produced consistent profit throughout the 7-year period, with an Information Ratio of 0.95 and unfunded return on notional of 1.23% (123bp, see Table 1).

% Return on Notional

Our CDS trades are unfunded, i.e. no capital is committed. To express the € P+L as a percentage, we look at the (€ P+L / € 10y Notional Traded), for each curve trade which we call the % Return on Notional. Typically we trade 20 trades each month (10 steepeners and 10 flatteners), giving €20m Notional Traded. When we hold trades longer than a month, a larger notional is outstanding in each month. The % Return on Notional is an annual return.

Table 1: Results of Backtesting since October 2000

Base Case Parameters, High Grade names, no bid / offer, 4 month holding period.

Metric	Result
#Trades	1,580
Overall P+L (€ on €1m 10y equivalent notional, in each trade)	6,481,253
Information Ratio	0.95
% Return on Notional	1.23%
% Correct Curve Movements	66.01%
% Profitable Trades (Model Success)	70.38%
Average P+L Per Trade (€ on €1m 10y equivalent notional, in each trade)	4,102
# Months with Profit	74
# Months with Loss	5
Average Monthly P+L (€ on €1m 10y equivalent notional, in each trade)	82,041
% Correct Predictions for Steepeners	68.0%
% Correct Predictions for Flatteners	64.1%
Average Absolute Curve Change (bp)	10.68
Average Absolute Curve Change for a Correct Prediction (bp)	8.53
Average Absolute Curve Change of steepners (bp)	11.20
Average Absolute Curve Change of flatteners (bp)	10.17

Source: JPMorgan

As Table 1 shows, our back-test produced surprisingly successful results. This simple strategy, taking only model outliers, correctly produces profitable trades 70.38% of the time and estimated whether a CDS would steepen or flatten 66.01% of the time (this is statistically significant at 1% level[3]) and produced noticeable profits, despite not taking into account the individual company situation of any of the CDS. There were only five months (out of 79) where the strategy did not generate a profit.

Defining Success

We identify trades to put on by taking curves that are far from the predicted curve. If we have a CDS whose curve is flat compared to the predicted curve, we will put on a steepener. We could therefore determine success in two different ways (mostly they coincide, but not always):

a) Our steepener steepens, i.e. the 10y-5y curve is steeper at the trade end than when we put on the trade.

b) Our trade produces a profit. If we Market-Weight our trade (see Appendix I), this will typically mean that the curve moves towards the predicted curve.

An example will help illustrate this. In Figure 5 we have a single name with a 5y spread of 210bp and 10y-5y curve of 60bp at the start. The aggregate curve model predicts that for a 5y spread of 210bp the 10y-5y curve should be 110bp, so the actual curve is 50bp flat (110bp - 60bp) to the aggregate curve. We will want to put on a steepener.

[3] Using a simple binomial hypothesis test where the probability of a correct prediction is 0.5.

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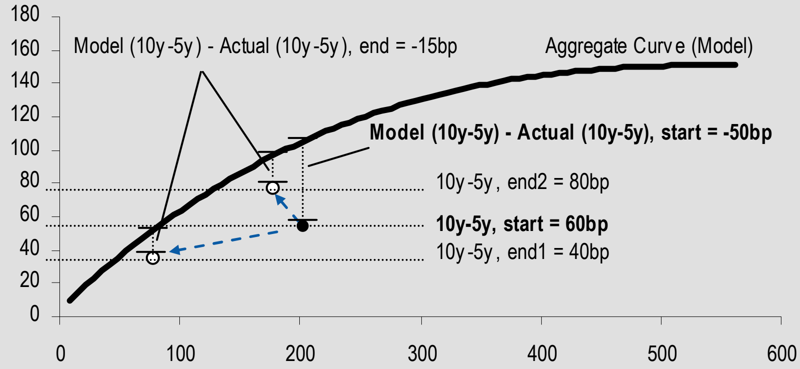
Figure 5: Illustration of Measures of Success

x-axis: 5y spread (bp); y-axis: 10y-5y spread (bp). Dots illustrate 5y versus 10y-5y points for a single name at the start and end of our trade periods. The thick black line is the Aggregate Curve, or the Model.



Source: JPMorgan

Figure 5 shows two possible end states (1 and 2). In 'end1' the 10y-5y curve has flattened to 40bp. In that sense the steepener has been unsuccessful, in that the curve has flattened. However, at the same time the 5y has tightened to 90bp so that the model predicted curve at that level is only 55bp. Given the 10y-5y curve at end1 is actually 40bp, the curve has moved towards the aggregate curve and is now only 15bp flat (from 50bp flat at the start). In that sense, the steepener was successful in that the curve is less flat to the model and has moved *towards* the aggregate curve.

In 'end2' the 10y-5y curve has steepened to 80bp. In that sense the steepener has been successful; the curve has steepend. At the same time the 5y has tightened to 190bp so that the model predicted curve at that level is 95bp. Given the 10y-5y curve at end2 is actually 80bp, the curve has moved towards the aggregate curve and is now only 15bp flat (from 50bp flat at the start). In that sense, the steepener was successful also in that the curve is less flat to the model.

Our end1 scenario shows that we could have a steepening trade we define as unsuccessful as it actually flattened, but successful in that the model predicted it should move towards the aggregate line, which it did. The weighting of the trades is important here and our new 'Market Weighting' ensures we have a profit if a name moves towards the aggregate curve. See Appendix I for more on Market Weighting trades.

For our results, we show the success **both** in terms of % of trades where the curve moves in the right direction (e.g. steepeners that steepen) **and** also the % of trades that are profitable, as they move towards to aggregate curve.

In addition to our simple tests in the previous section, this trading strategy back-test further shows that there is a relationship between a single name's steepness relative to the aggregate credit curve and whether it will subsequently steepen or flatten. We now analyse how these results varied through time.

ii. Results Through Time

Higher spread periods produced higher profits, but lower information ratios due to the higher volatility of returns.

Looking at how our trading strategy performed over time, in Table 2 we see that the strategy performs well over the entire seven year testing period. Despite the differing credit market conditions over the cycle, it still correctly produces profitable trades with a success rate of at least 60% in every year period and produces good profits. An annual unfunded return on notional of 0.83% (83bp) or greater was maintained for each full year.

Table 2: Individual Year Data

Base Case Parameters, High Grade names, no bid / offer, 4 month holding period.

	2000 (3 Months Only)	2001 (11 Months Only)	2002	2003	2004	2005	2006	2007 (5 Months Only)
# Months with Profit	3	10	8	12	12	12	12	5
# Months with Loss	0	1	4	0	0	0	0	0
% Correct Curve Movements	68.33%	62.27%	69.58%	78.33%	69.58%	55.00%	64.58%	56.00%
% Profitable Trades (Model Success)	61.67%	60.45%	66.67%	77.50%	65.42%	77.92%	76.25%	69.00%
P+L (€*)	156,788	965,792	1,532,164	1,552,201	766,914	675,487	664,804	167,104
Average monthly P+L (€)	52,263	87,799	127,680	129,350	63,909	56,291	55,400	33,421
Information Ratio	1.22	1.08	0.78	1.32	3.24	2.51	2.00	1.53
% Annual Return on Notional	0.78%	1.32%	1.92%	1.94%	0.96%	0.84%	0.83%	0.50%
% Correct Predictions for Steepeners	83.33%	39.09%	55.83%	91.67%	95.83%	69.17%	53.33%	60.00%
% Correct Predictions for Flatteners	53.33%	85.45%	83.33%	65.00%	43.33%	40.83%	75.83%	52.00%

Source: JPMorgan. Shading indicates a short year, where P+L will be smaller.

* On €1m 10y equivalent notional, in each trade

Some Explanation of Why This Works

Overall, this shows that throughout the cycle, the market views the 5y spread as a good indicator of the risk of a company and also views the 10y-5y curve as primarily a function of this 5y risk. In other words, our model accurately captures the single most important factor driving curve steepness. This level of curves' steepness changes throughout the cycle – as Figure 8 shows – but it is always a function of the 5y risk of the company. So in a credit downturn the 10y-5y curve can be a lot flatter for very high spread names, but the curve will still be in some sense a function of the 5y risk (i.e. spread). It also suggests that the aggregate curve is actually roughly the place a correctly valued single name CDS curve "should" be. Some names can have large differences from this aggregate curve over a particular period, but this corrects over time. Trading this signal therefore provides a profitable strategy.

Volatility of Returns

Whilst the average annual returns of the strategy were consistently positive, the monthly volatility of these returns varied over the cycle. Figure 6 shows this monthly P+L over the seven year trading period. There are two distinct periods: Between 2000 and 2003 there was a high rate of return, but also a high volatility in profit; from 2004 to 2007 there were smaller returns on the notional, but profit was more consistent and reliable.

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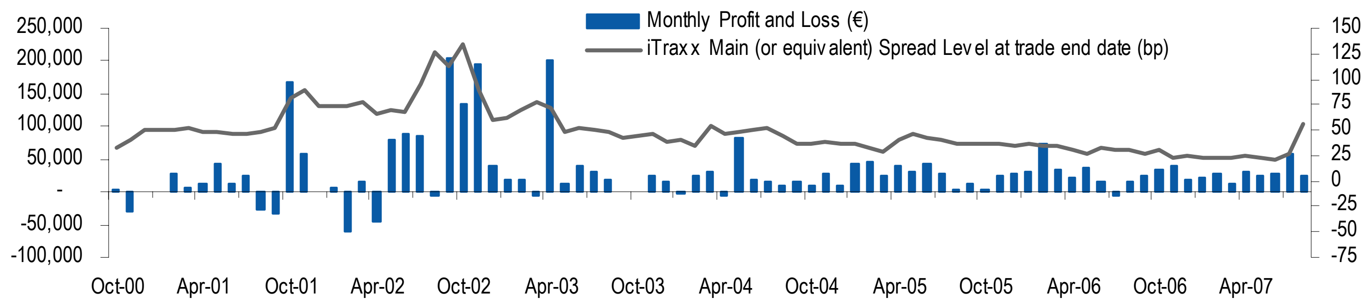
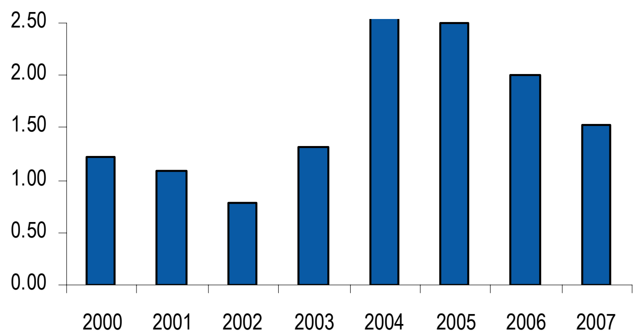
Figure 6: Monthly Profit and Loss Over Time

Left axis: Monthly P+L (€); Right axis: Investment Grade Spreads (bp)



Source: JPMorgan

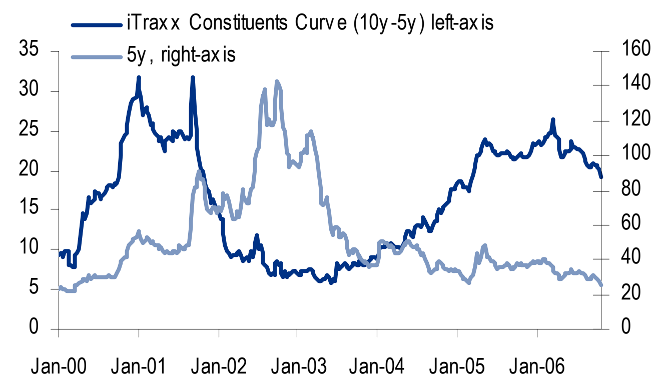
Figure 7: Strategy Information Ratio by Year



Source: JPMorgan

Figure 8: 10y-5y Investment Grade Curves Over Time

Left axis: 10y-5y spread curve (bp); Right axis: 5y Spread (bp)



Source: JPMorgan

Looking at the annual Information Ratios (Average Monthly Returns / St Dev of Monthly Returns) in Table 2 and Figure 7 highlights that the strategy was much more stable from 2004 onwards than before this time. Although overall profits (P+L) were greater in earlier years, volatility of these profits was also much higher, as seen in the lower information ratios for 2000-2003. This trend was mainly due to the much larger volatilities in the individual single name CDS and curves at this time (as Figure 8 shows, these years were the cyclical downturn years for corporate credit, with much higher spreads and larger spread moves). In nine months over this period where we had very large P+L, there were one or two of the individual CDS which experienced a very large curve movement within the month (a greater than 100bp curve move). 10y-5y curves were also less liquid at that point and so more extreme movements could be seen. In a stable liquid environment, such extreme moves within one month would not be expected and so the strategy should be more stable and reliable.

All this indicates that the strategy is a robust one. Despite being simple and ignoring many key drivers of spread movements, the model can cope with a variety of different economic scenarios and environments to correctly produce profitable trade signals over two thirds of the time.

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iii. Flatteners versus Steepeners

Flatteners generate greater profits than steepeners from just spread movements, but including Time Value (Carry + Slide) makes steepeners much more profitable.

In general, this research note is focused purely on the **spread movements** from curve trades, as we are trying to see whether our model successfully predicts names that will flatten or steepen in future periods. For our testing, we look at an equal basket of flatteners and steepeners. However, when we move on to analyse the profitability of just flatteners or just steepeners, we need to consider the time value of the trades to fairly compare the profit produced, since time value dramatically differs for steepeners and flatteners.

Table 3 shows that the percentage of profitable predictions is similar for flatteners and steepeners (around 70%). **However, the P+L from just curve moves (ignoring Time value for now) is significantly different, with Flatteners generating over 2.5 times the profit that Steepeners generate** (€4.7m for Flatteners, compared to €1.8m for Steepeners). However, when we consider the P+L including Time value (carry and slide), we get a very different picture. In general, market-weighted steepeners have positive slide and carry, and market-weighted flatteners have negative slide and carry[4]. This can be seen from our results in Table 3, where the Average Carry and Slide P+L Per Trade from Flatteners are both negative, while those from Steepeners are positive. When we add this Time (Carry + Slide) P+L we reverse the profitability order, with Steepeners now generating nearly double the profit of Flatteners (€2.6m for Flatteners, compared to €4.6m for Steepeners). This would indicate that trading just the steepeners on their own has been a much more successful strategy, although this introduces a directionality into the trading as curve steepness tends to be directional (as shown in Figure 8, although the nature of the directionality changes through time[5]).

Table 3: Results for Steepeners and Flatteners

Base Case Parameters, High Grade names, no bid / offer, 4 month holding period.

	Steepeners	Flatteners
% Correct Curve Movements	67.97%	64.05%
% Profitable Trades (Model Success)	70.13%	70.63%
P+L from Spread Changes (€ on €1m 10y equivalent notional, in each trade)	1,761,288	4,719,965
Total P+L from Spread Changes and Time (€ on €1m 10y equivalent notional, in each trade)	4,636,315	2,641,867
Average Spread Change P+L per Trade (€ on €1m 10y equivalent notional, in each trade)	2,229	5,975
Average Slide P+L Per Trade (€ on €1m 10y equivalent notional, in each trade)	819	-1,532
Average Carry P+L Per Trade (€ on €1m 10y equivalent notional, in each trade)	2,820	-1,106

Source: JPMorgan

For example, in 2001, 2002 and 2007 (periods of high market volatility), flatteners were profitable trades with 88%, 87% and 82% success rates, whereas steepeners only had a profitable success rate of 33%, 47% and 56% respectively. Over 2004 and 2005 (a period of lower volatility) the steepeners outperformed the flatteners.

[4] See Appendix I for a more detail description of market-weighted trades.
[5] See *Curves, Carry and the Credit Cycle* (J Goulden, 20th November 2006).

iv. High Yield Curve Results

High yield names exhibit the same general behaviour as investment grade names, although the model is less strong. Additionally, larger profits come with higher P+L volatility.

For high yield names our model-based trading strategy has a slightly lower success rate than the high grade names in predicting profitable trades (it gets it right 58% of the time versus 70% for high grade CDS over four months). Table 4 shows these results. However, P+L figures are much larger (€7.4m for HY versus €6.5m for HG) due to the larger spreads and spread movements of the high yield names.

This, however, comes with much higher volatility and the Information Ratio of 0.46 for high yield names is much lower than the 0.95 we were able to achieve for high grade names, holding the trades for four months. Interestingly, when we hold high yield curve trades for a shorter period – only one month – we find an improved performance, with the information ratio now 0.79 and the % Return on Notional now up to 2.25% (225bp) from 1.40%. This indicates that high yield curve mis-pricings are less persistent and that other, more fundamental drivers of high yield spreads start to assert themselves over longer periods of time or that the high yield market reacts more quickly to mis-pricings. This makes the model more successful over shorter holding periods in high yield, whereas in investment grade, holding for several months is better than just holding for a month.

Table 4: Results from High Yield Back-testing

Base Case Parameters, High Yield names, no bid / offer, 4 and 1 month holding periods.

Metric	4 month Holding	1 month Holding
#Trades	1,576	1,617
Overall P+L (€ on €1m 10y equivalent notional, in each trade)	7,352,866	3,035,510
Information Ratio	0.46	0.79
% Return on Notional	1.40%	2.25%
% Correct Curve Movements	56.47%	57.20%
% Profitable Trades (Model Success)	58.38%	55.29%
Average P+L Per Trade (€ on €1m 10y equivalent notional, in each trade)	4,666	1,877
# Months with Profit	65	67
# Months with Loss	14	14
Average Monthly P+L (€ on €1m 10y equivalent notional, in each trade)	93,074	37,475
% Correct Predictions for Steepeners	66.3%	67.9%
% Correct Predictions for Flatteners	46.6%	46.5%
Average Absolute Curve Change (bp)	22.62	9.63
Average Absolute Curve Change for a Correct Prediction (bp)	21.21	8.94
Average Absolute Curve Change of steepners (bp)	27.78	11.12
Average Absolute Curve Change of flatteners (bp)	17.46	8.14

Source: JPMorgan

In high yield we also see the trend of the 2000 to 2004 period being higher return but higher volatility that we found in investment grade.

The larger overall profits from high yield trades are mainly due to the larger spread movements of such names, resulting in some very profitable trades. All investment grade names remain fairly close to the aggregate curve in our model, but the average distance from the curve increases as spreads increase. This means there is generally more potential profit from a wide-spread name than one trading at tighter spreads.

The fundamental explanation we would give for why our model success rates are higher for high yield names than for investment grade names is that default probability differentiation in credit is difficult and that is certainly true of default probabilities through time (and hence curves). For investment grade, the market is therefore focused on 5y spreads and largely prices the 10y-5y curves from them. Hence most names are close to our aggregate curve model. However, for high yield, investors generally estimate default probabilities more carefully and have a real view of the timing of these defaults. Curves for individual names can therefore be more divergent from the aggregate model and there are fewer names with which to compare for higher spreads. This seems to lead to the market differentiating more, thereby giving more differences from the model. The fact that our model has good results even in high yield shows that this curve differentiation does reverse as the pull to the aggregate curve does reassert itself. But, given high yield companies are subject to more focus on specific default rates and default timing, the pull to the aggregate curve is less strong.

Liquidity may play a role here too. As high yield curves have historically been less liquid (this is not necessarily the case now) the larger differentiation could quickly reassert itself as the market looks to the aggregate curve for guidance as to the 'fair' level, given the difficulties in accurately assessing 5y/5y forward default probabilities.

v. Factoring in Costs

The results presented so far have assumed trading mid-to-mid, without transaction costs, as we wanted to see whether the model we propose has any predictive value in terms of future moves. Implementing this in practice would mean also accounting for typical costs of the trades, which we now analyse.

When trading the top and bottom 10 names, the profitability of the trading strategy reduces as we add increasing bid / offer costs up to normal market levels of 3bp (a typical level for investment grade names, as shown in Table 5). The average bp curve move for correctly estimated trades of 8.53bp is eaten into by the 3bp cost and the fact that not all trades are successful.

In practice, an investor systematically following this model is unlikely to trade all 10 steepest and flattest curves but could rather focus on a smaller number to reduce costs. Table 5 shows that if we trade the Top / Bottom 3 outlier curves only (as opposed to 10), even with a 3bp cost we can generate a % Return on Notional of 1.50% (150bp) and an information ratio of 0.45 (using standard assumptions). As we can see, the much higher average bp curve move for correctly estimated trades is 14.52bp for only 3 names traded, which is less affected by the 3bp cost. This comes with a trade-off and we can see that reducing the number of names increases the volatility and the information ratios are generally lower.

Table 5: Profit per Trade in Basis Points

Base Case Parameters, High Grade names, 4 month holding period. 0bp, 1bp and 3bp are the results using 0bp, 1bp and 3bp bid-offer costs.

Top / Bottom 10 Curves Traded	0bp	1bp	3bp
Average P+L Per Trade*	4,102	3,320	1,756
Total P+L*	6,481,253	5,245,886	2,775,152
Information Ratio	0.95	0.77	0.41
% Return on Notional	1.23%	1.00%	0.53%

Top / Bottom 3 Curves Traded	0bp	1bp	3bp
Average P+L Per Trade*	7,297	6,529	4,992
Total P+L*	3,458,809	3,094,562	2,366,069
Information Ratio	0.66	0.59	0.45
% Return on Notional	2.19%	1.96%	1.50%

Top / Bottom 10	bp
Ave bp Curve Move Per Trade	10.68
Ave bp Curve Move for Correctly Estimated Trade	8.53

Top / Bottom 3	bp
Ave bp Curve Move Per Trade	17.18
Ave bp Curve Move for Correctly Estimated Trade	14.52

Source: JPMorgan. *€ on €1m 10y equivalent notional, in each trade.

4. Names Furthest from the Aggregate Curve Perform Best

We have seen that on average single name curves move towards the aggregate curve, but it is only points furthest away from the aggregate curve which consistently make a noticeable movement towards the curve and make for the most profitable trades.

We have seen that the ten single name 10y-5y curves furthest above and below the aggregate curve tend to move towards the curve in the following month. What about less extreme outliers, do they also move towards the aggregate curve and provide us with useful trading signals? We now turn to the trading strategy back-test on less extreme points, to investigate if and when points appeared to stop steepening and flattening in the way we expect.

Our base case (previously) was to put on 10 flatteners and 10 steepeners each month for the 10 furthest points above and below the aggregate line. Table 6 shows the results for each successive cohort of 10 outliers, i.e. 11-20 is the ranked 11th outlier to the 20th outlier for both the flattest and steepest curves.

Table 6: Results from Backtesting Non-Outliers

Base Case Parameters, High Grade names, no bid / offer, 4 month holding period.

Metric	#1-#10	#11-#20	#21-#30	#31-#40	#41-#50
#Trades	1,580	1,579	1,580	1,580	1,580
Overall P+L (€ on €1m 10y equivalent notional, in each trade)	6,481,253	2,252,494	2,092,537	1,164,590	622,556
Information Ratio	0.95	0.87	0.90	0.54	0.39
% Return on Notional	1.23%	0.43%	0.40%	0.22%	0.12%
% Correct Curve Movements	66.01%	62.13%	59.94%	55.89%	51.01%
% Profitable Trades (Model Success)	70.38%	62.82%	59.87%	57.28%	52.72%
Average P+L Per Trade (€ on €1m 10y equivalent notional, in each trade)	4,102	1,427	1,324	737	394
# Months with Profit	74	72	69	64	56
# Months with Loss	5	7	10	15	23
Average Monthly P+L (€ on €1m 10y equivalent notional, in each trade)	82,041	28,513	26,488	14,742	7,880
% Correct Predictions for Steepeners	68.0%	64.1%	62.9%	57.8%	54.2%
% Correct Predictions for Flatteners	64.1%	60.1%	57.0%	53.9%	47.8%
Average Absolute Curve Change (bp)	10.68	5.13	4.07	3.87	3.97
Average Absolute Curve Change for a Correct Prediction (bp)	8.53	4.24	3.82	3.83	3.76
Average Absolute Curve Change of steepners (bp)	11.20	5.19	3.73	3.55	3.86
Average Absolute Curve Change of flatteners (bp)	10.17	5.08	4.41	4.19	4.08

Source: JPMorgan

We can see from Table 6 that a profit, albeit small, was being made from even trading up to 50 single names furthest above and below the curve (i.e. the vast majority of the single names from iTraxx Main). As we would expect, the % Returns on Notional decreased with more names to a return of only 0.12% of notional for the 41-50 names and a lower Information Ratio of 0.39. Information Ratios are above 0.5 (considered "good" in Grinold and Kahn's schema[6]) for the top 40 outliers and

[6] See *Active Portfolio Management*, Grinold and Kahn.

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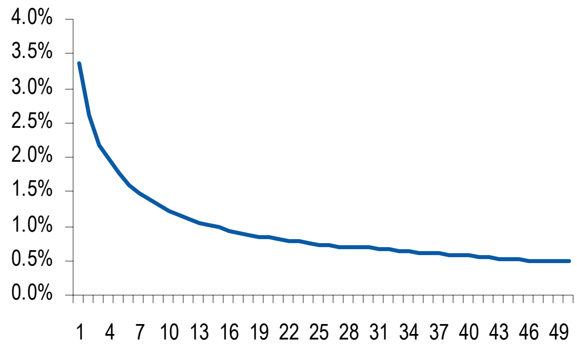
prediction rates – both of profitable trades and successful curve predictions – are only above 60% for the top 20 outliers. **It would seem reasonable to pay less attention to any names not within these top 20 steepest and flattest, as they have less pronounced reversion to the mean curve and so produce less successful trades.**

The fact that even with 50 names we have a slightly positive return, reinforces the point that generally all points do move towards the curve. We have seen this before in Figure 4 where we saw that single name curves are attracted to the aggregate curve. The linear recurrence model in Figure 4 ($x_{n+1} = 0.8 \times x_n + \varepsilon_n$ with ε_n normally distributed error term, n indicates a month number) shows that the curve acts as an attractor – curves gradually move towards the aggregate curve, but for single names already close to the aggregate curve this movement is minimal (as x_n is small, x_{n+1} will be more similar to x_n in bp terms).

Another way of seeing the appropriate cut-off point for the number of outliers that are successful trades is shown in Figure 9 and Figure 10, which show that the rate of return and the percentage of profitable trades both decrease significantly as we place trades on CDS closer to the aggregate curve (i.e. higher rank of outlier, where 1 = the largest outlier from the aggregate curve and 50 = the 50th largest outlier from the aggregate curve which will be quite close to the aggregate curve). The % Annual Return on Notional falls dramatically as we include more names up to 10 names but continues falling at a more steady rate from there. The percentage of correct predictions decreases in an almost linear way the more 'outlier' names are included beyond around 5 names. These graphs both confirm that the trading strategy is only really profitable when applied to the CDS furthest from the aggregate curve. For CDS close to the curve the success of the model is more limited.

Figure 9: Percentage Annual Return on Notional

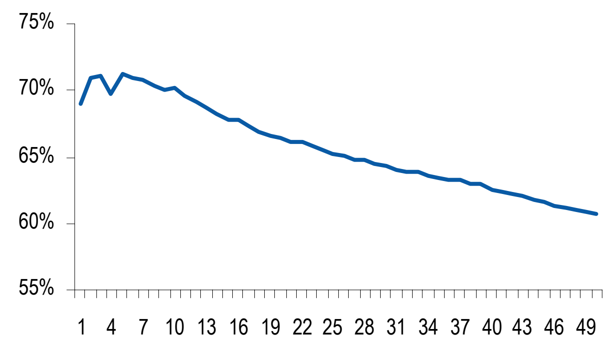
x axis: No. of outlier names traded; y axis: % Annual Return



Source: JPMorgan

Figure 10: Percentage of Profitable Trades (Model Success)

x axis: No. of outlier names traded; y axis: Percentage of Profitable Trades



Source: JPMorgan

We now look to finish the main analysis by looking at whether the 'aggregate' curve predicts where names will flatten or steepen to over the coming period.

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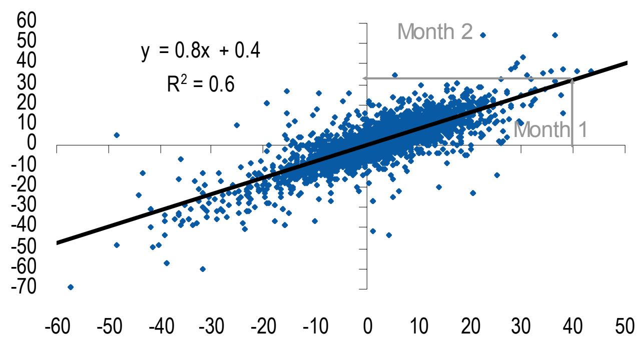
5. Steep Names Stay Steep, Flat Names Stay Flat

CDS generally stay consistently steep or flat to the aggregate 10y-5y curve (i.e. steep or flat), even if they do move towards the curve.
Although we have seen that a single name 10y-5y curve that is above the aggregate credit curve for any given 5y spread is likely to *flatten* and a CDS positioned below the aggregate curve is likely to *steepen*, Figure 11 and Figure 12 show that steep names are likely to *remain steep* and flat names *remain flat*. In other words, single name curves move *towards* the aggregate curve, but not all the way. Figure 11 shows the difference from the curve in each month compared to the next. Although a gradient less than 1 indicates that points move towards the curve on average (their difference from the aggregate curve decreases in a subsequent month), the fact the gradient is greater than zero indicates that points generally stay similarly positioned relative to each other.

Figure 11: Scatter Diagram of Difference from Aggregate Curve on Each Month Against the Subsequent Month

x axis: Distance from Aggregate Curve in Month 1 (bp)

y axis: Distance from aggregate curve in month 2 (bp)

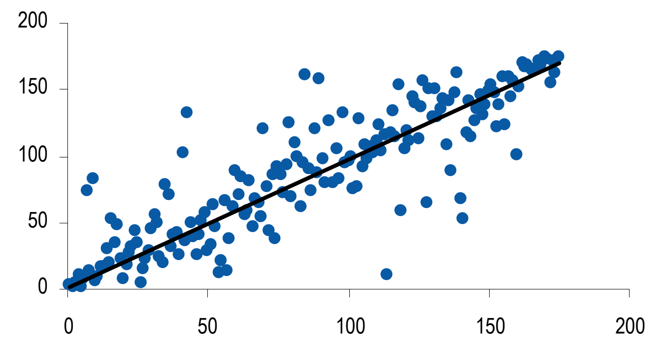


Source: JPMorgan

Figure 12: Scatter Diagram of CDS Rank on 01/06/2007 Against 02/07/2007

x axis: Ranked distance from Aggregate Curve in Month 1 (bp)

y axis: Ranked distance from Aggregate Curve in Month 2 (bp)



Source: JPMorgan

Figure 12 shows a similar conclusion using the rank of outliers – if CDS A is further above the curve than CDS B (ranks higher) in one month, we expect CDS A to remain further above (still ranks higher) for the next month. Figure 12 shows a particular month's ranking, but the trend is consistent over time, although the strength of the relationship varies somewhat.

So, on average, names stay consistently flat or steep relative to the general trend. This indicates that despite the points furthest away moving *towards* the aggregate curve, single name CDS curves seem to have a fundamental position steep or flat to the aggregate curve. Therefore the aggregate curve only partially explains the steepness of a CDS. For the real outlying curves, there seems to have been a significant market mispricing and these correct moving towards the aggregate curve – this enables the trading strategy to remain profitable. However, we shouldn't expect a steep curve to flatten *all the way* to the aggregate curve, as this analysis shows steep curves are most likely to stay fundamentally steep.

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6. Conclusion and Explanation

We have seen that our aggregate curve model, using 5y spreads to predict 10y-5y curves, systematically allows us to spot curves that are too steep or too flat. It successfully gives profitable trade signals 70% of the time and can be the basis of a profitable trading strategy, with Information Ratios of 0.95. The fact that a 'blind' curve model ignoring any single name inputs other than 5y spread can help to position for future curve movements, deserves some explanation as a conclusion.

Fundamentally, the shape of the 10y-5y curve is a function of both forward conditional default probabilities[7] and term-premia to compensate for uncertainty about these future default probabilities. In a fully efficient market, we should expect these to be entirely company-specific. That is to say, in a world where we are able to form accurate views about the default probabilities of all companies year-by-year, we should not expect the 10y-5y curve to have a strong relationship to the 5y spread. One company with default risk up to 5y resulting in a 5y spread of 50bp, may have its default risk stable from 5y to 10y resulting in a flat 10y-5y curve (perhaps an oil company that faces some near-term exploration risk which after that will result in very stable credit quality, conditional on survival). Another company may have a 5y spread of 50bp but have continuing addition of risk from years 5 to 10 (say a telecom company that has to face a continually evolving technology environment). This may justify a 10y-5y curve of 50bp. So, for any given 5y spread of 50bp we *should* a priori have no way of knowing the 10y-5y curve and there should be no such thing as an aggregate credit curve.

In practice this is not what we see. We have shown that there is a very strong relationship between the 10y-5y curve and the 5y spread and we have shown that outliers to this aggregate curve tend to 'mean revert' towards it. This allows us to position these curve trades with success.

The way we would explain this is due to the difficulties of determining accurate future default probabilities. Default is a seldom-observed tail event, particularly for high grade companies (the 1y default probability for a BBB company is around 0.24% historically observed). It is difficult enough correctly estimating the 5y spread of a company. Estimating the company's default profile over time and the accurate level of the curve is even more difficult. It would seem that the credit markets therefore rely heavily on the 5y spread level to determine the riskiness of a company over time and therefore its curve. There is also safety in numbers, using the aggregate or average curve steepness for a given 5y spread as a guide for individual names, regardless of their individual credit profiles. That is why the 10y-5y aggregate curve for a given spread level is an attractor for single names. However, there is some discerning in the market. We know that some names should have steeper curves due to forward uncertainty – telecoms with their technology risk are a good example – and we have seen that companies are consistently above (steep) or below (flat) the aggregate curve. We just don't know how much this is worth and when market moves push names too far away from the pack, they revert in subsequent periods.

[7] Upward-sloping curves imply rising conditional default probabilities, that is, deteriorating credit quality over time. See *Trading Credit Curves I* (J Goulden, 21st March 2006).

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This is also why the predictive power of the model is lower for high yield names where the investor base typically has a much stronger view of default profiles through time and so the 5y point is relied on less as the only point that matters.

As the credit markets continue to become deeper, more sophisticated in taking a view on future default probabilities and investors are more able to isolate these views with trades, we would expect this trend to lessen and our model will weaken. However, for the immediate future the current status quo will most likely continue. Spotting outliers on our aggregate curve model should continue to yield profitable predictions and we will continue to focus on it in our trade idea generation.

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Appendix I: The Aggregate Curve Model

This Appendix explains the components of the aggregate curve model we use.

Methodology

In order to test how steep or flat a curve is based on its difference from the aggregate curve, we need to have a rigorous choice of what we mean quantitatively by 'steep', 'flat', 'difference' and 'aggregate curve'. This Appendix goes through these components.

1. Choice of Curve

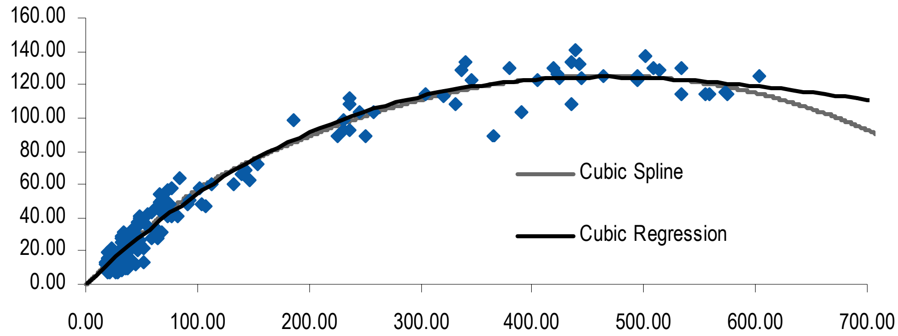
Using a cubic regression was the most successful type of regression for plotting the aggregate curve.

The 'aggregate curve' is the line of best fit on the 5y against 10y-5y scatter diagram. There are, however, different possible ways to calculate this curve (see Figure 13). For this back-testing strategy we tested logarithmic, quadratic, cubic and cubic spline regressions. In the research note *Cubic Splines and Credit Curves* (J Due, 4 May 2005), we argued that cubic spline interpolation should provide a smoother best fit for the curve. Cubic splines, however, have not been used as the means of plotting the curve in this piece. We have found that they offer only a very slightly better R^2 value compared with other graph types for most situations. When cubic splines were tested against other regression techniques, they actually produced slightly less profit and lower information ratios than simply using a cubic interpolation (Table 7). Whilst this difference is minimal, it showed that (for the data tested) the cubic spline did not offer significant benefits and so the simpler cubic interpolation was used.

This result is unlikely to be because of a fundamental advantage of cubic regressions over cubic splines, but rather because more consideration is required when using cubic splines, namely we need to decide where the joins of the spline are and these can vary over time. In our testing, the joins in the cubic spline were fixed, which meant as 5y spreads got tighter and wider, the graph could become distorted. In Figure 13, the cubic spline regression looks less representative of the trend at higher 5y spreads due to the fixed join points. Thus despite it having a lower R^2 value, we might expect predictions of which CDS will steepen or flatten to be more reliable when using the simple cubic regression.

Figure 13: Regression Lines for a Cubic Regression and a Cubic Spline Regression for all Single Names in the Active iTraxx Main and Crossover Indices as of 08/08/2007.

x axis: 5y Spread, bp, 10y-5y Spread, bp



Source: JPMorgan

Table 7: Results for Different Regressions

Base Case Parameters, High Grade names, no bid / offer, 4 month holding period.

Metric	Cubic	Quadradic	Cubic Spline	Logarithmic
#Trades	1,580	1,580	1,580	1,580
Overall P+L (€ on €1m 10y equivalent notional)	6,481,253	5,890,044	6,244,565	6,080,565
Information Ratio	0.95	0.83	0.93	0.79
% Return on Notional	1.23%	1.12%	1.19%	1.15%
% Correct Curve Movements	66.01%	65.70%	65.25%	61.33%
% Profitable Trades (Model Success)	70.38%	68.67%	69.76%	63.61%
Average P+L Per Trade (€ on €1m 10y equivalent notional)	4,102	3,728	3,975	3,848
# Months with Profit	74	72	74	72
# Months with Loss	5	7	5	7
Average Monthly P+L (€ on €1m 10y equivalent notional)	82,041	74,558	79,045	76,969
% Correct Predictions for Steepeners	68.0%	68.2%	67.1%	63.2%
% Correct Predictions for Flatteners	64.1%	63.2%	63.4%	59.5%
Average Curve Change (equivalent 10y bp)	10.68	10.64	10.73	8.16
Average Curve Change for a Correct Prediction (equivalent 10y bp)	8.53	8.55	8.59	6.57
Average steepening of steepners (equivalent 10y bp)	11.20	11.23	11.46	7.69
Average flattening of flatteners (equivalent 10y bp)	10.17	10.05	10.02	8.63

Source: JPMorgan

Since the cubic regression gave slightly better overall results than the other regression methods – it had the highest Information Ratio and Percentage Return (see Table 7). So the cubic regression method was used. It also performed better than the other methods when other parameters (such as the length of trade and the weighting strategy) were changed.

2. Choice of Distance (or Difference)

Using the *actual basis point difference* was the most effective method of measuring distance from the aggregate curve.

The difference from the curve is intended to be a measure of how much a single name curve deviates from the aggregate curve. The two following different 'difference' methods were tested:

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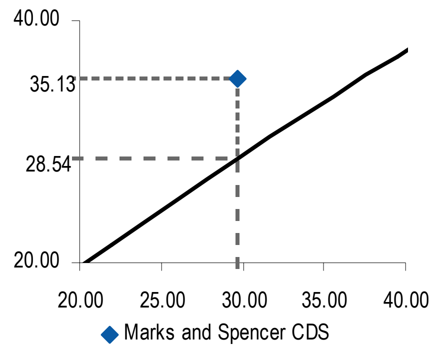
1. **Actual basis point difference:** The difference from the model is the 10y-5y spread of a single name curve minus the 10y-5y spread of the aggregate curve at the same 5y point.
2. **Ratio difference:** This uses the ratio of the actual 10y-5y spread for a single name against the 10y-5y spread of the aggregate curve at the same 5y point.

We show an example of these different measurements in Figure 14.

Figure 14: Example of Difference Measurements

x axis: 5Y Spread, bp, 10y-5y Spread, bp. Black line represents the aggregate curve.



Source: JPMorgan

For the Marks and Spencer CDS on 01/06/7 (shown in Figure 14) we calculate the difference from the aggregate curve for each method:

Actual Difference: 35.13bp - 28.54bp = 6.59bp

Ratio Difference : 35.13bp/28.54bp = 1.23

Both measurements recognize the CDS as steep relative to the curve, since the actual difference is positive and the ratio difference is greater than 1.

In the testing, the actual basis point difference performed much better in terms of higher profits, gave a higher percentage of profitable trade predications and produced larger Information Ratios (Table 8) and so was used for the subsequent testing.

Table 8: Results for Different Difference Strategies

Base Case Parameters, High Grade names, no bid / offer, 4 month holding period.

Metric	Actual Spread Difference	Ratio Spread Difference
#Trades	1,580	1,580
Overall P+L (€ on €1m 10y equivalent notional)	6,481,253	3,674,272
Information Ratio	0.95	0.54
% Return on Notional	1.23%	0.70%
% Correct Curve Movements	66.01%	61.27%
% Profitable Trades (Model Success)	70.38%	65.70%
Average P+L Per Trade (€ on €1m 10y equivalent notional)	4,102	2,325
# Months with Profit	74	66
# Months with Loss	5	13
Average Monthly P+L (€ on €1m 10y equivalent notional)	82,041	46,510
% Correct Predictions for Steepeners	68.0%	64.9%
% Correct Predictions for Flatteners	64.1%	57.6%
Average Curve Change (equivalent 10y bp)	10.68	7.93
Average Curve Change for a Correct Prediction (equivalent 10y bp)	8.53	7.01
Average steepening of steepners (equivalent 10y bp)	11.20	7.44
Average flattening of flatteners (equivalent 10y bp)	10.17	8.43

Source: JPMorgan

This shows that although some market practitioners think of curves in terms of ratios (for example 10y-5y as a ratio of 5y spread), for the purposes of our predictive aggregate model the *actual* spread difference is more important.

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The method of calculating the difference from the line can probably be improved. The actual basis point difference does not appreciate the fact that one expects differences from the curve to increase as the 5y spread increases, since points fit the curve much more accurately for lower 5y spreads. The ratio difference does account for this but can become distorted at more extreme spread levels (the distance is made too large for lower spreads and too small for larger spreads). We are also assuming that the 5y spread is completely driving the 10y spread by only looking at the vertical distance from the curve. This is not necessarily valid since the 5y spread could be mis-priced by the market in the same way the 10y spread could be.

3. Choice of Weighting Strategy

Market-Weighted trades produced the most successful results.
There are several ways we could weight our curve trades[8]. Different trade constructions will have different risk exposures and different profit and loss characteristics. This means that results obtained using one curve trade over another could be distinctly different[9].

We considered 3 different weighting schemes:

Equal Notional Weighting:	The same notional is traded on the 10y and 5y legs. Because 10y risky annuities are higher than 5y ones, profit and loss is largely dependent on market directionality. 5y:10Y weighting is 1:1.
Duration-Weighting:	The 5y notional is weighted by the 10y Duration / 5y Duration to make the trade MTM neutral for a 1bp parallel shift in spreads. 5Y:10Y weighting is generally around 1.7:1.
Market-Weighting:	5y and 10y trade notionals are weighted according to the gradient of the aggregate curve at the same 5y point, so that the trade is MTM neutral if curves move parallel to the *tangent* of the aggregate curve. 5Y:10Y weighting is generally about 1.7-3.5:1

Market-Weighting is a new weighting scheme which takes into account the directionality of curves and the model we use. We will illustrate the differences between the strategies with an example.

Example:
Consider Marks and Spencer CDS on the 1st June 2007.

[8] For more on curve trade weighting see *Trading Credit Curves II* (J Goulden, 20th Mar 2006).
[9] Since our analysis was focused on curve movement rather than other aspects affecting profit and loss, we have focused on the effect of spread changes. For most of the analysis we have chosen to focus less on Carry, Slide, Convexity, Horizon effects and Default Risk.

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Table 9: Marks and Spencer Levels

Spreads in bp.

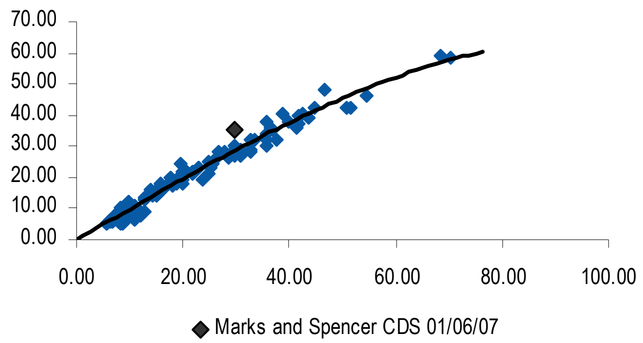
	5y Spread	10y Spread	10y-5y Spread	5y Risky Annuity	10y Risky Annuity
02/07/2007	34.19	70.03	35.84	4.47	7.77
01/06/2007	29.65	64.78	35.13	4.48	7.82

Source: JPMorgan

The 10y-5y curve for Marks and Spencer lies above the aggregate 10y-5y curve (see Figure 15) and so we might decide to put on a flattener.

Figure 15: Marks and Spencer CDS Relative to Aggregate Curve

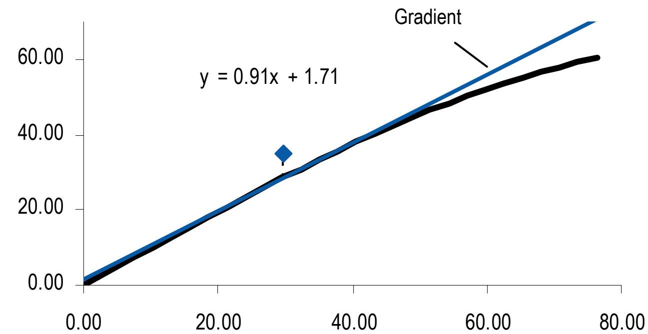
x axis: 5y Spread, bp, y axis: 10y-5y Spread, bp



Source: JPMorgan

Figure 16: Tangent for Marks and Spencer CDS

x axis: 5y Spread, bp, y axis: 10y-5y Spread, bp



Source: JPMorgan

Equal Notional: For €10m notional on the 10y leg, an equal notional trade would trade €10m on the 5y leg as well.
Duration-Weighting: For €10m notional on the 10y leg, a duration-weighted trade would trade €17.4m (7.82 / 4.48 × 10m) on the 5y leg.
Market-Weighting: Since the gradient of the tangent to the aggregate curve at a 5y spread of 29.65bp is 0.91 (see Figure 16), a market-weighted trade would trade €33m (7.82 ÷ 4.48 × (1+0.91) ×10m) on the 5y leg for €10m on the 10y leg.

Table 10: Trade Notionals

	5y Notional (€m)	10y Notional (€m)
Equal Notional Flattener	10.0	10.0
Duration weighted Flattener	17.4	10.0
Market-Weighted Flattener	33.3	10.0

Source: JPMorgan

Market-weighting is a new weighting scheme which takes into account the directionality of curve trades and the exact signal our model is giving, we therefore explain this weighting in more detail in the grey box before continuing our example.

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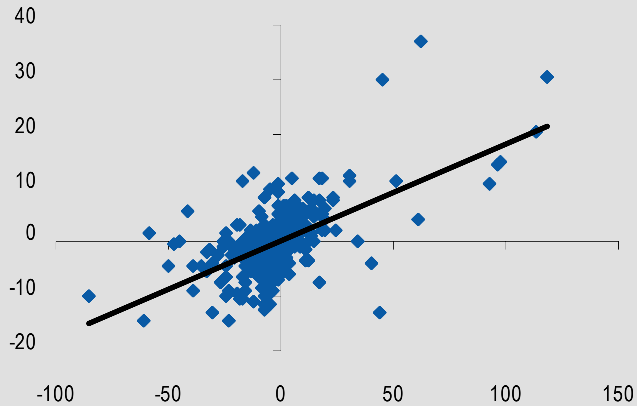
Market-Weighted Curve Trades

The key advantage of duration-weighting a trade over using equal notional is that it is unaffected by parallel spread shifts and so reduces the directionality of the curve trade. However, curves are still directional – steepening for higher spreads, as shown in Figure 17 – and so there is still a degree of directionality in the trade. **The fundamental point of Market-weighting is to reduce market directionality in the trade.** By using the tangent of the model curve (as in Figure 16), Market-Weighting takes into account the fact that curves are directional. Except for in very high spread and default periods, investment grade curves will steepen as spreads move higher. We will therefore need to weight more in the 5y point of our curve trade to stay neutral to market moves and isolate just curve moves due to mis-pricing. In our Marks and Spencers example we trade €33m 5y notional for a €10m 10y notional.

Figure 17: Directionality of 10y-5y Curves with 5y Spreads

x-axis: iTraxx Main 5y spreads (bp); y-axis: iTraxx Main 10y-5y curve (bp)



Source: JPMorgan

Market-weighting also takes the model's view of 'steepness' (i.e. distance above or below the aggregate curve) into account more than the other weighting strategies. If the model indicates a CDS appears too steep, it means the 10y-5y spread level is above that predicted by the aggregate curve for that 5y spread level. If it is going to 'flatten' then the model is only predicting this distance from the curve will decrease. If the 5y spread widens, the 10y-5y aggregate curve also steepens. This means if the 5y spread widens but the 10y-5y curve steepens less than the 10y-5y aggregate curve, the CDS has *flattened relative to the curve*. Market-Weighting acknowledges this as a flattening and so a flattener weighted in this way produces a profit. Duration-weighting views any increase in the 10y-5y spread as a steepening, and so would lose money, even if the CDS moved closer to the aggregate curve. This is the case in the example with Marks and Spencer in June 2007, which we now return to.

Returning to our example, Figure 18 shows the model was correct in its prediction that the Marks and Spencer CDS would move closer to the curve, and so (in this sense) the CDS has 'flattened'. We also notice that the 10y-5y spread has actually increased slightly, from 35.13 to 35.84bp. The Market-Weighting hedges out the directionality of curves. This curve has effectively flattened as it has stayed at a constant curve even through spreads have increased.

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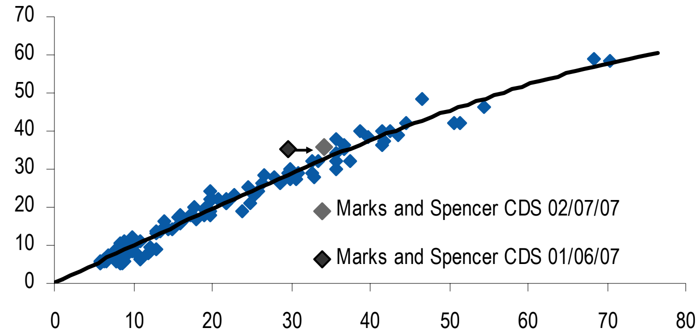
Figure 18: 10y-5y CDS Aggregate Curve for Single Names on 01/06/07

x axis: 5y spread bp, y axis: 10y-5y spread bp



Source: JPMorgan

Table 11 shows that the Market-weighted strategy has made profit from the spread movements in this example, since the CDS has moved towards the curve, but the other weighting strategies have lost money.

Table 11: MTM for the Trades

		Notional (€)	Entry Spread (bp)	Spread after 1 Month (bp)	Spread Change (bp)	Risky Annuity	MTM (€)	Total (€)
Equal notional Flattener	5y Leg	10	29.65	34.19	4.54	4.47	20,294	
	10y Leg	10	64.78	70.03	5.25	7.77	-40,793	-20,499
Duration Weighted Flattener	5y Leg	17.4	29.65	34.19	4.54	4.47	35,311	
	10y Leg	10	64.78	70.03	5.25	7.77	-40,793	- 5,481
Market-Weighted Flattener	5y Leg	33.3	29.65	34.19	4.54	4.47	67,578	
	10y Leg	10	64.78	70.03	5.25	7.77	-40,793	26,786

Source: JPMorgan

Although this example was chosen to show when market-weighting could outperform the other weighting methods, we found that over the entire back-test, market-weighting trades gave better returns. Table 12 shows that the market-weighted scheme consistently performed best (it had the highest Overall +L, Information Ratio and % Return on Notional). Duration-weighting performed reasonably well, but the equal notional weighting did not perform particularly well, giving an information ratio of only 0.23.

Table 12: Results from Testing Different Weighting Strategies from 2000

Base Case Parameters, High Grade names, no bid / offer, 4 month holding period.

Metric	Equal Notional	Duration Weighted	Market weighted
#Trades	1,580	1,580	1,580
Overall P+L (€ on €1m 10y equivalent notional)	1,610,440	5,204,651	6,481,253
Information Ratio	0.23	0.57	0.95
% Return on Notional	0.31%	0.99%	1.23%
% Correct Curve Movements	66.01%	66.01%	66.01%
% Profitable Trades (Model Success)	54.30%	64.75%	70.38%
Average P+L Per Trade (€ on €1m 10y equivalent notional)	1,019	3,294	4,102
# Months with Profit	48	61	74
# Months with Loss	31	18	5
Average Monthly P+L (€ on €1m 10y equivalent notional)	20,385	65,882	82,041
% Correct Predictions for Steepeners	68.0%	68.0%	68.0%
% Correct Predictions for Flatteners	64.1%	64.1%	64.1%
Average Curve Change (equivalent 10y bp)	10.68	10.68	10.68
Average Curve Change for a Correct Prediction (equivalent 10y bp)	8.53	8.53	8.53
Average steepening of steepners (equivalent 10y bp)	11.20	11.20	11.20
Average flattening of flatteners (equivalent 10y bp)	10.17	10.17	10.17

Source: JPMorgan

Market-Weighting and Default Risk

Although market-weighting is most appropriate for trading our model signals and for reducing any market directionality in curve trades it can introduce default risk.

In the same way that duration-weighting a steepener (selling 5y protection and buying 10y protection) involves selling more 5y protection (typically around 1.7 times more) and thereby taking on more default risk, market-weighting trades exacerbates this. In order to reduce effect of the directionality of the curve – which means the 10y point moves *more* than the 5y point for any given move – we sell even more notional protection in the 5y point, according to the gradient. This will mean we take on more default risk.

For our back-test, none of the names selected defaulted. However, if one of the names on which we had a steepener had defaulted, we would have had a large P+L loss, although if a flattener had defaulted we would have made a large profit. Investors using the model prediction should take this default risk into account when positioning the trades.

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Appendix II: Length of trade holding period

The model produces more successful predictions (% of correct predictions is higher) if trades are left on for longer than one month. This, however, decreases the return on notional.

In our main analysis, we mostly look at keeping trades open for four months. Table 13 stress-tests this, showing our back-test results holding trades open for one, two, three, four, five and six months separately. Trades were still put on each month.

Table 13: Results from Holding Trades For Different Lengths of Time

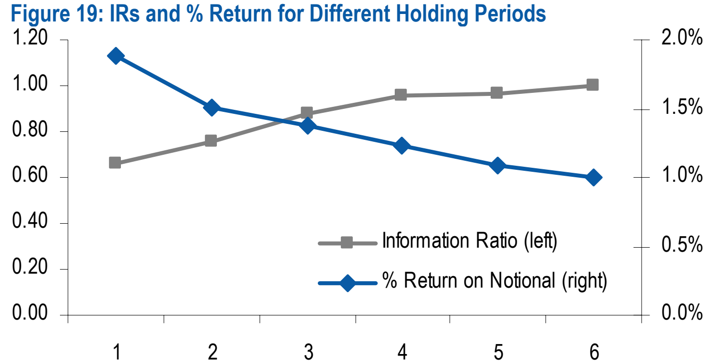
Base Case Parameters, High Grade names, no bid / offer.

Metric	1	2	3	4	5	6
#Trades	1,620	1,600	1,580	1,580	1,560	1,540
Overall P+L (€ on €1m 10y equivalent notional)	2,546,756	4,035,562	5,415,128	6,481,253	7,106,943	7,735,403
Information Ratio	0.66	0.75	0.88	0.95	0.96	1.00
% Return on Notional	1.89%	1.51%	1.37%	1.23%	1.09%	1.00%
% Correct Curve Movements	58.52%	62.13%	64.49%	66.01%	65.71%	66.04%
% Profitable Trades (Model Success)	58.40%	64.38%	67.97%	70.38%	71.15%	72.21%
Average P+L Per Trade (€ on €1m 10y equivalent notional)	1,572	2,522	3,427	4,102	4,556	5,023
# Months with Profit	71	72	74	74	71	70
# Months with Loss	10	8	5	5	7	7
Average Monthly P+L (€ on €1m 10y equivalent notional)	31,441	50,445	68,546	82,041	91,115	100,460
% Correct Predictions for Steepeners	66.4%	66.5%	67.0%	68.0%	66.9%	66.4%
% Correct Predictions for Flatteners	50.6%	57.8%	62.0%	64.1%	64.5%	65.7%
Average Curve Change (equivalent 10y bp)	5.00	7.62	9.35	10.68	11.73	12.66
Average Curve Change for a Correct Prediction (equivalent 10y bp)	3.88	5.97	7.46	8.53	9.25	9.96
Average steepening of steepners (equivalent 10y bp)	4.90	7.70	9.79	11.20	12.45	13.58
Average flattening of flatteners (equivalent 10y bp)	5.09	7.54	8.91	10.17	11.01	11.74

Source: JPMorgan

Figure 19 shows that Information Ratios are higher if trades are held open for longer than one month for investment grade curves, rising to 1.00 for a 6-month holding period. Holding trades open for 4-6 months appears to be optimal, as information ratios do not increase significantly after 4 months but the % Return on Notional continues to decrease (Table 13). As holding time increases, the market has already partially corrected for a single name curve being mis-priced and so subsequent profits only increase at a slower rate. Conversely, we saw previously that for high yield names, a shorter holding period was more successful.

Figure 19: IRs and % Return for Different Holding Periods



Source: JPMorgan

For investment grade names, holding a trade for twice the length of time doubles the notional committed (since trades are still being put on each month). We see from Table 13 that although we generate more profit, this is not in proportion to the additional notional committed, and so the percentage return on notional decreases. Volatility does not increase significantly with a greater trading length (under this strategy), which is why information ratios are increasing, even though annual percentage return is decreasing (Figure 19)

This is true if we ignore costs. If bid-offer costs are incorporated, then it is more profitable to hold trades for a longer period of time since bid-offer costs are only paid once and therefore eats away less of the larger P+L we make by keeping the trades open for longer.

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Appendix III: Current Steepest and Flattest Curves

In this appendix, we outline the current 10 steepest and flattest names in Main and Crossover indices as calculated by our aggregate curve model.

Table 14 shows the 10 steepest names in iTraxx Main S8 according to the aggregate curve in our Daily Analytics report (October 4, 2007). The model in our Daily Analytics uses the cubic spline regression method instead of the cubic regression to fit the aggregate curve (the regression methods are largely similar in highlighting outliers). Table 15 shows the current 10 flattest names in iTraxx Main S8. According to our model's signals, we expect the steeper names to flatten and the flatter names to steepen. We have also given the notional ratios (5y notional versus 10y notional) for duration-weighting and market-weighting strategies in the final columns.

Table 14: iTraxx Main S8 Steepest names

Sector	Name	5y Spread (bp)	10y Spread (bp)	10y-5y (bp)	Distance from Aggregate curve (bp)	Duration weighted	Market weighted
Consumer	Experian Finance	35	76	41	15	1.91	3.07
Consumer	Cadbury Schweppes	39	75	36	8	1.91	3.02
TMT	Stmicroelectronics	25	51	26	7	1.93	3.25
Energy	United Utilities	24	50	26	7	1.93	3.26
Consumer	Altadis	49	90	41	7	1.90	2.87
Consumer	Marks And Spencer	38	73	35	7	1.91	3.03
Consumer	Safeway Limited	52	94	42	6	1.90	2.84
TMT	Reed Elsevier	25	52	26	6	1.93	3.24
Consumer	Metro	32	62	30	6	1.92	3.12
TMT	Wolters Kluwer	29	57	28	6	1.93	3.19

Source: JPMorgan, Spreads at COB 3 Oct

Table 15: iTraxx Main S8 Flattest names

Sector	Name	5y Spread (bp)	10y Spread (bp)	10y-5y (bp)	Distance from Aggregate curve (bp)	Duration weighted	Market weighted
Fin Sen	Commerzbank	45	51	5	-27	1.91	2.95
Fin Sen	Banco Espirito Santo	39	47	8	-21	1.92	3.03
Fin Sen	Banca Monte	35	41	6	-20	1.92	3.09
Fin Sen	Deutsche Bank	35	42	7	-19	1.93	3.10
Fin Sen	Banco Bilbao Vizcaya Argentaria	35	44	8	-18	1.92	3.08
Fin Sen	Unicredito Italiano	31	38	7	-17	1.93	3.15
Fin Sen	Banco Santander Central Hispano	33	41	8	-17	1.93	3.11
Fin Sen	Swiss Reinsurance Co	32	40	8	-17	1.93	3.13
Fin Sen	Aegon	31	39	8	-16	1.93	3.15
Fin Sen	Credit Suisse Group	31	38	8	-16	1.93	3.16

Source: JPMorgan, Spreads at COB 3 Oct.

Table 16 and Table 17 show the current 10 steepest and flattest names in iTraxx Crossover S8.

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Table 16: iTraxx Crossover S8 Steepest names

Name	5y Spread (bp)	10y Spread (bp)	10y-5y (bp)	Distance from Aggregate curve (bp)	Duration weighted	Market weighted
Upc Holding	381	522	141	22	1.59	1.79
Wdac Subsidiary	391	532	141	21	1.58	1.78
Cable And Wireless	174	273	98	20	1.75	2.24
Gecina	138	226	87	20	1.80	2.36
Havas	238	351	113	19	1.70	2.08
International Power	309	434	125	17	1.65	1.94
The Rank Group	309	434	125	17	1.64	1.93
Kabel Deutschland	431	571	140	15	1.56	1.72
The Nielsen Company	386	521	135	15	1.59	1.79
Nordic Telephone Company	312	436	124	15	1.64	1.92

Source: JPMorgan, Spreads at COB 3 Oct.

Table 17: iTraxx Crossover S8 Flattest names

Name	5y Spread (bp)	10y Spread (bp)	10y-5y (bp)	Distance from Aggregate curve (bp)	Duration weighted	Market weighted
Banca Italease	235	235	0	-94	1.7	2.08
Fce Bank	427	470	43	-82	1.7	1.82
M-Real	526	634	108	-24	1.5	1.62
Nxp	432	539	108	-18	1.6	1.75
Cir S.P.A.	228	310	82	-10	1.7	2.13
Alliance Boots Limited	462	582	120	-8	1.6	1.68
Thomson	111	162	51	-7	1.8	2.45
Heidelberg cement	99	148	49	-5	1.9	2.50
Grohe Holding	589	719	130	-4	1.5	1.53
Hellas Telecommunications	467	592	125	-3	1.5	1.67

Source: JPMorgan, Spreads at COB 3 Oct.

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