The tipping point

Recognising and identifying 'tipping points' – where a financial institution's control and risk environment become distressed – could significantly reduce potential losses. By Niklas Hageback

WHEN financial institutions investigate the underlying conditions behind large-scale operational risk debacles, they realise that small and insignificant causes, which in isolation would not have mattered much, can often cause severe losses if acting together. Normal conceptions, that is, that there should be a scaled relationship between cause and effect, seem to be put out of play.

Anecdotal evidence points to the possibility that huge operational risk losses are preceded by tipping points. By recognising and identifying the existence of tipping points that can tilt a financial institution's control and risk environment into a distressed condition, the op risk management's capabilities to introduce risk-reducing activities will be significantly enhanced and hence losses of disastrous magnitude can be avoided.

Idiosyncratic features

For credit and market risk, it can make perfect sense for a financial institution to add many different types of counterparties or securities to its portfolio. According to modern portfolio theory, this will reduce specific risks through diversification without necessarily reducing the overall portfolio's expected return and thus improve the risk-return relationship.

However, for op risk, diversification is not a straightforward concept. The reason is that op risks are normally not taken, other than indirectly, with a view to earning an expected return. From the op risk perspective, additional op risk causes can in some cases reverse the diversification effect into 'worsification'. For example, where there is a rogue trader, it is only when a number of op risk exposures act in concert that a loss becomes possible. Some of the underlying causes of the typical rogue trader event (as history has shown us) have been:

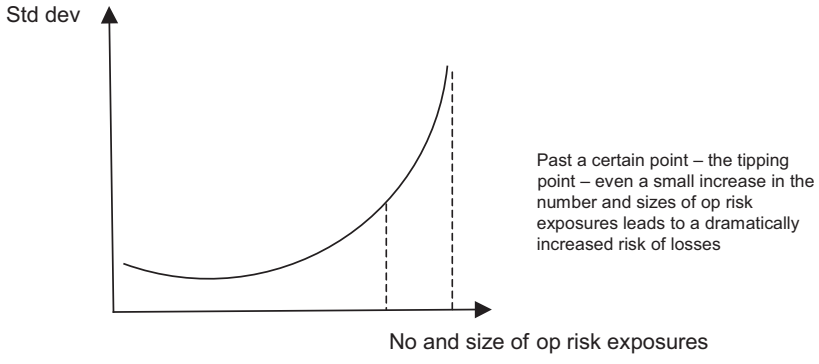
- Fraudulent behaviour manifested through the rogue trader.
- A control breakdown, such as the lack of segregation of duties and manipulation of accounting practices.
- Insufficient communication between internal audit and senior management.
- A lack of understanding of complex financial instruments in the organisation, especially among senior management.

Beyond a certain point, a tipping point, either by adding an interacting op risk cause and/or through an increase in the level of existing op risks, the likelihood of a rogue trader loss is greatly increased. Had the controls worked properly, had there been a better understanding of how the huge profits were made and had appropriate lines of communication existed, then the rogue trader could never have initiated the fraudulent activity or got caught out at an early stage. The effect of worsification for op risk would typically happen within a business activity, whereas the effect of diversification would still largely apply between significantly different business activities and geographical areas.

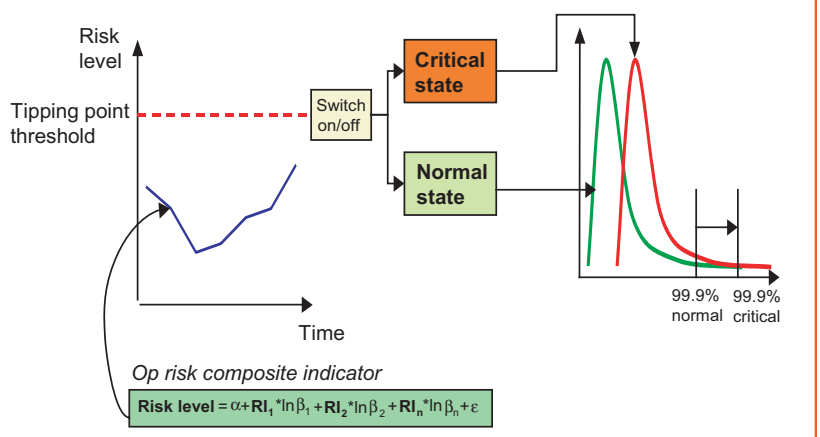
How do we model tipping points?

■ **Tipping points – a primer.** Epidemiology, or the study of the spread of viruses and other diseases, is one scientific approach that can be applied as an explanatory model to better understand the evolution of large-scale op risk losses.

1. 'Worsification' and tipping points



2. A graphical overview of the switch regime measurement



The outbreak of a typical viral epidemic follows a consistent pattern. At a certain point in time of an epidemic, the virus will reach critical mass, and from there on, any small and seemingly insignificant changes, that previously would not have affected the evolution of the virus, can now cause huge differences in the scale of the epidemic. That critical moment is what epidemiologists call a tipping point, when a steadily fluctuating occurrence abruptly peaks and begins to increase at an exponential rate. Past the tipping point, the likelihood of a severe epidemic has increased significantly.

The concept of tipping points has also been successfully applied to describe social epidemics such as the spread of certain types of fashion, crime waves, etc.

■ **Switch regimes.** Attempting to model op risk losses should, in its most simplistic version, switch between two regimes – a low-risk loss distribution and a high-risk loss distribution. When a financial institution's control and risk environment is stable, the risk of losses is low and therefore a low-risk regime is used to estimate the capital charge. When the control and risk environment becomes unstable, the model switches to a high-risk regime that can better reflect the higher likelihood of losses. The switches between the regimes are dictated by tipping points. A more realistic model would, of course, include a sliding scale of loss distributions corresponding to the whole range of risk levels. From the measurement aspect, it is, however, the high-risk regimes that are the primary focus.

■ **Designing the measurement model.** When constructing a measurement model that is able to capture the unique features of op risk, certain design issues that must be considered. To represent the overall op risk environment, a set of proxy op risk indicators needs to be developed, whose interaction and aggregated fluctuations can provide an ongoing analysis of the financial institution's risk levels. The basic assumption is that through risk indicators we can capture and track all risk exposures in the op risk universe.

But how then are the risk indicators selected and weighted to get the appropriate representation of op risk exposures and dependencies? The method is in fact based on an ongoing trial-and-error process that aims to establish the ideal selection of risk indicators, which will be a dynamic composition and change over time, as emphasis on certain risks and controls differs. The most important factor is the input and judgment from business experts, as well as the study of the causal drivers behind historical losses. We will, however, not know the exact nature of the relationship between the risk indicators and how that can affect the overall capital value. Given these constraints, the use of a neural network is particularly suitable to model tipping points as it can capture both non-additive and non-linear features.

A neural network is an information processing structure that feeds a set of inputs, in this case the data from the risk indicators, through transformation units into a set of outputs. For the transformation units, a sigmoid can typically be applied – its output varies continuously, but not necessarily linearly, as the value of the risk indicator changes. The sigmoids are used to stress the degrees and weights of the interdependencies between the risk indicators to highlight at what point the loss levels could start to take a turn for the worst. Combinations where loss levels starts to indicate exponential increases are identified as tipping points. To determine the optimal arrangement of interconnecting weights, a least-square regression is often used. The output layer is hence expressed as a nonlinear regression equation, where the risk indicator's values are updated continuously, such as monthly, to provide the most recent information on the status of the risk levels, and hence the capital value is updated.

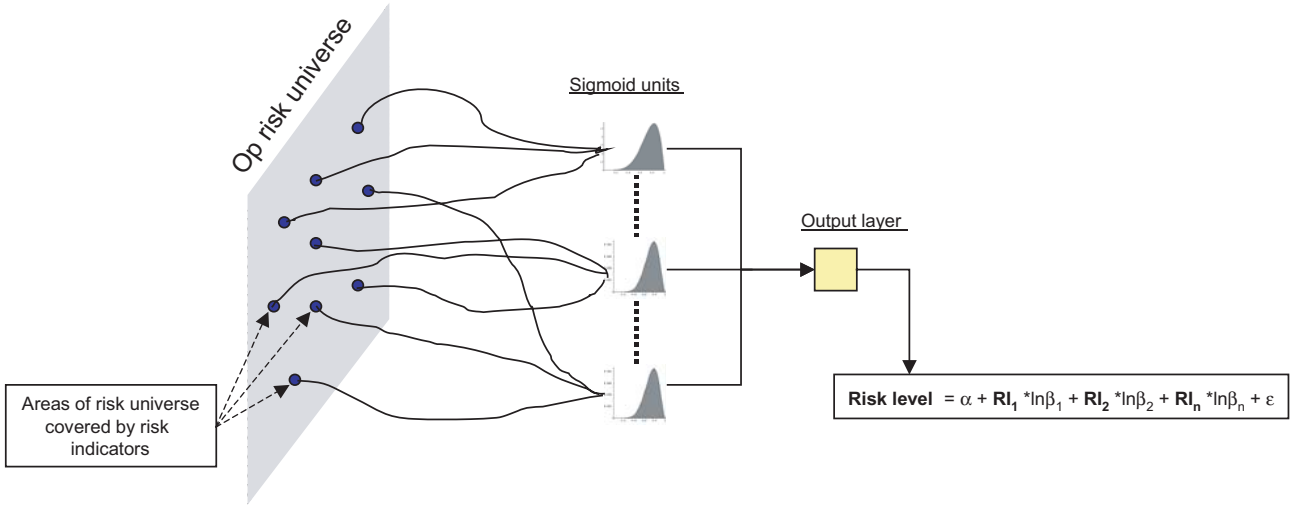
The neural network is linked to the switch regime model through a switch that is activated when the value of the set of risk indicators exceeds the tipping point threshold, as identified through the sigmoid units, and the critical regime loss distribution is applied for capital calculation. The shift in capital levels between normal state and critical state are calibrated through incorporating extreme losses, both internal and external loss data, into the critical state loss distribution.

The calibration and fine-tuning to improve the predictive power of the capital model is a gradual process, but the exercise in itself is tremendously useful, as it will provide senior management with pivotal information about the sometimes hidden dependencies between op risk exposures.

Summary

Op risk contains features that rarely occur in the other risk types, such as where a negligible increase of an op risk exposure – which normally would not have mattered much – can in the wrong context lead to a dramatically increased probability of loss. Introducing concepts from other sciences, such as tipping points and switch regimes, can improve the accuracy and calibration of capital calculation, as these cater more efficiently to the idiosyncratic aspects of op risk than

3. A neural network is used to identify tipping points



traditional measurement techniques. Most financial institutions' op risk capital methodologies therefore need to be re-designed to be able to articulate changing levels of risk synchronised through the inception of tipping points. This will help promote the capital methodology as a truly risk-sensitive managerial steering instrument to ensure the desired risk-reward ratio by correspondingly penalising or rewarding the business lines' behaviour.

A tipping point analysis would also help in meeting the Pillar II requirements for the stress testing of modelling assumptions and inputs.

However, to enable the analysis, decomposition and ultimately the prevention of large-scale op risk losses, additions and amendments to the op risk toolset are necessary. Emphasis on developing analytics to better understand potential negative dependencies between single risk causes that can trigger severe losses is crucial, as is the production of management information that indicates early signs of transformation from the normal state of the control and risk environment into a critical state.

The cost benefit analysis of the investments in additional op risk capabilities versus the magnitude of op risk losses puts one thing clearly in perspective: being able to capture and to act on tipping points will provide huge protection for a financial institution's P&L, and acts as an important safeguard for its reputation. OR&C

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