When swans are grey: VaR as an early warning signal

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Abstract  The market events of 2008 will be remembered as much for their extreme volatility as for a widespread failure of the risk management, which contributed to the near collapse of many firms thought to be among the leaders in that field. This paper identifies a key deficiency in the way that the historical data are currently utilised in the estimation of risk. This deficiency stems from the conception of the marketplace as an equilibrium-seeking and continuous system and it led to the financial firms’ unpreparedness for sudden market reversals. A different framework for risk estimation is proposed based on linking the risk modelling with the existing literature on financial instability. One possible application of the proposed method to the estimation of value-at-risk (VaR) is demonstrated, and empirical tests comparing it with the traditional methods are performed using S&P 500’s history from 1989 to 2010. The new measure, called the instability VaR, is shown to dominate all traditional methods of calculation.

Keywords: market crises, VaR, early warning indicators, market bubbles, risk mispricing, financial instability hypothesis

INTRODUCTION
Market events of 2008 will be remembered as much for their extreme volatility as for a widespread failure of the risk management, which contributed to near collapse of many firms, had various causes and went far beyond deficiencies in risk measurement techniques. Nevertheless, underestimation of risk played a real part and the obvious lesson of that disaster should be that the financial industry must look for significant improvements in the performance of risk estimates. This analysis proposes a fundamental change to the way that historical data are used in the estimation of risk. It will show how the accuracy of one common metric called value-at-risk (VaR) can be significantly improved with the application of this new method, which is motivated by the idea of self-sustaining
boom-bust patterns and their relation to pricing of risk. While the paper will focus on VaR, the ideas presented here are general and can be applied to the estimation of any risk statistic.

**PROBLEMS WITH CURRENT VAR IMPLEMENTATION**

VaR is the most commonly used metric of market risk. However, VaR is frequently the subject of criticism, and this paper will consider some of the arguments against it that carry the most validity.

The most often voiced objection to VaR stems from the obvious inappropriateness of the normal distribution for the modelling of medium- to short-term financial returns. The fact that the short-term returns are not distributed according to a bell curve can be hardly disputed at this point. It is enough to consider the simple fact that daily returns of the S&P 500 display a kurtosis of greater than 7 over the three years even prior to August 2008. A popular version of this argument against VaR can be found in Nassim Taleb’s *Black Swan: The Impact of the Highly Improbable*. However reasonable it appears, this argument should not be levelled at VaR as a metric of risk, but rather at one particular way of calculating VaR, namely the parametric or normal distribution VaR based on a particular way of incorporating historical data.

This misunderstanding is based on a confusion of the concepts of measure and that of the metric. Measure is an operation for assigning a number to something; there could be many ways of doing so. Metric is the interpretation; for example, VaR is a metric, see Holton. Parametric VaR, Monte Carlo VaR and historical VaR are all different measures of the risk metric called VaR.

VaR has a statistical definition (it is a quantile of a distribution), and nothing in this definition implies that it has to be based on a bell curve calibrated exclusively on recent returns as is the case with most accepted models today. In other words, there are different ways of measuring the metric called VaR. Extreme value theory methods do not assume any particular overall distribution and Monte Carlo simulation VaR can be based on many distributions, including various power law distributions that Taleb favours. These distributions can model the effects of the ‘fat tail’, which frequently and painfully asserts itself in the financial markets, although, as will be seen, there are practical problems with those versions of VaR as well. Lack of awareness of the basic distinction between the measure and the metric sometimes leads to definitions of VaR which state that it is only valid during ‘normal conditions’. It is astonishing that anyone would even consider using a risk measure that only functions when one does not need it. The goal in this study is not to discard VaR, but rather to make sure it better accounts for the drastic market reversals that seem to always catch quantitative risk systems by surprise.

**THE REAL PROBLEM: EQUAL WEIGHTED AND DECAY TIME WEIGHTED ESTIMATORS**

The main problem that makes the current risk measurement dangerously inadequate lies not in a distributional assumption, but rather in the way that the historical data is incorporated in the risk estimates. The current methods for using past observations gradually became axioms that are completely divorced from
the market realities or any new economic thinking. Currently, there are two common methods for incorporating the past observations into the estimates of risk metrics. This paper will call them the equal weighted (EW) and decay time weighted (DTW). The equal weighted estimator of (co)variance (for a normal distribution, which is being used here, the risk and variance are assumed to be synonymous) is derived directly from statistics where an unbiased estimator of (co)variance is equal to:

\[
\text{EW} \sigma_{j,k}^2 = \frac{1}{n-1} \sum_{i=1}^{n} [r_{j,i} * r_{k,i}]
\]  

(1)

where:

\( r_{j,i} \) — return of asset \( j \) or \( k \) at time \( i \)

\( n \) — number of observations.

The VaR is then calculated as:

\[
\text{VaR} = k * \sigma_{j,k}
\]  

(2)

where:

\( k \) — scaling based on the confidence level of VaR.

In terms of economics the implicit assumption in the use of this method for modelling variability of the returns is that a system is being observed that is relatively stable over the time period of observation and is projected to continue this behaviour into the future period covered by the risk forecast. This assumption seems to be inspired by the economic theories which purport the existence of a long-term equilibrium in the economic and financial system. Nevertheless, there are two obvious practical problems with this approach for the purposes of the risk estimation.

Problem 1: If a sudden crisis erupts after a period of moderate volatility and low or moderate correlations, the risk estimate leaves the risk analyst completely unaware of what extreme conditions could do to their portfolio. The historical data gathered during the period of moderate or low volatility that persisted just before the crisis will severely understate the risk potential in the market. Problem 2: In addition, the equal-weighted estimator adjusts very slowly to changes in the market conditions and may indicate low risk long after it is obvious to even the most casual observer that the high-volatility period has commenced.

The DTW estimator is an attempt to correct the second of these problems by making the estimate more sensitive to the recent market conditions. The DTW (co)variance estimate could be written as:

\[
\text{TDW} \sigma_{j,k}^2 = \left(1 - \lambda \right) * \sum_{i=1}^{n} \left[ \lambda^{i-1} * r_{j,i} * r_{k,i} \right] / \sum_{i=1}^{n} \left(1 - \lambda \right) * \lambda^{i-1}
\]  

(3)

\( \lambda \) — exponential decay factor

\( l, i \) — indicators of time

\( r_{j,i} \) — return of asset \( j \) or \( k \) at time \( i \).

It can be seen that in this calculation the more recent periods are meant to carry progressively more information and are weighted accordingly. The implicit economic assumption can be understood in relation to the EW estimator and consists of allowing the market and the financial equilibrium to vary more rapidly with time. The DTW approach does indeed solve the
slow adjustment problem mentioned above. Nevertheless, it cannot fix the more important first problem and still leaves a risk manager unprepared for the possibility of a sudden change in the market structure after a period of moderate volatility and correlations. In other words, although it allows for changes in the market structure, it is still only a reflection of the presently observed volatility and assumes a certain continuity that is simply not observed in practice.

As an example, consider Figure 1. In it can be seen S&P 500 returns and the two methods of estimating 99 per cent VaR for the S&P 500, one using the EW method and the other using the DTW method. The exponential weight is 0.94, which was the best performing weight in this sample for the DTW. It has been used because it allowed complete benefit of the doubt to the existing method. Figure 1 confirms something that is widely recognised, namely that both existing methods gave absolutely no warning of the impending 2008 meltdown.

The new paradigm of risk measurement must minimise the extrapolation from quiet periods to the tails of the distribution. A market structure during the extreme event is likely to be drastically different from the one observed in the trading range or even in the moderate volatility periods before the crisis. Incorporating this fact does not necessarily mean that a financial firm should be permanently braced for the crisis, an approach that would be neither practical nor healthy for the economy. Instead one should look for ways to correct the assumptions embedded in the current process to improve the accuracy of the risk estimates.

ENDOGENOUS FINANCIAL INSTABILITY

To proceed further one must identify some theoretical framework that resembles reality to a greater degree than the aforementioned assumptions of a
relatively stable ‘equilibrium’ state. There are a number of economic approaches that can be helpful in this regard. De Long et al.\(^3\) show a model of market bubbles in which rational traders who follow positive-feedback strategies are buying with rising prices and selling with falling prices, thus producing self-sustaining trends which ultimately end in a crash. The situation of demand rising with the price not infrequently encountered in financial markets upsets traditional supply-demand relationships and makes traditional equilibrium approaches incapable of dealing with the real world fluctuations. De Long et al.’s model formalises a permanent theme in the literature on self-reinforcing bubbles which goes back as far as Bagehot.\(^4\)

Going further, Hyman Minsky\(^5\) identified the key features of the credit cycle which tend to drive large boom-bust sequences. According to the financial instability hypothesis (FIH), fundamental relationships in the real economy and financial markets change with the change in the behaviour of the participants and particularly with the change in the behaviour of the financial intermediaries. For example, after a period of prosperity, an increase in the risk-taking activities takes place and rising leverage builds, setting up the potential for a violent downturn. Some interruption will expose the unsustainability of leverage levels leading to a credit contraction and a potential collapse in the asset values.

Minsky summarised his insights in two theorems of the financial instability:

‘The first theorem of the financial instability hypothesis is that the economy has financing regimes under which it is stable and financing regimes in which it is unstable. The second theorem of the financial instability hypothesis is that over periods of prolonged prosperity, the economy transits from financial relations that make for a stable system to financial relations that make for an unstable system.’\(^5\)

Soros\(^6\) extensively discusses his view of boom-bust sequences. His description, although less rigorous than Minsky’s, gives a useful view into the mechanism of self-sustaining bubbles via the mechanism he calls ‘reflexivity’. Economy can deviate very far from a theoretical equilibrium for long periods of time, because many so-called ‘fundamentals’ under certain conditions can become highly intertwined with prices, which are supposed to reflect them. The views of both Minsky and Soros explain how the risk gets built up to an extremely high level owing to purely endogenous market forces. The stage is then set for a dramatic reversal. In an exceptionally lucid explanation of systemic risk, Danielsson and Shin\(^7\) write:

‘One of the implications of a highly leveraged market going into reversal is that a moderate fall in asset value is highly unlikely. Either the asset does not fall in value at all, or the value falls by a large amount.’

Let us now summarise these insights in a framework that will help to develop a risk modelling approach, which can truly estimate risks, that is provide an early warning of the instability potential.

**FRAMEWORK FOR THE INSTABILITY RISK APPROACH**

1. Financial market behaviour can be very roughly divided into two states: a stable state where a financial economy is an
equilibrium-seeking system producing random deviations and an unstable one where it becomes a deviation-amplifying system. (Of course, there are many different specifications possible but the aim is to capture only the most important aspects to build tractable models.)

(2) Currently used weighting schemes allow the latest observed data to dominate the sample in any conditions. This leads to a severe understatement of risks and an overstatement of diversification benefits during the low volatility/low correlation stable phase and to an overstatement of risks in the bottom of the cycle.

(3) An unstable state is characterised by the multiple feedback loops of liquidation resulting in a unique environment which has no linear relation to the stable state. Therefore, data gathered in stable periods carry exceedingly little value for the estimation of risks.

(4) As the risk taking behaviour in the economy grows, a risk statistic should assign a greater weight to the data gathered during the unstable periods.

It is important to note that the first three assumptions, while contrary to the currently prevailing paradigm, are not new, since they are implicitly incorporated in the extreme value theory (EVT) approach to financial risk estimation. EVT is a statistical framework, which has been extensively used by financial risk researchers to overcome the deficiencies of the EW and DTW approaches and the resulting focus on stable periods. EVT relies on a theorem, which postulates that extreme values from different distributions can be modelled as coming from the generalised extreme value distribution (GEVD). It relies on the asymptotic properties of the independent and identically distributed (i.i.d.) sample maxima and in that sense is similar to the central limit theorem for sums of i.i.d. variables. If one now makes an assumption that extreme observations gathered from different periods over a long time are independently and identically distributed, then one can gather enough historical outliers to estimate the parameters of the GEVD using the maximum likelihood methods. A good summary of the EVT approaches can be found in Embrechts et al.8 (1997). EVT has been shown to be a powerful tool, see for example, Longin9 or Phoa,10 with a much better predictive power in the tail than attained by the current approaches. Still, there are some serious obstacles to its practical use in everyday risk management and it is that use that one is most concerned with here. EVT presupposes unconditional distribution of the extreme values and is a purely statistical framework with no linkages to the economic conditions at large. Thus, even if it accurately represents the risk of a tail event, it leaves the risk manager with a risk estimate that is more or less constant through time. (This is because EVT methods use all available extreme observations in history to satisfy the asymptotic properties and fill the sample, so that new extreme observations usually do not significantly change the estimate.) This constant estimate is bound to be quite high. The result is that, if this estimate is acted on, it will produce a permanent bracing for the crash, a state which was explicitly alluded to earlier, as neither feasible in a competitive financial economy nor desirable for the economic development. In other words, it may correctly estimate the tail, but it says
nothing about the potential changes in its likelihood. This is why it is necessary to draw on the ideas outside of a purely statistical framework to estimate the instability potential of the economy. The author here argues that statistics should be strictly subordinate to the economic reasoning in risk modelling and that heuristics should be used where they are necessary.

**INSTABILITY ESTIMATOR OF THE PARAMETRIC VAR**

The conclusions in the above framework lead to the new paradigm for the inclusion of the past data in the risk estimation process. As the excess risk-taking persists, a financial economy becomes increasingly vulnerable to all types of shocks. This framework motivates the following definition of a new class of risk estimates:

Instability estimator of risk (IER) is calculated by assigning progressively greater weight to the observations from the extreme portion of the sample when two conditions are present:

1. Risk is mispriced for a period of time
2. The trend of worsening risk mispricing stops and shows signs of reversal.

Risk mispricing can potentially be measured by a variety of more or less easily observed metrics. In this class of metrics one can include price-to-earnings ratios, junk credit spreads, housing price-to-rent ratios, sovereign spreads, financial sector leverage and others. The extreme sample observations will carry more weight when two conditions in the definition are met in relation to the risk (mis)pricing metrics.

In the interest of the simplicity of presentation, one can take the most basic and perhaps most widely used type of VaR, the parametric VaR, and start with the EW and DTW methods of using the past data for its estimation. One will then introduce an instability estimator of parametric VaR. The testing of the instability estimator will show that, even with an obviously simplistic parametric VaR, it can do a good job of capturing tail risks.

**Construction of the instability estimator of parametric VaR**

EW and DTW estimators of VaR have already been described above. This paper will now describe the instability estimator and run back tests comparing the three of them. Since parametric VaR is being used, the instability estimator of (co)variance will take the following form:

\[
\text{Instability estimator } \sigma_{j,k}^2 = W_{EX} \times \frac{1}{n} \sum_{t=1}^{c} \left[ r_{j,t}^{EX} r_{k,t}^{EX} \right] + (1 - W_{EX}) \times (\text{EW } \sigma_{j,k}^2)
\]

where:

- \(W_{EX}\) — weight assigned to the extreme observations (similarly to EVT methods, in order to find enough of these extreme observations one must widen the available sample as much as possible. In this study, the available sample for extreme observations used starts on 31st December, 1930)
- \(c\) — is the number of observations that satisfy the criteria to be chosen as extreme data points.
\( r^{EX}_{j,t} \) — selected extreme period return of the asset \( j \) or \( k \) at time \( t \)
and the instability estimator of parametric VaR for asset \( j \):

\[
VaR = k \times (\text{INST} \sigma_{j,t})
\]

where:
\( k \) — scaling based on the confidence level of VaR.

In practice there are two key choices that need to be made:

1. How to separate the stable from unstable periods?
2. What is the form and parameters of the weighting function in the formula above, in other words, how to measure the risk-taking activity and its reversal?

The answer to the first question can be fairly straightforward. Since one cares about the tail events that are not well captured by the existing methods, one can label as ‘unstable’ all of the past observations that were outside the 2.33 deviation band (that would be equivalent to violating 99 per cent parametric VaR), where standard deviation is calculated using the EW method using all of the history available.

The second problem is considerably trickier. The goal is to test the IER concept on a broad market index, specifically the S&P 500, so one needs to choose only the most broadly applicable measures of risk pricing. For the risk-pricing part of the definition a trailing one-year average price to earnings ratio of the S&P 500 and a trailing one-year average credit junk spread will be used. For the metric of risk-pricing reversal part a 180-day percentage change in the average credit junk spread will be used. This will allow the concept to be tested without delving into the issues of the generalisation of the IER concept to the multiple asset/multiple factor model.

With the above considerations in mind, the weighting function can be introduced:

\[
W_{EX,i} = \min \left( \frac{D_{CPE,i} + D_{CJS,i}}{\max \left( \frac{2 \times D_{CJS,i}}{20}, 1 \right) - 1, 0.3} \right)
\]

where:
\( i \) — time at which the risk (mis)pricing metric is observed and VaR is estimated Risk mispricing metrics:
\( D_{CPE,i} \) — reverse decile of one-year average PE in the historical sample of all such average PEs (where deciles are made fractional through multiplying decimal percentage ranks by ten, ie a rank of one (highest possible value) becomes a decile rank (that is reverse decile) of ten (highest possible contribution to weight))
\( D_{CJS,i} \) — decile of one-year average junk spread

Risk mispricing reversal metric:
\( DC_{CJS,i} \) — reverse decile of 180-day change in the average one-year junk spreads (sources of data are Standard and Poors, Merrill Lynch, and Haver Analytics)

It is clear from this weighting function that the weight of extreme periods should be highest when smoothed PE is high, smoothed junk spreads (JS) are low and 180-day change in smoothed junk spreads (DJS) is high (ie spreads are trending up after a period of risk mispricing). The combined weight of PE
and JS as representing risk mispricing is equal to one half, while the weight of DJS, as representing the warning of the end of mispricing, is also equal to one half. All this follows the definition of the IER above. The combined deciles are divided by 20 and one is subtracted from the total. The highest possible value of the sum of deciles is 40, so the weight of the extreme sample will vary from zero to one directly proportionally with the increase in the sum of deciles of the original signals. The maximum function ensures that when the sum of signals is below 20, the weight is zero and not negative, while the minimum function caps the total weight of the extreme periods to 30 per cent of the sample to avoid calculating VaR based on only a small number of observations in the tail. (The results are not changed significantly with small or even moderate changes in these settings, thus indicating robustness.)

It should be clear that formula (5) occupies in the IER paradigm the same place occupied by the exponential decay weighting in the presently accepted one, that is, its purpose is to indicate which periods carry more valuable information. The present paradigm assumes that recent periods are always more valuable, while the IER is based on the assumptions that there are other factors that govern this relative importance of data points.

Let us summarise what would be expected from the instability estimator based on the formulae (4) and (5). The instability estimator is essentially a weighted average of the EW estimator and a similar calculation, but based only on the extreme periods (the first term on the right-hand side of formula (4)). The weight between those two terms varies with the signals for the risk-taking activities of the boom-bust cycle.

**VISUAL TESTING**

Figures 2–5 summarise in graphical form some of the key advantages of the IER method. In Figure 2 it is seen that, just as in 2008, both EW and DTW methods did not provide any early warning about the Long Term Capital Management (LTCM) crash. Instability VaR on the contrary showed sharply increased risk after the Asian currency crisis and kept the risk elevated leading up to August of 1998, just as LTCM loaded up on short-volatility trades they viewed as exceptionally attractive, perhaps because they were using the standard methods of VaR calculation.

Figure 3 shows a similar story prior to the dot-com bubble crash. Both EW and DTW methods showed low risk and DTW even showed a significant decrease in VaR at the worst possible moment just a few weeks leading up to the beginning of meltdown in April 2000. Instability VaR on the other hand showed a dramatic increase in risk in January 2000.

While early warning should be a critical objective for risk models, it is important that financial firms put themselves in a position to benefit from the boom and not be permanently braced for crisis. (Of course, the issue is being discussed from the perspective of the individual user given the financial system that is in place now. The aggregate effects on the economy are a different story and regulators would do well to consider other uses for this model to possibly smooth out the risk-taking cycle.) Figure 4 shows that this would indeed be the case with the instability VaR approach. For the period from the beginning of 2002 to the end of 2006, the risk would largely be the same as under EW and
DTW methods. The two exceptions are a few months at the end of 2004 and the second half of 2005. The author does not view these false alarms as failures of the model; rather they represent 'tests of the bubbles', as
discussed by Soros. The only way to distinguish a burst of the bubble from a ‘test’ is *ex post*.

Figure 5 repeats Figure 1, but with the instability VaR added. Instability VaR clearly showed increased risk starting in July 2007 and did not decrease despite numerous minor rallies and some ‘lull before the storm’. The performance of the EW and DTW in this period was already discussed.

### STATISTICAL TESTING

The results of the testing are summarised in Tables 1 and 2. Table 1 shows the percentage of time that the actual return for the S&P 500 breaks through the 99 per cent VaR band. This test is based on Basel traffic light test but we will use a much bigger sample that encompasses different portions of the cycle to avoid the deficiency of the short sample in the Basel VaR testing. The traffic light test, also called the binomial test, is based on the idea that, with a large enough sample, an adequate VaR model should have the percentage of its violations being close to 1 per cent for the 99 per cent confidence VaR.

It is obvious from Table 1 that both EW and DTW methods show significant deficiencies in all periods. Instability VaR, on the other hand, shows good results for all periods, even the most challenging ones for a risk model, such as the one from the end of 2006 to the end of 2008.

Finally, Figure 3 shows the statistical test based on the likelihood ratio (LR) suggested by Kupiec. LR is given by the following formula:

$$LR = -2 * LN\left(\frac{(1 - q)^{n-v} * q^v}{(1 - r)^{n-v} * r^v}\right)$$  (6)
where:

- $n$ — number of observations in the sample
- $v$ — number of violations (i.e., number of times that 99 per cent VaR was breached)
- $q$ — desired violation rate
- $r$ — empirical violation rate (i.e., $v/n$).

The null hypothesis being tested here is:

$$H_0 : r = q$$

This statistic is the chi-square distributed with one degree of freedom. Using the chi-square tables, one can infer the lower and upper bounds for the number of violations that would need to be observed in order not to reject the hypothesis that the 99 per cent VaR is violated 1 per cent of the time (i.e., that it is likely a 99 per cent VaR or something close to it is being produced).

### Table 1: Percentage of periods where 99 per cent VaR was violated

<table>
<thead>
<tr>
<th>Period</th>
<th>Per cent violations (Basel)</th>
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<tbody>
<tr>
<td></td>
<td>EW (%)</td>
</tr>
<tr>
<td>31st December, 2006 to 31st December, 2008</td>
<td>4.75</td>
</tr>
<tr>
<td>31st December, 2006 to 31st December, 2008</td>
<td>1.97</td>
</tr>
<tr>
<td>31st December, 2001 to 21st May, 2010</td>
<td>2.99</td>
</tr>
<tr>
<td>31st December, 1997 to 21st May, 2010</td>
<td>1.90</td>
</tr>
<tr>
<td>31st December, 1993 to 21st May, 2010</td>
<td>1.75</td>
</tr>
<tr>
<td>26th April, 1989 to 21st May, 2010</td>
<td>1.82</td>
</tr>
</tbody>
</table>
Again, it can be seen that the instability estimator dominates the group. It is also seen that EW and DTW estimators are consistently rejected by a wide margin. For example, for the whole period from 26th April, 1989 to 21st May, 2010 actual S&P 500 returns violate the EW VaR 97 times and DTW VaR 103 times. The implied 90 per cent confidence range for the correct binomial distribution is between 40 and 68 violations. Instability VaR gives 55, near the middle of the range. The same situation holds for all other subsamples.

**CONCLUSIONS**

The failure of the financial risk estimation to give any warnings of danger is widely known, especially after the 2008 crash. This paper suggests a modified calculation of the popular value-at-risk (VaR) measure with a link to the pricing of risk in the financial economy. Comparing the accuracy of this measure over the past 21 years of the S&P 500 returns against the commonly used equal weighted (EW) and decay time weighted (DTW) estimates of parametric VaR shows that it can provide significant improvement in the estimation of market risk. Implementation of the instability estimator of risk (IER) will allow the well-known deficiencies of VaR to be addressed without abandoning the metric known for its ease of use and communication. Further research into instability risk measures could proceed in a number of directions. The first direction would be to adapt the approach outlined above to a multi-asset class framework by refining the proxies for the risk-taking activity across various asset classes. This could take the form of looking for a more nuanced and accurate index of various types of leverage (including hidden leverage) and adding sector and asset class specific risk-pricing metrics, eg sector-specific credit spreads or house price to rent for the real estate market. The second direction could be the implementation of advanced optimisation algorithms for the data weighting function. The choice was made not to do that here in order not to clutter the presentation of a novel measure with the additional complex algorithm which itself must be fine tuned and evaluated, but it would present an interesting topic as a separate study to find if improvement on the presented relatively simple algorithm could be obtained. The third extension of research would be to apply the concept of instability VaR to different distributions like the multivariate Student

<table>
<thead>
<tr>
<th>Period</th>
<th>10% confidence bound</th>
<th>EW</th>
<th>DTW</th>
<th>Instability</th>
</tr>
</thead>
<tbody>
<tr>
<td>31st December, 2005 to 21st May, 2010</td>
<td>From 6 to 18</td>
<td>33</td>
<td>32</td>
<td>17</td>
</tr>
<tr>
<td>31st December, 2001 to 21st May, 2010</td>
<td>From 12 to 30</td>
<td>40</td>
<td>44</td>
<td>21</td>
</tr>
<tr>
<td>31st December, 1997 to 21st May, 2010</td>
<td>From 22 to 42</td>
<td>55</td>
<td>60</td>
<td>26</td>
</tr>
<tr>
<td>31st December, 1993 to 21st May, 2010</td>
<td>From 30 to 54</td>
<td>82</td>
<td>83</td>
<td>47</td>
</tr>
<tr>
<td>26th April, 1989 to 21st May, 2010</td>
<td>From 40 to 68</td>
<td>97</td>
<td>103</td>
<td>55</td>
</tr>
<tr>
<td>31st December, 2006 to 31st December, 2008</td>
<td>From 2 to 9</td>
<td>24</td>
<td>18</td>
<td>8</td>
</tr>
</tbody>
</table>
The author is currently pursuing all three directions.

References