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Byström, Hans

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PO Box 117
221 00 Lund
+46 46-222 00 00

The Age of Turbulence, Credit Derivatives Style

Hans Byström

Department of Economics, Lund University, Box 7082, 220 07 Lund, Sweden

(Phone: +46 46 2229478 Fax: +46 46 2224118 e-mail: hans.bystrom@nek.lu.se)

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Abstract. This paper focuses on the many extreme credit default swap spread movements observed during the recent credit crisis and on how the tails of the spread (and price) change distribution significantly differ from those of the normal distribution even for diversified credit derivatives portfolios. Particular focus is put on the sudden shift in the behavior of the credit default swap market in the summer of 2007. During the first month of the crisis, July 2007, we find the extreme turbulence in the credit derivatives market to be comparable only to the turmoil in the equity market in October 1987 and in October 2008. As a result of this extreme behavior and the dramatic regime shift observed in 2007, credit derivatives portfolio Value at Risk estimates based on extreme value theory are found to be much more accurate than those based on normal or historical distributions, both during the crisis and in the comparably tranquil times leading up to the crisis.

Keywords: value at risk; VaR; extreme value theory; credit default swap index; credit crisis; credit derivative

JEL classification codes: G01; G10; G33; C16

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The recent credit crisis started in mid-2007 and its epicenter was, initially, the US housing market and structured credit products backed up by (sub-prime) US mortgages. The crisis has since spread to many other areas of the financial system and more recently it has also affected the wider economy. In tandem with this general credit reprisal the credit derivatives market went from being a *very* volatile market (see Byström [2008]) to an *extremely* volatile market. The magnitude of typical daily (and monthly) credit spread changes has surpassed the wildest imaginations and the overall cost of credit has doubled many times since the onset of the crisis. In mid-June 2007, the cost of insuring corporate debt in Europe against default hit a low-point at about 20bp and in mid-December 2008 it reached a high of 213bp.

This paper tries to stress *how extreme* the movements in the credit derivatives market have become (we show how multi- σ credit spread- and price changes have become the name of the day) and *how useless* the normal distribution assumption is, and always has been, in the credit derivatives market. The paper builds on Byström [2007] where margin requirements for future credit derivatives exchanges were calculated using extreme value theory (EVT). Here, however, instead of focusing on margins, we focus on Value at Risk (VaR) calculations (the maximum loss not exceeded with a given probability over a given period of time) and on how useless VaR-estimates based on the normal distribution are in the credit derivatives market. Moreover, we also present some descriptive statistics for the most extreme spread/price changes for a typical portfolio of investment grade credit derivatives before and during the crisis. The onset of the crisis in July 2007 coincides with a very clear regime shift in the data that needs to be considered in the modelling of credit derivatives for many years to come.

We focus on the most important credit derivatives market, the credit default swap (CDS) market. A credit default swap is basically a tradable insurance contract that provides protection against bankruptcy and other credit events. One of the fastest growing corners of the CDS market is the CDS *index* market. CDS indexes pool together single-name credit default swaps into liquid, tradable indexes and these indexes are now widely used as indicators of market-wide credit quality. Here, we have chosen to look at the *iTraxx* Europe CDS index, one of the most important indexes tracking the cost of insuring corporate debt against default, from its launch in June 2004 up until June 2010. We have defined the starting date of the crisis as July 18,

2007, i.e. the day *Bear Stearns* reported large losses in two of its hedge funds. In this way the six-year time period is split into two approximately equally long sub-samples dubbed the pre-crisis period and the crisis periods.

Our study is one of the first to empirically investigate the behavior of the credit derivatives market during the credit crisis. As mentioned above, the empirical set-up is very similar to that of Byström [2007] but with a more direct focus on risk management. More importantly, while Byström [2007] focuses on "normal" market conditions, we look at the extreme behavior during a period of considerable stress. As such, the paper should be viewed as a companion paper to Byström [2007]. To this end, the following quote from Byström [2007] (i.e. well before the credit crisis) summarizes the agenda quite well "*Although the General Motors episode [of 2005] might not repeat itself, it should nonetheless be a lesson for the future; whether or not the credit environment becomes riskier over the next couple of years, similar sudden changes in CDS spreads most likely will strike the CDS index market from time to time*".

THE CREDIT DEFAULT SWAP INDEX MARKET

Over the last ten years the credit default swap (CDS) market has been one of the fastest growing segments of the derivatives world. The CDS market is comparatively liquid and it enables market participants to buy or sell protection against a certain reference entity defaulting on its liabilities. While a single-name credit default swap protects the buyer against a default by *one* specific underlying reference entity a credit default swap index protects the buyer against *market-wide* defaults. More exactly, a credit default swap index is created by bundling together several (10-150) single-name credit default swaps into an equally-weighted portfolio whose average spread is labelled the CDS index spread.

CDS indexes are fairly new instruments and the most well known CDS index family is the *Markit iTraxx* index family which was launched in June 2004 (under the *Dow Jones iTraxx* label). There are several different *iTraxx* indexes covering different segments of the credit market and in this study we look at the mother-index, the (5-year) *iTraxx* Europe index. This index pools together 125 liquid credit default swaps referencing 125 different European investment-grade firms. The particular credit default swaps are selected based on their trading volume over

the last six months and every six months some names are replaced by other more heavily traded ones.

In this paper, we explicitly focus on Value at Risk calculations and this requires us to compute CDS prices associated with the CDS spreads quoted in the market. We have therefore chosen to convert the daily CDS spread changes to daily CDS "price" changes following standard market practice assuming a linear relationship between yield changes and price changes

$$\frac{\Delta P}{P} = -MOD \cdot \Delta Y \quad (1)$$

where ΔY is the spread change and $\frac{\Delta P}{P}$ is the percentage price change. MOD is the modified duration of the CDS contract and in this paper we have assumed that the 5-year *iTraxx* CDS index has a constant MOD equal to 4.4 (the average of the three estimates in Rajan and McDermott [2007], Eurex [2007], and Gisdakis [2007]).

EXTREME SPREAD CHANGES IN THE CREDIT DEFAULT SWAP INDEX MARKET

This section presents some evidence of the extreme behavior of the CDS market during the credit crisis. More specifically, we have chosen to look at the 5-year *iTraxx* Europe CDS index spread over the time period June 2004-June 2010 (see Figure 1).¹ As described above, in addition to the spreads we also study prices (see Figure 2). The sample is divided into a pre-crisis period with 785 daily spread/price changes and a crisis period with 739 daily spread/price changes.

Some descriptive statistics are presented in Table 1 and the *iTraxx* Europe CDS index spread/price is obviously not only volatile but very fat-tailed as well.² The most striking deviation from normality, however, is the number and magnitude of the largest (positive and negative) spread and price changes (see Figures 3 and 4). The number of multi- σ events (i.e., spread/price changes far out in the tails) is much higher than if the data was normally distributed, particularly during the crisis, and in the rest of this section we will give some examples of just how extreme this behavior is and of how important it is to acknowledge for risk management purposes.³

During the crisis, many CDS index spread changes are larger than +/-10% During the 3-year crisis period there are 23 daily spread changes that are larger than +10% and 13 daily spread changes that are larger than -10%. Meanwhile, during the 3-year pre-crisis period there is only 1 spread change that is larger than +10% and 2 spread changes that are larger than -10%. In other words, more or less all the most extreme spread changes (and there are many of them) come in the crisis period. Moreover, if we look at the price changes, a similar pattern appears. Even though the price-volatility, overall, is many times lower than the spread-volatility the relative difference between the rather tranquil pre-crisis period and the turbulent crisis period is even more significant when we look at prices. During the crisis period there are 16 (28) price changes that are larger than +0.5% (-0.5%) while during the pre-crisis period there is actually no single price change that is larger than +/-0.5%.⁴

During the crisis, many CDS index spread changes are much larger than the largest spread changes ever seen before the crisis. During the crisis period, a total of 6 (9) positive (negative) daily spread changes are larger than any spread change seen during the pre-crisis period. Moreover, 35 (13) spread changes are larger than the second-largest spread change ever observed before the crisis. Again, this is evidence of how *sudden* and how *extreme* the crisis-induced change in the dynamics of the CDS market has been. And again, the picture is even more extreme in the price-dimension where the crisis period contains a total of 80 (123) positive (negative) daily price changes that are larger than any price change seen during the pre-crisis period. That is, more than 27% of the daily price changes observed from July 2007 onwards are more extreme than the most extreme price change observed in the equally long time-period before July 2007.

During the crisis, the most extreme CDS index spread changes are very large The most extreme daily spread changes during the crisis are around +/26%. This can be compared to the largest spread changes during the equally long pre-crisis time period (+15% and -11%). The situation is, again, even more extreme when we look at price changes. The most extreme daily price changes during the crisis are around +/-1.4% compared to +/-0.2% or so before the crisis.

Clearly, in the CDS market, multi- σ price changes have for the last three years not only been plentiful but extreme as well.

A comparison of multi- σ events in the credit derivatives market and the stock market reveals many similarities The largest daily credit spread changes during the crisis represent spread movements of more than 13 (pre-crisis) standard deviations. A corresponding daily S&P500 stock return, i.e. a $13\text{-}\sigma$ event, would have to be around $\pm 9\%$. Now, up to late 2008 this was not even close to anything one had seen in the US stock market since the October crash 1987. However, in September 2008, in the wake of the Lehman Brothers collapse, the extreme behavior in the credit market spilled over to the stock market. In October 2008 alone, the number of $13\text{-}\sigma$ stock returns (measured as of before the crisis) was 4 and the number of returns above $\pm 3\%$ was 13. Clearly, the behavior in late 2008 was unique and we have not seen this kind of stock market behavior again. And even though the regime shift is much less extreme in the stock market, the credit derivatives market and the stock market both show quite similar patterns of a pre-crisis regime and a crisis regime. The stock market lags the credit market and the stock market changes much less than the credit market, but the overall picture is the same.

A comparison of the credit derivatives market in July 2007 with the stock market in October 2008 reveals striking similarities Over the first month (22 trading days) of the credit crisis 11 daily spread changes, i.e every second spread change, is larger than ± 5 standard deviations. A corresponding return history in the US stock market (S&P500) is a month where every second day sees a stock return above $\pm 3.25\%$. More exactly, the *expected* sequence of 11 extreme returns in S&P500 (adjusted to compensate for the much higher volatility in the CDS market) would be -9.1%, -6.5%, -4.1%, -3.9%, -3.4%, 3.4%, 3.6%, 4.3%, 5.5%, 7.4% and 8.6%. Now, in October 2008 this was exactly what we observed. Exactly 11 returns were indeed above $\pm 3.25\%$ and the *actual* sequence of the 11 returns was -9.5%, -7.9%, -6.3%, -5.9%, -4.1%, -3.9%, -3.5%, 4.2%, 4.7%, 10.2% and 11.0%. The similarity between the credit market in July 2007 and the equity market in October 2008 is remarkable!

VALUE AT RISK ESTIMATES IN THE CREDIT DEFAULT SWAP INDEX MARKET

The results in the previous section indicate that extreme (non-normal) price changes are very common in the most well known segment of the credit derivatives market (the CDS index market). This might turn out to be a problem in risk management of credit derivatives portfolios and in this section we therefore investigate the usefulness of the normal distribution in Value at Risk (VaR) calculations of credit default swap portfolios (proxied by the *iTraxx* Europe CDS index). Moreover, as an alternative to the normal distribution, and as a result of the extreme behavior of the largest price changes in this particular market, we suggest a simple and easy-to-implement extreme value theory-based approach as a viable alternative in VaR calculations of credit derivatives positions.

The main idea behind extreme value theory (EVT) is to focus on the tails of a distribution. Extreme value theory has been around for a long time (Fisher and Tippett [1928], Gnedenko [1943], Gumbel [1958]) and it has sound theoretical underpinnings at the same time as it is easy to implement in practical (real-world) situations. As a result, EVT has been applied to a range of different practical (engineering) problems over the years. Moreover, lately we have also seen EVT being applied to problems in finance and insurance (Embrechts, Kluppelberg and Mikosh [1997], and in Reiss and Thomas [1997]).

Extreme value theory models can be divided into two broad groups; the models where the focus is on those observations in the data that exceed a certain high threshold (peaks-over-threshold (POT) methods), and the models where the focus is on blocks of data and on the maxima or minima within these blocks (block maxima methods). In this paper we use the POT method and the main reason for this is its more efficient use of data.

POT methods focus solely on the observations (price changes) that exceed a certain high threshold, u , and Balkema and de Haan [1974] and Pickands [1975] have shown that for a large class of distributions the excess distribution of observations above the threshold can be approximated by the so-called generalized Pareto distribution (GPD). This (excess) distribution contains two parameters, the tail index ξ and the scale parameter α , and by fitting it to the empirically observed historical price changes above the threshold u we try to infer the "true"

shape of the extreme tail(s) of the CDS index price change distribution. This parametrization of the tail, in turn, is used to get an expression for the EVT-based VaR estimate (the quantile) associated with a certain probability p :

$$VaR_p = u + \frac{\alpha}{\xi} \left(\left(\frac{n}{N_u} p \right)^{-\xi} - 1 \right) \quad (2)$$

n is the total number of price changes in the data set and N_u is the number of price changes above the threshold u . For a more detailed derivation of (2) we refer to Byström [2007] or Embrechts, Kluppelberg and Mikosh [1997].

Our purpose is to compare the EVT-based VaR estimates in (2) to corresponding VaR estimates implied by the normal and the historical distributions. Our hypothetical investor holds a well-diversified portfolio of credit default swaps (as a protection buyer *or* protection seller) and we define the VaR estimate as the potential percentage daily price change in a long or short position in the *iTraxx* Europe index (i.e., the quantile at a certain small probability ranging from 0.01% to 5%). These quantiles/VaR estimates are (mathematically) identical to the margins in Byström [2007] and the argument is again that quantiles calculated by EVT-methods are likely to outperform those based on either the historical distribution (less reliance on outliers and the possibility to compute extreme VaR estimates) or the normal distribution (more realistic tail-behavior and a separate treatment of the positive and the negative tail).

We start by presenting the results for the entire sample, i.e. the time-period 2004-2010. After that, we will treat the pre-crisis period and the crisis period separately. To begin with, for the *EVT-method* the tail threshold, u , has to be chosen appropriately; if it is too low it leads to the asymptotic theory breaking down and if it is too high it leads to a lack of (excess) observations in the tail. Here, we set the number of excess observations to 114, i.e. 7.5% of the total number of price changes, which is right in the middle of the 5 – 10%-range suggested by McNeil and Frey [2000]. The thresholds for the two tails are found to be +0.18% and -0.21% (see Table 2). The tail index, ξ , and the scaling parameter, α , are then estimated using maximum likelihood and these estimates are also found in Table 2. The corresponding *normal* VaR estimates are

computed by multiplying the historical standard deviation with the appropriate quantile (1.64, 2.33,...) and adding the historical mean CDS price change, and the *historical* VaR estimates are simply given by ordering and counting the historical CDS price changes in the tails.⁵

The results in Table 3 show *EVT*-based VaR estimates that are very similar to the ones based on the realized (historical) distribution at all modest probability levels. For the more conservative VaR measures one of the weaknesses of the historical distribution reveals itself, however; you cannot calculate VaR at more conservative levels than you have historical observations (in our case 1/1524). Meanwhile, the VaR estimate calculated using the normal distribution is progressively becoming lower and lower (relative to *EVT*) the further out in the tails we go. At the most extreme levels (one-in-ten-thousand events) *EVT* suggests daily price changes of around 2% while the normal distribution suggests changes of a mere 0.7%. Turning to the number of exceedences in the right-hand part of Table 3 we find the number of exceedences of the *EVT*-based VaR measures to be very similar to the expected ones.⁶ The normal distribution, meanwhile, clearly underestimates the risk at all levels except at the 0.05 level where it instead overestimates the risk. To summarize; VaR estimates based on extreme value theory are found to be significantly more accurate than those based on either the normal distribution or the historical distribution. The *EVT*-based VaR estimates are neither too large nor too small. Another interesting finding in Table 3 is the *EVT*-method's asymmetric treatment of the two tails. The normal distribution clearly does not capture the relatively thicker negative tail in the way *EVT* does (it erroneously produces very similar VaR measures in both tails and this gives a larger number of exceedences in the negative tail).

The results in Table 3 remain essentially unchanged when we divide the data into a pre-crisis period and a crisis period and look at each time-period separately. Before the onset of the crisis in July 2007 the credit derivatives market was much more tranquil than during the crisis and a natural question to ask is whether the extreme value theory (*EVT*) based model discussed in this paper perhaps only works in turbulent times. The answer is no. In Tables 4 and 5 we see that the superior performance of the *EVT*-based Value at Risk estimates presents itself in tranquil as well as in volatile times (the *EVT*-parameter estimates can be found in Table 2). To sum up; regardless if we look at the negative or the positive tail, regardless if we look at high

or low confidence levels, and regardless if we look at the crisis period or the relatively tranquil years preceding the crisis the best Value at Risk model is always the one based on extreme value theory.

CONCLUSIONS

In this paper we have focused on the many extreme (multi- σ) credit default swap (CDS) spread changes seen during the recent credit crisis. Compared to the situation before the start of the crisis in July 2007 the number and magnitude of the extreme observations is striking. The paper further demonstrates that extreme value theory (EVT) based VaR estimates are much more accurate in the European CDS market than those based on the normal or historical distribution, both during the crisis years and in the years preceding the crisis. The difference is particularly significant at more conservative VaR levels. Therefore, considering the ease with which EVT-based VaR measures are computed we find EVT to be a better choice for the typical risk manager in the highly volatile credit derivatives market.

Notes

¹The CDS index data is downloaded from the *International Index Company* web page and from *Datastream*.

²In March and September each year, new series of the *iTraxx* index are introduced. In this process, some of the underlying names are often replaced by new names and the sometimes fairly extreme spread movements caused by the change of constituents in the CDS index are excluded from this study (we are not studying the effect of the semi-annual change of index composition but the day-to-day spread dynamics).

³It should be kept in mind when interpreting the figures in this paper that single-name credit default swaps are likely to show an even more extreme behavior than the indexes since some of the most extreme observations are diversified away when the individual swaps are combined into an index.

⁴It should be stressed that the nature of the CDS index is that of a diversified, albeit credit-risky, fixed-income like portfolio (with an average annual credit spread of 0.66% across the sample) and daily price changes of 0.5% must be considered very large.

⁵From an absolute perspective our in-sample results are of course, most likely, better than any results one can expect in a more realistic (future-looking) out-of-sample setting. However, since our perspective is a more relative one with the aim of comparing different methods we stick to our setup for reasons of unambiguity, simplicity and clarity.

⁶The expected number of exceedences is equal to $p \cdot n$ where p is the probability level and n is the number of observations in the sample.

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Figure 1 Daily 5-year *iTraxx* Europe CDS index spread (bp) over the time period June 21, 2004 - June 1, 2010.

Figure 2 Daily 5-year *iTraxx* Europe CDS index price over the time period June 21, 2004 - June 1, 2010.

Figure 3 Daily 5-year *iTraxx* Europe CDS index spread changes (%) over the time period June 21, 2004 - June 1, 2010.

Figure 4 Daily 5-year *iTraxx* Europe CDS index price changes (%) over the time period June 21, 2004 - June 1, 2010.

Table 1 Descriptive statistics for the 5-year *iTraxx* Europe CDS index (daily spread changes and daily price changes (%)) over the time period *June 21, 2004 - June 1, 2010* (divided into a pre-crisis period, *June 21, 2004 - July 17, 2007*, and a crisis period, *July 18, 2007 - June 1, 2010*). Skew indicates skewness and Kurt indicates excess kurtosis.

	daily spread changes			daily price changes		
	pre-crisis	crisis	all	pre-crisis	crisis	all
Mean (%)	-0.12	0.24	0.05	0.0017	-0.0079	-0.0029
Stdev (%)	1.91	5.23	3.90	0.03	0.26	0.18
Skew	0.60	-0.04	0.10	0.03	-0.06	-0.16
Kurt	8.84	3.44	7.47	15.67	4.60	12.15
Top-10 (%)	14.94	25.54	25.54	0.25	1.40	1.40
	8.77	21.97	21.97	0.22	1.23	1.23
	8.59	20.09	20.09	0.13	0.95	0.95
	7.29	16.84	16.84	0.12	0.88	0.88
	7.22	16.59	16.59	0.10	0.87	0.87
	6.82	16.46	16.46	0.10	0.79	0.79
	6.82	14.68	14.94	0.09	0.78	0.78
	6.45	14.48	14.68	0.09	0.78	0.78
	5.48	14.36	14.48	0.08	0.77	0.77
	5.20	12.68	14.36	0.08	0.71	0.71
Bottom-10 (%)	-5.04	-11.10	-11.15	-0.08	-0.75	-0.75
	-5.09	-11.58	-11.58	-0.09	-0.78	-0.78
	-5.11	-11.67	-11.67	-0.11	-0.78	-0.78
	-5.32	-12.11	-12.11	-0.12	-0.80	-0.80
	-5.48	-12.74	-12.74	-0.13	-0.82	-0.82
	-5.66	-15.74	-15.74	-0.13	-0.86	-0.86
	-5.75	-18.29	-18.29	-0.15	-1.01	-1.01
	-6.57	-19.18	-19.18	-0.17	-1.04	-1.04
	-10.23	-26.98	-26.98	-0.20	-1.04	-1.04
	-11.15	-27.73	-27.73	-0.20	-1.37	-1.37

Table 2 GPD parameters for the 5-year *iTraxx* Europe CDS index over the time period *June 21, 2004 - June 1, 2010* (divided into a pre-crisis period, *June 21, 2004 - July 17, 2007*, and a crisis period, *July 18, 2007 - June 1, 2010*). n is the total number of price changes and N_u is the number of price changes above the threshold, u . ξ is the tail index and α is the scale parameter.

		pre-crisis	crisis	all
Positive Tail	n	785	739	1524
	N_u	59	55	114
	$u(\%)$	0.03	0.32	0.18
	ξ	0.395	0.168	0.078
	α	0.0002	0.0016	0.0017
Negative Tail	n	785	739	1524
	N_u	59	55	114
	$u(\%)$	-0.03	-0.32	-0.21
	ξ	0.498	-0.033	0.222
	α	0.0002	0.0024	0.0014

Table 3 *Entire period.* Value at Risk (the size of a one-day % price change occurring with a certain low probability, p) and number of exceedences at various probability levels for the *iTraxx* Europe CDS index market estimated using data from the time period *June 21, 2004 - June 1, 2010*. The column labelled *EVT* contains the Value at Risk and number of exceedences using extreme value theory (GPD) and the column labelled *normal* contains the Value at Risk and number of exceedences using the normal distribution. The column labelled *historical* contains the true VaR for the realized (historical) distribution and the column labelled *expected* contains the corresponding expected number of exceedences.

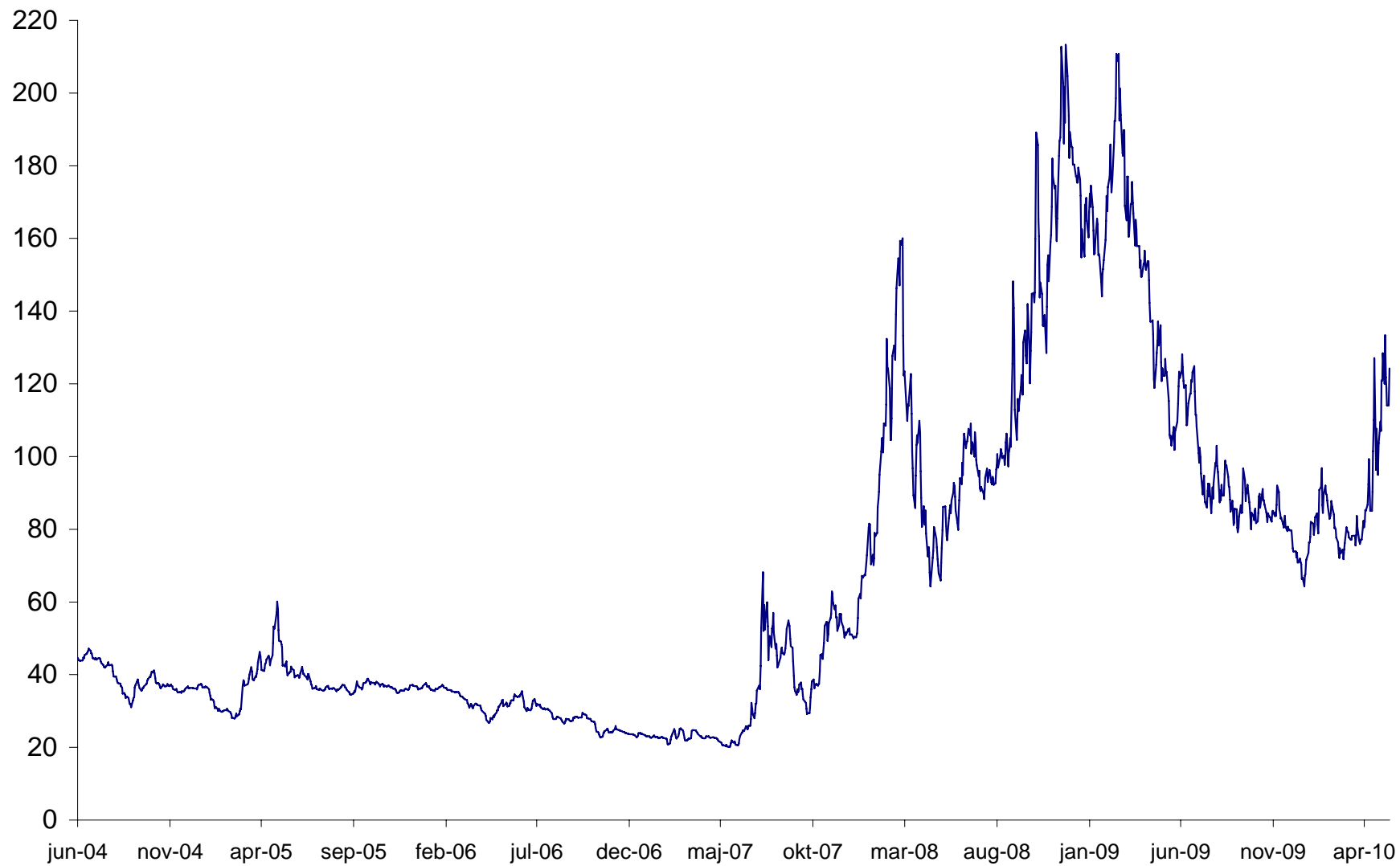
		VaR (%)			exceedences (no.)		
	p	<i>EVT</i>	<i>normal</i>	<i>historical</i>	<i>EVT</i>	<i>normal</i>	<i>expected</i>
Pos. Tail	0.05	0.26	0.29	0.26	77	64	76
	0.01	0.56	0.42	0.53	12	29	15
	0.005	0.71	0.46	0.78	10	24	8
	0.001	1.08	0.56	1.23	2	12	2
	0.0005	1.25	0.59	<i>n.a.</i>	1	11	1
	0.0001	1.70	0.67	<i>n.a.</i>	0	10	0
Neg. Tail	p	<i>EVT</i>	<i>normal</i>	<i>historical</i>	<i>EVT</i>	<i>normal</i>	<i>expected</i>
	0.05	0.28	0.30	0.27	73	62	76
	0.01	0.58	0.42	0.65	19	31	15
	0.005	0.75	0.47	0.78	9	29	8
	0.001	1.26	0.56	1.03	1	22	2
	0.0005	1.54	0.60	<i>n.a.</i>	0	18	1
0.0001	2.39	0.67	<i>n.a.</i>	0	13	0	

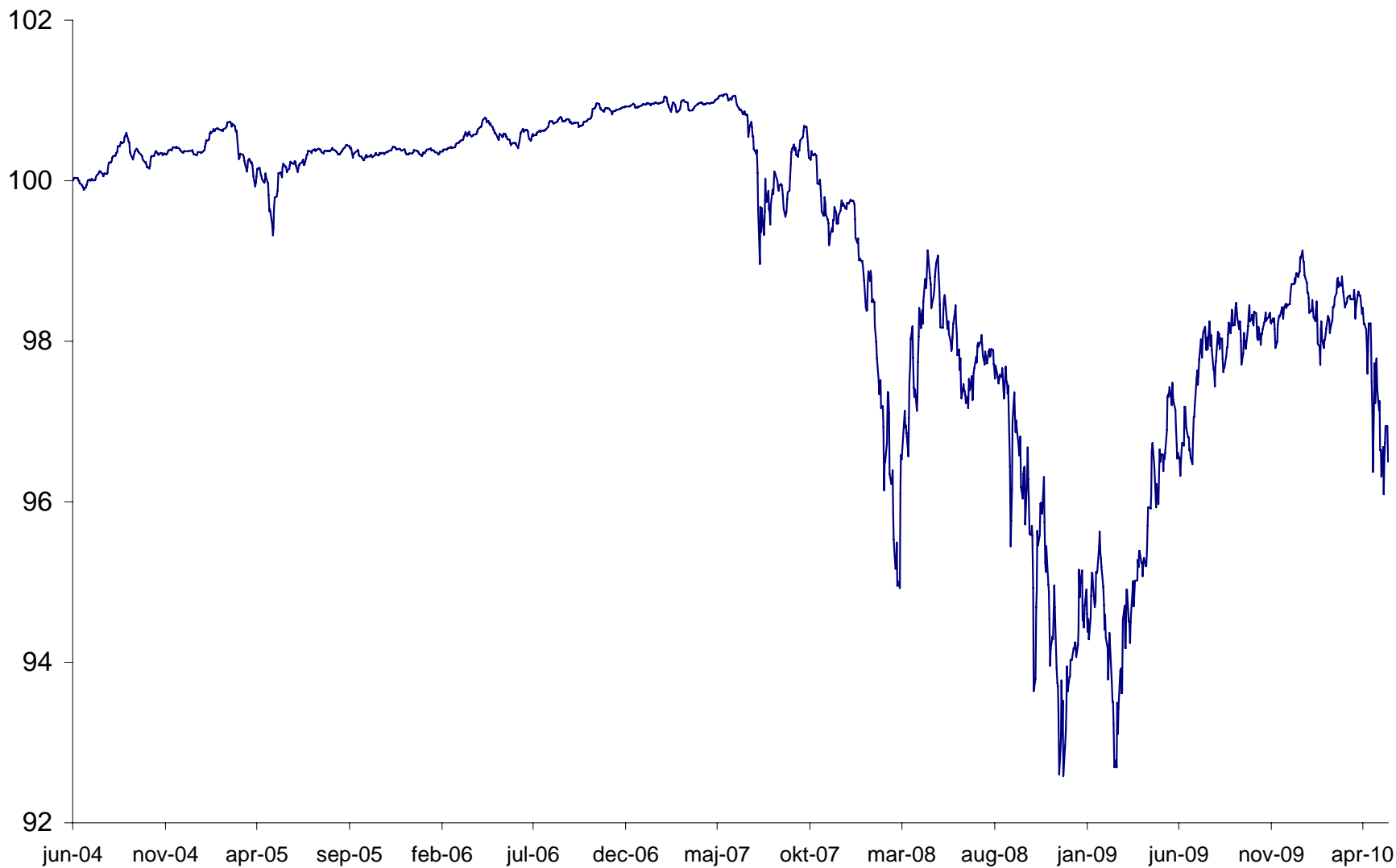
Table 4 *Pre-crisis period.* Value at Risk (the size of a one-day % price change occurring with a certain low probability, p) and number of exceedences at various probability levels for the *iTraxx* Europe CDS index market estimated using data from the time period *June 21, 2004 - July 17, 2007*. The column labelled *EVT* contains the Value at Risk and number of exceedences using extreme value theory (GPD) and the column labelled *normal* contains the Value at Risk and number of exceedences using the normal distribution. The column labelled *historical* contains the true VaR for the realized (historical) distribution and the column labelled *expected* contains the corresponding expected number of exceedences.

		VaR (%)			exceedences (no.)		
	p	<i>EVT</i>	<i>normal</i>	<i>historical</i>	<i>EVT</i>	<i>normal</i>	<i>expected</i>
Pos. Tail	0.05	0.04	0.05	0.04	43	21	39
	0.01	0.08	0.07	0.09	8	10	8
	0.005	0.11	0.08	0.12	4	8	4
	0.001	0.21	0.10	<i>n.a.</i>	2	5	1
	0.0005	0.28	0.10	<i>n.a.</i>	0	4	0
	0.0001	0.54	0.12	<i>n.a.</i>	0	4	0
Neg. Tail	p	<i>EVT</i>	<i>normal</i>	<i>historical</i>	<i>EVT</i>	<i>normal</i>	<i>expected</i>
	0.05	0.04	0.05	0.04	41	27	39
	0.01	0.09	0.07	0.11	9	12	8
	0.005	0.13	0.08	0.15	6	12	4
	0.001	0.28	0.09	<i>n.a.</i>	0	8	1
	0.0005	0.39	0.10	<i>n.a.</i>	0	8	0
0.0001	0.88	0.11	<i>n.a.</i>	0	7	0	

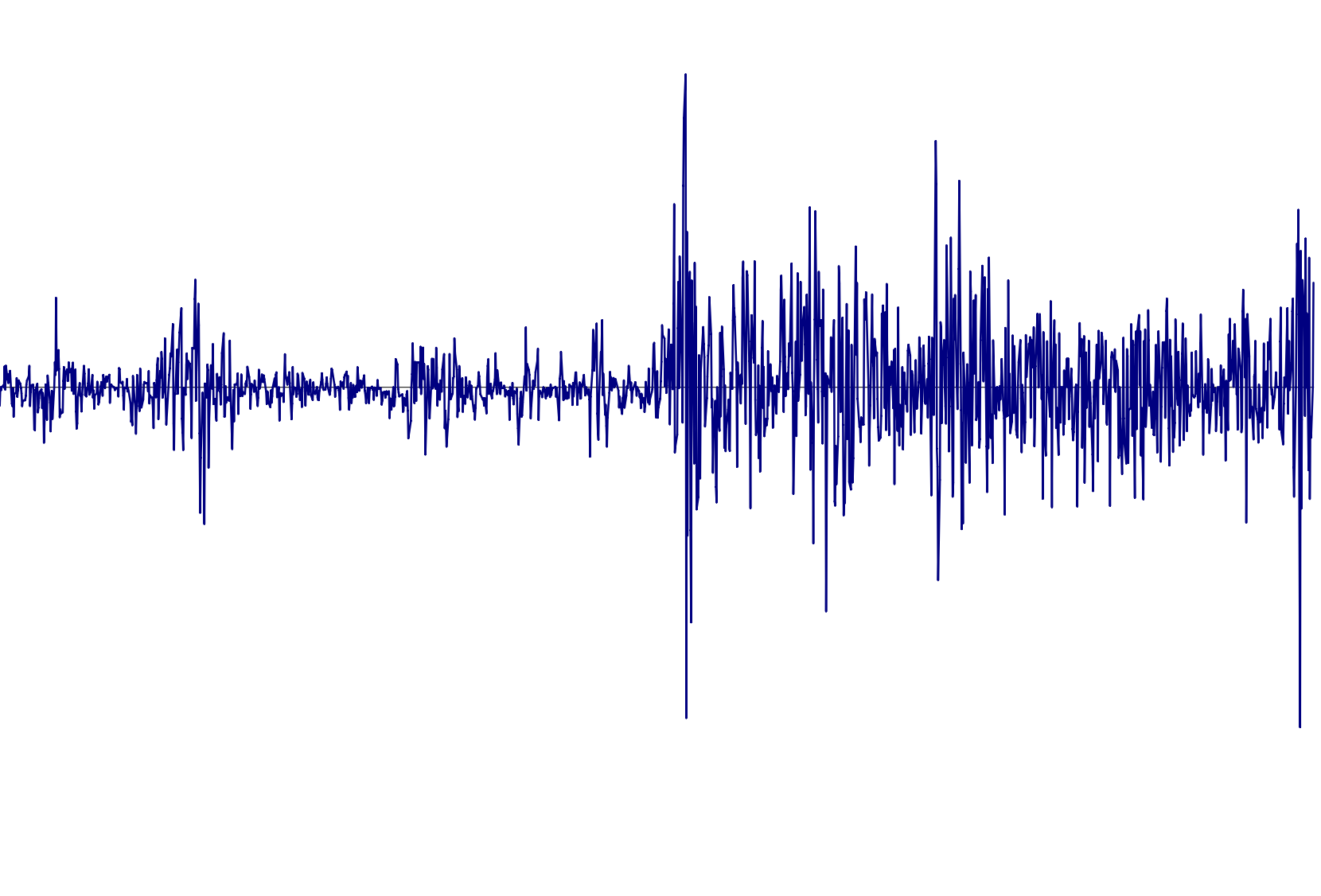
Table 5 *Crisis period.* Value at Risk (the size of a one-day % price change occurring with a certain low probability, p) and number of exceedences at various probability levels for the *iTraxx* Europe CDS index market estimated using data from the time period *July 18, 2007 - June 1, 2010*. The column labelled *EVT* contains the Value at Risk and number of exceedences using extreme value theory (GPD) and the column labelled *normal* contains the Value at Risk and number of exceedences using the normal distribution. The column labelled *historical* contains the true VaR for the realized (historical) distribution and the column labelled *expected* contains the corresponding expected number of exceedences.

		VaR (%)			exceedences (no.)		
Pos. Tail	p	<i>EVT</i>	<i>normal</i>	<i>historical</i>	<i>EVT</i>	<i>normal</i>	<i>expected</i>
	0.05	0.38	0.42	0.39	39	29	37
	0.01	0.70	0.59	0.78	10	11	7
	0.005	0.87	0.65	0.88	4	10	4
	0.001	1.34	0.79	<i>n.a.</i>	1	5	1
	0.0005	1.59	0.84	<i>n.a.</i>	0	5	0
	0.0001	2.28	0.95	<i>n.a.</i>	0	2	0
Neg. Tail	p	<i>EVT</i>	<i>normal</i>	<i>historical</i>	<i>EVT</i>	<i>normal</i>	<i>expected</i>
	0.05	0.41	0.43	0.39	34	31	37
	0.01	0.78	0.61	0.80	9	18	7
	0.005	0.93	0.67	1.01	4	13	4
	0.001	1.27	0.80	<i>n.a.</i>	1	7	1
	0.0005	1.41	0.85	<i>n.a.</i>	0	5	0
	0.0001	1.72	0.96	<i>n.a.</i>	0	4	0





30%
20%
10%
0%
-10%
-20%
-30%
-40%



2,0%
1,5%
1,0%
0,5%
0,0%
-0,5%
-1,0%
-1,5%
-2,0%

