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Quantification of Operational Risk: A Scenario-Based Approach

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In this article, I identify challenges to the loss distribution approach in modeling operational risk. I propose a scenario-based methodology for operational risk assessment, which recognizes that each risk can occur under a number of wide-ranging scenarios and that association between risks may behave differently for different scenarios. The model that is developed internally in the company provides a practical quantitative assessment of risk exposure that reflects a deep understanding of the company and its environment, making the risk calculation more responsive to the actual state, ensuring that the company is attending to its key operational risks. In this model qualitative and quantitative approaches are combined to build a loss distribution for individual and aggregate operational risk exposure. The model helps to portray the company's internal control systems and aspects of business environment. These features can help the company increase its operational efficiency, reduce loss from undesirable incidents, and maintain the integrity of internal control.

1. INTRODUCTION

The credibility of the risk quantification depends on the appropriateness, completeness, and accuracy of the data used for building the model. One of the biggest challenges companies may face in trying to adopt an enterprise risk management program is the difficulty of quantifying risks for which a very limited amount of experience data is readily available. Unlike many financial risks, where one can easily make certain assumptions about the distribution of key risks, internal databases of historical operational loss events are rarely available. There is a growing recognition that we need to identify operational risks and quantify them to form a risk mitigation strategy. However, limited historical data make quantification of such risks a challenging task.

In view of the limited available historical data, it has become increasingly common to augment the information base when considering risk assessment by consulting multiple experts (Clemen and Winkler 1999). Traditional quantification methods relying only on hard data fail to quantify the vast majority of key operational and strategic risks (Segal 2011). The analysis in this article is largely based on expert judgment. We use a combination of qualitative and quantitative techniques to allow for the complexity of operational risk. We present a scenario-based model that helps in better understanding risk exposure and provides a practical quantitative approach that reflects a deep understanding of the company and its environment, making the risk calculation more responsive to the actual state. Techniques are developed to derive loss distributions for individual and aggregate operational risk exposure. Although the method described in this article is in the context of measuring operational risk, it can also be used in modeling strategic risk, which may constitute a bigger threat to the financial strength of the company than operational or other financial risks and for which a very limited amount of experience data is readily available.

The article is organized as follows. The definition of operational risk and its major categories are presented in Section 2. Section 3 reviews approaches for calculating operational risk capital allocation from a regulatory perspective. The framework of the loss distribution approach used to aggregate frequency and severity distributions and the challenges of using these models in quantifying risk exposure are presented in Section 4. In Section 5 we present a qualitative risk assessment to identify key risks. In Section 6 we develop discrete risk scenarios for each of the key risks as a first step in the quantification process. In Section 7 we develop a scenario-based model for individual operational risk exposure that combines qualitative and quantitative approaches. Interactivity between risks and enterprise risk exposure is discussed in Section 8. A risk assessment survey is presented in Appendix B.

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2. OPERATIONAL RISKS

Basel II defines operational risk as "the risk of loss resulting from inadequate or failed processes, people and systems or from external events." This definition includes legal risk but excludes strategic and reputational risk (Girling et al. 2010). A similar definition for operational risk has been adopted by Solvency II (Gatzert and Kolb 2012). The operational risk taxonomy used in Basel II and Solvency II, as illustrated by Wilson (2015), is given in Table A1 in Appendix A.

3. REGULATORY FRAMEWORK FOR OPERATIONAL RISK

In the banking field, Basel II was the first regulatory initiative to require an assessment for operational risk and the allocation of capital to safeguard against that risk. Sweeting (2011) describes the three approaches of Basel II for calculating operational risk capital allocation.

1. The basic indicator approach that applies a fixed percentage (15%) to the average gross income over the last three years (provided the gross income is positive).
2. The standardized approach that applies varying percentages (ranging from 12% to 18%) to gross income for different business lines and averages the total over the last three years.
3. The advanced measurement approach in which banks use internal and external data to model operational risk, if they can demonstrate to regulators the reliability and appropriateness of these models. The resulting estimate is subject to a floor set at 75% of the capital charge calculated under the standardized approach (see Scott and Jackson 2002).

The basic indicator and standardized approaches are not risk based. They apply regulator proxy measurements with no attempts to measure operational risks accurately, and they relate the amount of capital to the size of the bank but do not provide business leaders with information for operational decision making. The advanced measurement approach better reflects the business environment and the company's internal control systems (Crouchy et al. 2006).

In the insurance field, the European Insurance and Occupational Pensions Authority (EIOPA), previously known as the Committee of European Insurance and Occupational Pensions Supervisors (CEIOPS), outline a methodology to calculate the capital charge for operational risk that considers the basic standard capital requirement, total earned premium for life and nonlife insurance obligations, and technical provisions for life and nonlife insurance as well as expenses for unit-linked business (for more details see International Actuarial Association 2009; CEIOPS 2010; EIOPA 2013).

Although these requirements might guarantee the satisfaction of regulators who are primarily concerned with preventing insolvencies, they do not play a significant role in increasing operational efficiency, reducing loss from undesirable incidents, maintaining the integrity of internal control, and protecting the company's reputation.

The *current* emphasis on *risk management* stems from a body of research that essentially states that impact on value should be the primary concern of managers. This is a value-centric/reputational approach to risk management as opposed to a regulatory/capital-centric approach. Jones and Robinson (2012) define risk management as "the process whereby organizations methodically address the risks attached to their activities with the goal of achieving sustained benefit within each activity and across the portfolio of all activities."

4. THE LOSS DISTRIBUTION APPROACH

The loss distribution approach, also called the actuarial approach, has been extensively used in recent literature for modeling risk; see, for example, Franzetti (2011), OpRisk Advisory and Towers Perrin (2009), Shevchenko (2011), and Shevchenko and Peters (2013). It presents a practical approach to modeling risks for which a large amount of objective external quantitative experience data is readily available (typically financial and insurance risks). The estimated loss distribution combines the loss frequency distribution and the loss severity distribution. The Poisson and negative binomial are usually proposed as models for frequency of losses, and the Weibull, Frechet, Gumbel, exponential, Pareto and generalized Pareto are proposed to measure the severity of losses (Franzetti 2011). Goodness of fit tests such as Kolmogorov-Smirnov or Anderson-Darling can be used to check that data conform to the selected model. If more than one model is suggested, a comparison can be made based on the Schwarz Bayesian criterion, where a penalty is extracted for employing additional parameters based on the principle of parsimony (see Klugman et al. 2008).

A Monte Carlo simulation is often used to perform the convolution of both frequency and severity distribution to find the aggregate loss distribution over a specified period of time. Value at risk (VaR) is often used as a risk metric to assess the need for capital to cover risk for each risk category and line of business. The copula approach is commonly used for describing the dependence between risk factors.

Despite its popularity, substantial unresolved methodological challenges are associated with the loss distribution approach. Some of these challenges are given below:

1. The loss distribution approach does not differentiate between risks for which there exists a large set of experience data and those risks for which a very limited amount of experience data is readily available. It requires the existence of a complete risk database to provide sufficient data points to assist in declaring which frequency and severity distributions to use and to estimate their parameters. This might be problematic for various reasons:
   i. Data on operational failures in the history of a given company are very limited and might not be available, particularly low-frequency high-impact events.
   ii. External loss data are difficult to use directly due to different volumes, risk culture, controls, processes, and mitigation in place. External data can be used only after scaling individual loss data to the size of the original company and considering the current state of its risk profile (Samad-Khan et al. 2006).
   iii. The underlying assumption that the past is a reliable representation of the future may result in under-representing events that never happened in recent memory and for which data are not available and over-representing events that happened very frequently in the past and that have already been mitigated.
   iv. Data of collapsed companies are not available, which results in survival bias.
   v. With limited data of operational losses, it is not possible to test the goodness of fit of a theoretical to an empirical frequency distribution with a reasonable degree of significance or test for correlation between events.
2. Although simulations provide a basis for rich quantitative assessment of risk, they require sufficient information on the statistical distributions and interdependence of risks. In the absence of such information, as noted by Andersen et al. (2014), the old adage of garbage-in garbage-out applies to this technical approach.
3. Each risk can occur under a number of wide-ranging scenarios, and the intensity and severity of a risk are different for different scenarios.
4. Methods used for describing correlation between risks are based on a single correlation assumption, thus ignoring the correlation between risk scenarios and the fact that extreme events for multiple risks tend to occur together.

5. IDENTIFICATION OF KEY RISKS

The list of relevant risks presented in Table A1 is quite large. In this section we propose a semiqualitative risk assessment to narrow down this list of risks to a list of key risks that are material and can have a significant potential impact on the company and hence should be quantified. In this approach a series of qualitative judgments are transformed into a numerical risk score. A survey is designed and presented in Appendix B for this purpose. To complete the survey, semistructured personal interviews are conducted with subject matter experts with long years of personal experience and significant knowledge and understanding of their business and the environment in which it operates. Segal (2011) provides a suggested list of 25 to 30 risk assessment survey participants. The list includes the chief executive, risk, technology, financial and investment officers, heads of major business segments, and heads of compliance and strategic planning as well as experienced personnel in the industry and in the company. The questionnaire is designed to collect information on the quality of risk management, the business environment, and the effectiveness of internal control factors that can influence the company risk profile. Each questionnaire is given an identification number composed of two digits so that it can be easily identified and filed. The first digit refers to the participant (i) and the second to the risk analyzed (j). The questionnaire is compiled with items rated by a four-point scale, and a code is assigned to each possible response. Codes are consistent for all questions. A code of 0 assigned to response A indicates compliance with laws and regulations, and a code of 3 assigned to response D indicates that no or poor mitigation is in place. A compound index I_{ij} is constructed for each of the n participants and k risks, with four subranges based on the risk impact and its frequency, defined as follows:

$$I_{ij} = \begin{cases} 0\text{–}3 & \text{Insignificant,} \\ 4\text{–}7 & \text{Minor,} \\ 8\text{–}13 & \text{Moderate,} \\ 14\text{–}18 & \text{Major.} \end{cases} \quad i = 1, 2, \ldots, n \text{ and } j = 1, 2, \ldots, k \tag{1}$$

Let $I_i = \{I_{i1}, I_{i2}, \ldots, I_{ik}\}$ be the set of k indices, associated with the k risks to be ordered, for expert i. While it is unlikely that experts would agree on a single way of ordering the set of risks, most experts might agree on the set of key risks. Arithmetic averaging is the most common technique used to aggregate multiple individual scores to a group score. The deviation of each individual index from the mean is also computed to see how far experts are from consensus. This information can then be shared to stimulate dialogue, narrow the difference gap, and generate agreement among the group on the list of key risks. Chatterjee (1981) also suggests using the trimmed mean (discarding the highest and lowest scores). Both the simple and trimmed averages assign equal weights to all experts. It is used when the level of expertise is the same for all experts. Varying ways of assessing differential weights to different experts can be considered. Weights can be used to reflect the relative quality of the individual experts and hence account for the precision of individual judgments where higher weights can be assigned to more experienced experts (Clemen and Winkler 1999) or to more well-regarded experts (Chatterjee 1981). In addition, different weights can be assigned to different experts, depending on their degree of agreement with others, putting more confidence in an expert agreeing with most other experts.

An extensive literature in many disciplines is devoted to the problem of subjectivity in human evaluation and aggregation of multiple judgments. Much of this literature necessitates the introduction of more sophisticated analytical techniques, which can be too technical and less popular with business professionals. In addition to linear opinion pooling, logarithmic opinion pooling as well as varying Bayesian approaches of the aggregation of multiple experts' judgments are discussed (see, for example, Clemen 1986; Jouini and Clemen 1996; Clemen and Winkler 1999; Gerardi et al. 2009). These approaches allow incorporating qualities of individual sources, such as bias and precision, as well as dependence among sources.

Risks with an aggregated score of eight or higher (have a moderate or major potential impact on the company) are identified as key risks. It is those key risks that will be quantified in the remainder of this article. Quantifying key operational risks and performing cost-benefit analyses on potential mitigation strategies allow management to decide how key risks will be mitigated.

It should be remembered that the company is dynamic and operates in a dynamic environment. While focusing on key risks that have been identified as a priority, monitoring the full list of risks should be a continuous and developing process, to ensure that minor risks remain minor and any potential changes are identified.

6. SCENARIO-BASED MODEL

Segal (2011) illustrates that each risk is not likely to happen in a single scenario. Each operational risk can vary in its intensity or severity and has a broad range of financial effects on a company arising from different scenarios. Scenarios provide plausible alternatives about the future environment, or as defined by Burt et al. (2006) are "purposeful stories about how the contextual environment could unfold in time." As a first step in the quantification process, we develop discrete risk scenarios for each key risk. Each risk scenario describes a risk event, the likelihood of its occurrence, and its financial impact on the company. Subject matter experts, who are closest to the risk, are charged to develop discrete risk scenarios for key operational risks identified in Section 5. Scenarios must be defined clearly to eliminate ambiguity and reflect how the experience varies from the expected. These scenarios navigate the possible events that can affect the company in the future, given its current state and mitigation in place. To generate scenarios Dutta and Babbel (2014) propose that the company uses a scenario workshop, to be conducted by a corporate risk manager or an independent facilitator. The participants are business line managers, business risk managers, and experts with significant knowledge and understanding of their current business practices and the environments in which their business operates. Workshop participants discuss how things can go wrong to capture the full breadth of possibilities, taking guidance from external data.

7. INDIVIDUAL RISK EXPOSURE

Key operational risks are assessed from two perspectives, the likelihood of each risk scenario and its financial impact (changes to revenues and expenses for one or more years). In the absence of historical data on operational risks, we rely on the knowledge of experts, who are closest to the risk and have extensive industrial experience. Interviews with subject matter experts with decades of personal experience should be conducted by experienced people, who can assist experts in translating their qualitative assessment into a quantitative form. To minimize subjective bias, participants are not asked directly to provide scores for the likelihood of a risk event or its severity. Instead, a series of objective questions that are carefully designed to extract the useful information, experience, and experts' insights are posed. The historical data on occurrences of the risk event at the company, whenever available, can be used to validate probabilities assigned to various scenarios, taking into consideration the experts' judgment of any mitigation actions implemented and any unforeseen circumstances. The risk analyst leads the expert during a face-to-face individual interview through a series of linked questions, gradually eliciting uncertainties for the frequency of exposure and financial impact of each event, hence building the distribution of the expert's belief about those variables. The analyst must obtain assurance that the expert's judgments have been interpreted correctly in arriving at these distributions. Data for individual experts are *collected* and a summary of the *experts*' opinions are prepared by a facilitator. The Delphi method or the nominal group technique can be used to provide a structured way of communication. In these methods either an anonymous summary report is circulated for two or more rounds (in the Delphi method) or experts present their results to the group (in the nominal group technique). In both techniques discussions follow with the assistance of the facilitator, where participants are encouraged to reconsider their earlier answers, based on the feedback they receive in an attempt to decrease variability establishing a somehow consensus on the target distributions (for more detail on behavioral approaches and their comparison with mathematical approaches for combination of experts' judgments see Clemen and Winkler 1999).

Tables 1 and 2 describe a qualitative analysis of the frequency and financial impact of risk j by scenario. The financial impact of the event, described in terms of ranges, should consider direct damage (physical losses that occur as immediate consequences

TABLE 1
Qualitative Analysis of Frequency for Key Operational Risk j by Scenario

Scenario	Description of Event	Frequency of Occurrence	Score	Likelihood
Expected performance	Restoring to normal operating conditions	Regular occurrence	0	$1 - \sum_{i=1}^{4} p_{ji}$
Mildly pessimistic	Minor drift in business processes from expected	Likely	1	p_{j1}
Moderately pessimistic	Moderate drift in business processes from expected	Occasional	2	p_{j2}
Extremely pessimistic	Serious failure in internal processes/external events of damaging impact	Seldom	3	p_{j3}
Catastrophic	Severe events that may result in the company's inability to fulfill some or all of its business obligations	Unlikely	4	p_{j4}

of the event), as well as indirect losses (effects on services and activities that will be disrupted as a result of this event as well as loss resulting from damages to the company's reputation). The analysis presented in Tables 1 and 2 is carried out for each of the key operational risks.

We should note that in the process of constructing internal models for solvency capital requirement purposes, supervisors may prefer data-driven models over expert judgment–driven models. This may reflect the regulatory text, or it may reflect skepticism on the part of supervisors about how robust any such expert judgment is. However, for some operational risks no external objective data are available. Segal (2011) presents strong arguments for providing subjective estimates made by experts closest to the risk in response to claims that the estimated probabilities and financial impact cannot possibly be useful because it is all based on mere guesses.

The score assigned to the scenarios in Table 1 is an ordinal score or a categorical variable that can be expressed as a multinomial distribution. Let $N_i = (N_{j1}, N_{j2}, \ldots, N_{j5})$ be a multinomial random variable with parameters n and $p = (1 - \sum_{i=1}^{4} p_{ji}, p_{j1}, p_{j2}, p_{j3}, p_{j4})$ where

$n = \sum_{i=1}^{5} N_{ji}$ is the number of trials
N_{j1} : Number of trials in which an expected performance occurs
$\vdots$
N_{j5} : Number of trials in which a catastrophic event occurs.

The R package provides a simple mean of simulating this categorical data set from the multinomial distribution. The severity in a scenario can be a point estimate or an interval estimate. While using subjective estimates that rely mostly on experts' opinions, it is preferable to use interval estimates to capture the uncertainty of the potential *financial impact. Assuming* a *uniform* distribution of potential impact *within each interval,* the individual loss amounts associated with each of the five scenarios can then be

TABLE 2
Qualitative Analysis of Potential Financial Impact for Key Risk j by Scenario

Scenario	Description of Event	Financial Impact	Estimated Potential Impact (Dollars, Millions)
Expected performance	Restoring to normal operating conditions	No impact/insignificant	$(\theta_{j1}, \theta_{j2}]$
Mildly pessimistic	Minor drift in business processes from expected	Minor	$(\theta_{j2}, \theta_{j3}]$
Moderately pessimistic	Moderate drift in business processes from expected	Tolerable	$(\theta_{j3}, \theta_{j4}]$
Extremely pessimistic	Serious failure in internal processes/external events of damaging impact	Substantial	$(\theta_{j4}, \theta_{j5}]$
Catastrophic	Severe events that may result in the company's inability to fulfill some or all of its business obligations	Destructive	$(\theta_{j5}, \theta_{j6}]$

determined by generating N_{j1} variates from the uniform distribution over the interval $(\theta_{j1}, \theta_{j2})$, N_{j2} variates from the uniform distribution over the interval $(\theta_{j2}, \theta_{j3})$, etc. Simulation from the uniform distribution over the interval (a, b) is straightforward, since the distribution function of X is continuous and strictly increasing. Solving the equation $u = F_X(x)$ gives the unique value of $x = u(b-a)+a$ for any given value of u. The assumption of uniformity of loss amounts within a given interval is entirely related to the way the scenarios are defined. Uniformity can be met by adjusting the definitions of scenarios to appropriately uniform risk intervals (increasing the number of scenarios and hence shortening the intervals). An alternative approach is to use the midpoint of the interval in describing the individual loss and use the boundaries of the intervals to carry out sensitivity analysis to test the robustness of the results of the model.

By completing this process, we create the loss distribution that represents the company's loss exposure for this specific risk with scenarios represented in this distribution according to their relative likelihood of occurrence.

The value at risk and conditional tail expectation can be applied to loss distributions to assess the need for capital to cover operational risks. To accurately estimate these risk metrics, the limited actual experience (whenever available) can be combined with experts' estimates giving only partial weight to the limited experience and the remaining weight to experts' estimates. Klugman et al. (2008) provided an appealing method that can be used for combining the two quantities through a weighted average. Let VaR_{HIST}, VaR_{EXP}, and Z denote the value at risk calculated using the traditional approach that relies on historical data, the value at risk calculated using experts' estimates, and the credibility factor respectively. A weighted average is given by $ZVaR_{HIST} + (1-Z)VaR_{EXP}$ where $Z \in [0, 1]$. The credibility factor is the ratio of the coefficient of variation for full credibility $(Z = 1)$ to the actual coefficient of variation obtained from experience data. The more historical data we have, the more credible the traditional method is, the more we can rely on VaR_{HIST} and the larger Z is.

8. RISK INTERACTIVITY AND ENTERPRISE RISK EXPOSURE

Capital aggregation requires assumptions to be made about the interdependency of risks. While considering interdependency, it is important to realize that associations between risks may behave differently for different scenarios. Unrelated risks may become related under stress scenarios and can threaten the financial strength of the company, as things tend to go wrong together. Hence, input on dependency between risk scenarios of different risks is important.

Embrechts et al. (1999) offer strong warning against using correlation to measure interdependency of risks and point out that correlation is problematic, because multivariate normality is not a reasonable model for operational risk. While rank correlations (Kendall's tau and Spearman's rank correlation coefficient) overcome some of the theoretical deficiencies of linear correlation, they are still scalar measurements of dependence, which limits what they can reveal about the dependence structure of risk. Embrechts et al. (1999) point out the importance of moving away from scalar measurements of dependence, whether linear or rank, to a model that captures the dependence structure of risks.

The variance covariance approach and the copula approach are two approaches that are commonly used to incorporate multiple types of risks. The variance covariance approach assumes that risk factors have a multivariate normal distribution. Intercorrelations are estimated using historical data or expert judgment. The major disadvantage of this approach is related to the linearity assumption, which fails to explain nonlinear dependency that leads to a heavy tailed loss distribution (Mathur 2015).

The copula approach allows incorporating the marginal distributions that capture essential features of different risk types into a multivariate distribution, while allowing for the specification of the dependence structure between the risk factors. Rosenberg and Schuermann (2006) use normal and Student's t copulas to construct the joint risk distribution for a large international bank in an attempt to incorporate market, credit, and operational risk. They estimate risk distributions using a combination of publicly available data from regulatory reports, market data, and vendor data. The limitations of the Gaussian copula in dealing with tail dependence have been extensively discussed. Dupuis and Jones (2006) review recent literature on the extremal dependence and show the importance of model selection when fitting an upper tail copula to observed joint exceedances. Illustrations on four data sets are presented in their study: loss amount and allocated loss adjustment expense under insurance company indemnity claims, lifetimes of pairs of joint and last survivor annuitants, hurricane losses in two states, and returns on two stocks. Apart from the third data set, which comprises simulated losses of hurricane events, historical databases have been used for the three other illustrations.

In recent actuarial literature, studies have shown that there is often asymmetric tail dependence among the underlying risks, which cannot be captured by normal or t copulas. To calculate the loss distribution of the credit portfolio, Wang et al. (2014) proposed to model the dependence among the common risk factors by a class of multivariate extreme copulas as a generalization of bivariate Fréchet copulas. In their study, risk factors that influence the obligors' default as industrial fields or geographical regions are assumed to be observable. Tang and Yuan (2013) use Archimedean copulas and mixtures for the loss given default, which takes into account the severity of default. As an illustration of their method, simulated data are used to derive asymptotic estimates for the value at risk and conditional tail expectation of the loss given default. Hua and Xia (2014) study dynamic tail dependence structures between loss and show that the ACIG copula is a good choice, when there is intermediate upper tail dependence. The method is applied on a sample from the U.S. Medical Expenditure Panel Survey data.

Schlottmann et al. (2005) describe the integrated management of different sources of risk as one of the biggest challenges to the financial industry. They point out three important obstacles in this area: data problems particularly in the area of operational risk, differing time horizons, and heterogeneous distributional assumptions for different types of risks. Schlottmann et al. propose a multiobjective approach to aggregate risks across different risk types and different business units. Their approach, which does not require correlations between different risk types, allows the analyst to choose from a set of individually optimal solutions by evaluating the trade-off between the different risk types and the expected rate of return from the portfolio.

Segal (2011) proposes two approaches for capturing risk interactivity. In his first technique Segal defines n simulations, where each simulation represents one possible realization of the future involving multiple simultaneous risk events. If $m$is the number of key risks and each risk can happen in one of five scenarios (A–E), one replication of the simulation can be $(Risk_1 Scen_B, Risk_2 Scen_A, \ldots, Risk_m Scen_C)$. In this approach, simulations are designed randomly, where each of the five scenarios has the same chance of being selected. The probability of each simulation, as well as its financial impact on the company value, is then evaluated. Segal calculates the likelihood of each simulation by multiplying the likelihood of each individual scenario, assuming independence of all risk scenarios, and then multiplying by the correlation adjustment factor (CAF). CAF is the multiplicative product of individual pairwise correlation adjustment factors (IPCAF). For positively correlated scenarios, IPCAF will be larger than 1, increasing the simulation probability. For negatively correlated scenarios, IPCAF will be between 0 and 1, decreasing the simulation probability. IPCAF will be 1 for uncorrelated scenarios and 0 for perfectly negative correlations.

As an alternative, Segal (2011) proposes an improved approach for capturing risk interactivity. As opposed to a random selection of scenarios of the key risks for each simulation, Segal proposes developing deterministic simulation risk scenarios to reflect the risk interactivity. Subject matter experts will be asked to develop the simulation scenarios that reflect the interaction between risks. Segal makes no reference to how the likelihood of each simulation will then be calculated.

Bayesian networks can be used to capture risk interactivity between key risks, where the nodes represent the m risks (discrete variables) and arcs connecting pairs of nodes represent the relationships between these risks. Not every node will be connected to every other node, and independencies between risks are represented by a lack of arcs. The strength of the relationship between connected nodes is quantified by conditional probability distributions associated with each node (for more details see Korb and Nicholson 2010).

After identifying the key risks and creating mutually exclusive and exhaustive scenarios that represent the states the risks can take, we need to express the relationships between these risks in a graphical structure by choosing an ordering for the risks and adding arcs to nodes. While this might seem to be a daunting task, it should be noted that the vast majority of risk scenarios of operational risks are independent. Correlation between risks is usually heavy in extremely pessimistic and catastrophic scenarios. We finally need to define the strengths of those relationships in the form of a conditional probability table linking each child node to its parent's node. For each risk (node) we need to look at all the possible combinations of states of those parent nodes and specify the probability that the child will take each of its values.

If a sufficiently adequate historical database, recording past trends and capturing risk interactivity, is available, then such a database will be used in calculating conditional probabilities. However, in the absence of such historical data and the need to quantify these cause-and-effect relationships to incorporate risk interactivity in the model, human reasoning in the form of experts' estimates constitute the only remaining source of assessing the required probabilities. A common initial concern that can arise here is that these estimates can be very subjective. It should be noted, though, that these are estimates made by experts closest to the risk. It is clear that we do not preclude the possibility of using available historical data to assess dependencies. However, in the absence of such historical data and with the need to quantify these conditional probabilities to incorporate risk interactivity in the model, experts' estimates provide the most credible quantitative information.

Concerns might arise about the number of relationships and conditional probabilities that need to be specified in a Bayesian network, which can make the model intractable, highly time consuming to build, and expensive. Building a probabilistic network requires a careful trade-off between the desire for a large and rich model on one hand and the costs of construction, maintenance, and inference on the other hand. Druzdzel and Van der Gaag (2000) emphasize the importance of research efforts aimed at reducing the number of probabilities to be assessed in a Bayesian network and the tools for supporting the quantification task.

In addition to Bayesian networks, there are alternative models that allow for incorporating different expert opinions and consider the underlying cause-and-effect relationships and recognize the unknown complexity of operational risk modeling, such as fuzzy logic, artificial neural networks, and hidden Markov and decision tree models. Some models may be more appropriate in solving certain problems, given certain knowledge and data (for more details see Shang and Hossen 2013).

9. CONCLUSIONS

The most important advancement since Basel I was the inclusion of operational risks in an attempt to move banks in the direction of a holistic treatment of risks. However, the emphasis on traditional techniques that heavily rely on historical data results in the inability to quantify strategic and operational risks and leads most of the companies to focus most of their attention only on financial risks, which results in focusing limited mitigation resources on the wrong priorities. The basic and standardized indicators identified by the Basel accord to address quantification of operational risks are not risk based. They are totally unconnected to the operational system and control within the company. Loss distribution models currently in use to quantify risks require the existence of ample valid loss data for sufficient past periods.

Challenges of using these models to quantify operational risk are illustrated in this article. A more comprehensive scenario-based model for operational risk assessment is developed. The model reflects the knowledge of experts, who demonstrate a deep understanding of the company's business, threats and vulnerabilities, making the risk calculation more responsive to the existing business processes to ensure that the company is attending to its key operational risks. In this model I combine qualitative and quantitative approaches to build loss distributions for individual and aggregate operational risk exposure incorporating experts' opinion of risk dependencies. The underlying methodology does not preclude the possibility of using available historical data. While experts may base their judgment partially on available data, they should not assess risks retrospectively. Experts are continuously monitoring any changes in the strategy, changes in the risk management tactics, current and planned controls, new policies introduced to decrease operational risk losses, the level of management response to certain risks, the level of insurance coverage, mitigation decisions made to reduce the likelihood of a key risk occurring or its severity, and any changes in the internal or external environment, as well as the direction of the economy and sector growth. All this information cannot be captured in a model based on historical data only. Experts, who have a clearer image about the impact of operational risks, are capable of assessing risks prospectively. If experience of other firms as well as one's own is available, credibility theory allows us to give partial weight to this experience and give the remaining weight to expert judgment that reflects a deep understanding of the company and its environment, leaning more toward historical data if a large amount of objective external quantitative experience data is readily available providing a stable experience.

Unlike traditional methods which completely ignore the fact that associations between risks may behave differently for different scenarios, Bayesian networks can be used to capture risk interactivity between key risks, by defining the strengths of those relationships in the form of conditional probability distributions linking child nodes to their parents' nodes.

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Discussions on this article can be submitted until January 1, 2017. The author reserves the right to reply to any discussion. Please see the Instructions for Authors found online at http://www.tandfonline.com/uaaj for submission instructions.

APPENDIX A

TABLE A1
Basel II/Solvency II Operational Risk Classification as Cited in Wilson (2015)

Category	Subcategory	Risk
1. External fraud	External theft and fraud	• Robbery, extortion, or embezzlement • Theft of assets • Forgery • Check fraud • Impersonation (i.e., deliberately assuming a client/customer identity) • Fraudulent claims
	Systems security	• Unauthorized appropriation of confidential information • Computer malevolence (e.g., viruses, file destruction, hacking)
2. Internal fraud	Internal theft and fraud	• External theft or fraud events involving an employee • Receipt of bribes or kickbacks • Smuggling • Insider trading for own account
	Unauthorized activity	• Transaction intentionally not reported • Unauthorized transaction types • Intentional mismarking of positions • Invalid authorization of exposures or expenditures
	Systems security	• Unauthorized appropriation of confidential information • Computer malevolence (e.g., viruses, file destruction, hacking) • Data theft and disclosure
3. Employment practice and workplace safety	Employee relations	• Compensation, benefit, or termination events • Strikes, other organized labor activity events • Employee litigation/staff indemnification
	Workplace safety	• Workers' compensation events (e.g., workplace accidents, occupational diseases) • Civil liability (i.e., accidents of customers, partners, or suppliers)

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TABLE A1
Basel II/Solvency II Operational Risk Classification as Cited in Wilson (2015) *(Continued)*

Category	Subcategory	Risk
	Equality and discrimination Human resources management	• Inappropriate behavior (i.e., discrimination or harassment) • Inappropriate recruitment, training • Inappropriate remuneration policy • Inadequate staff assessment, management of poor performers • Excessive staff turnover • Departure/absence of a key staff resource • Breach of regulations (labor rights, collective conventions)
4. Clients/third party, products, and business practices	Suitability, information disclosure, and fiduciary duty	• Fiduciary breaches/guideline violations • Suitability/disclosure issues • Breach of privacy, misuse of confidential information • Overly aggressive sales activities, account churning
	Improper business or market practices	• Antitrust behavior, market manipulation • Improper external reporting practices • Improper trade/market practices • Insider trading (for the company's benefit) • Unlicensed activities • Money laundering activities • Discrimination events to customers or general public
	Defective products	• Inadequate model implementation • Breach of pricing policy • Noncompliant products with internal, external requirements • Inadequate approval of new products/activities • Inadequate processes, complex, sensitive operations
	Trade counterparty	• Nonclient counterparty performance • Miscellaneous nonclient counterparty disputes
	Sponsorship exposure	• Losses incurred due to exceeding client exposure limits (i.e., in asset management, wealth management)
	Selection	• Client fact-finding failures • Insufficient checks prior to contracting
	Advisory activities	• Inappropriate performance or advisory activity
5. Damage to physical assets	Natural/industrial disasters and malicious damage of property	• Natural disaster (floods, earthquakes, windstorms, etc.) • External losses (acts of terrorism, vandalism, etc.) • Industrial disaster losses
6. Business disruption and system failures	System failures	• Hardware or telecommunications failures • Software failures • Utility outages/disruptions
	Transportation and other disruption	• External strikes or blockades • Disruption due to manmade hazards • Weather, natural catastrophe, or pandemic disruption
7. Execution, delivery and process management	Transaction capture, execution, and maintenance	• Data miscommunication, entry, maintenance errors • Missed deadlines or responsibilities • Model/system misapplication/operation • Accounting error/entity attribution error • Delivery failure
	Client account management	• Missing client permissions and/or disclaimers • Missing or incomplete legal documents • Unapproved access given to accounts • Errors causing incorrect client records • Negligent loss or damage of client assets

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TABLE A1
Basel II/Solvency II Operational Risk Classification as Cited in Wilson (2015) *(Continued)*

Category	Subcategory	Risk
	Monitoring and reporting	• Failure to comply with mandatory reporting obligations • Inaccurate external reporting leading to losses • Inadequate internal reporting resulting in losses
	Suppliers and outsourcing	• Inadequate service level agreements (e.g., for IT services) • Inadequate investment mandate definitions • Other outsourcing failures • Inappropriate vendor disputes
	Contractual customer documents	• Legal documents missing/incomplete • Client permissions/disclaimers missing

APPENDIX B. OPERATIONAL RISK ASSESSMENT SURVEY

This risk assessment survey is to be used in conjunction with Table A1. The survey has been created to help you think about the key operational risks you may face as a company. Answering the questions honestly will help us assign a score to risk based on impact and probability.

Department/Area Name: ____
Person Completing Survey: ____
Position: ____
Questionnaire ID[1]: ____

Please circle the option that best describes how you feel about each question.

Q1 In regard to guidelines indicating policies and detailed procedures related to this risk, indicate whether:

A. Written guidelines are in place and are updated on a regular basis.
B. Written guidelines are in place but have not been updated over the past three years.
C. Written guidelines are in place; however, employees are not always familiar with these guidelines, and adherence to these guidelines is not always enforced.
D. No written guidelines are in place.

Q2 Have there been any incidents of this risk event in your department?

A. No incidents occurred during the past 10 years.
B. Occurs once every three to 10 years.
C. Occurs once every one to three years.
D. Occurs at least once per year.

Q3 What impact does this risk have on your department and its ability to operate efficiently?

A. Insignificant/no impact.
B. Mild impact on the business processes.
C. Moderate impact on the business processes.
D. Major impact that significantly affects the business processes and prevents you from operating efficiently.

Q4 How would you rate the management's efforts to mitigate this risk?

A. Risk management tactics are already in place to mitigate the likelihood and/or severity of this risk event.
B. Management is responsive and efficient in resolving issues as they arise.
C. Management records issues as they arise, but no noticeable action is taken.
D. Management is usually not responsive to issues as they arise.

Q5 To what degree can management of this department supersede the established guidelines related to this risk?

[1]The first digit refers to the participant (i) and the second to the risk analyzed (j).

A. Complete inability to get around established guidelines.
B. Capability to bypass some guidelines occasionally.
C. Capability to bypass guidelines frequently.
D. No written guidelines are in place.

Q6 When was the last time that your department was reviewed by either internal or external auditors?

A. Has been reviewed within the last three years.
B. Has been reviewed within three to six years.
C. Has not been reviewed for the past six years.
D. No system of internal/external reviews of departments is in place in the company.