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Modelling the mitigation impact of insurance in Operational Risk management

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Abstract

The paper is going to quantify the mitigation of the insurance as a risk mitigant in operational risk management for the commercial bank. Due to the uncertainties associated with the insurance policy, such as counterparty default, payment uncertainty and the liquidity risk (i.e., delayed payment), the recovery amounts are subjected to be kind of uncertainty. Thus, the efficiency of insurance as a risk mitigant may be discounted. We aim at going one step further to consider counterparty default, payment uncertainty and liquidity risk. While the counterparty default model focuses on calibration of the default time, the payment uncertainty is set as a non-increasing function depending on loss severity. The key conclusions are that counterparty default does not have significant impact on the capital calibration but still paramount in risk management, and insurance as a risk mitigant indeed improve the operational risk profile of bank and lower the capital requirement to some extent.

Key words: Operational risk; Insurance; Monte Carlo simulation; Counterparty default; Payment uncertainty

1. Introduction

Some highly publicized operational risk events, of which the $1.2 loss due to unauthorized trading activities which caused the collapse of Barings Bank in 1995 is worth being contemplated, have successfully caught the attention of the regulatory authority and the practitioners. And what is more, the trend towards greater dependence on technology, more intensive competition, and globalization have already boosted the potential of operational risk.

As a reaction, the Basel Committee on Banking Supervision (BCBS, 1999) established the principle of developing a pillar 1 minimum regulatory capital charge for other risk, including operational risk, in its 1999

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consultative paper [1]. For the first time, banks are required to reserve capital against risks other than credit and market risks. In 2001, BCBS (2001) suggested a 20% of the minimum regulatory capital at the beginning and then change the figure to 12% [2]. This adjustment is interpreted as a reaction to insurance application in operational risk management to some extent, because kind of insurance polices like bankers blanket bonds and professional liability insurance have already been put in place to protect banks from suffering operational risk events like external fraud and employee theft.

While the techniques for transferring the credit risk and market risk, such as credit derivatives and interest rate swaps, have an extensive history in financial market, insurance for transferring operational risk is still somewhat recent and inevitably subjected to less research. The BCBS notes that the potential of insurance as operational risks mitigant is ambiguous due to the factors such as counterparty default risk, liquidity risk (i.e., delayed payment), limits in the product range, the inclusion of insurance payment in internal loss data and moral hazard which would lead to a less than perfect coverage of operational risks [2]. As a result, there exist some uncertainties on the overall efficiency of insurance as an operational risk mitigant.

In the previous studies, Brandts (2004) [3] propose a model to recognize the insurance effects under Advanced Measurement Approach (AMA) based on common shocks, in which counterparty default risk and payment uncertainty are modelled by shock model. Bazzarello et al. (2006) [4] model insurance mitigation under loss distribution approach (LDA) in which residual term of the policy, payment uncertainty and counterparty default risk are considered; Gao et al. (2007) [5] quantify the insurance mitigation effects within the extreme value theory (EVT), in which residual term of the policy and payment uncertainty is concerned. Ottmann and Seibt (2005) [6] use the risk premium to evaluate the impact of insurance in operational capital charge. Kaishev et al. (2007) [7] proposed a new methodology taking the probability of joint survival of financial institution and the insurance provider as an operational risk measure.

In this paper, we aim at providing tools for going one step further to model the associated risks as counterparty default, payment uncertainty and delayed payment. Even though they are by no means exhaustive, they are the hot spot issues in the application of insurance under AMA [8]. We proposal a method pertained to LDA under which operational risk losses history could be simulated and assigned to insurance policy. Note that our study differs from the previous by explicitly modelling the counterparty default and subsequently decide which loss receives no compensation. What is more, we handle the delayed payment from the perspective of bank's own liquidity adequacy.

The remainder of this paper is organized as follows. Section 2 will present the modeling basics including a descriptive introduction to LDA and the model of counterparty default, payment uncertainty and liquidity risk. In Section 3, the empirical results are reported and interpreted. Section 4 is the final concluding remarks.

2. Incorporating insurance into LDA

By reviewing the recent literatures, we find that incorporating insurance policy into operational risk quantification under the framework of LDA will be applicable and convenient. LDA [9, 10, 11] is an actuarial technique that quantifies operational risk by estimating the frequency distribution of operational risk losses and the severity distribution of individual loss in term of the economic impact separately. Under the LDA, a loss history could be easily simulated via Monte Carlo simulation [12,13]. It is common to assume that the frequency distribution and severity distribution follow *Poisson distribution* and *Lognormal distribution*, respectively. Meanwhile, economical capital is measured by Value at Risk (VaR) and conditional VaR (CVaR), expected loss (EL) and unexpected loss (UL) are also considered.

In order to quantify the mitigation impact of insurance in LDA, we consider impacts of insurance to individual loss, while the impacts are subjected to uncertainties, such as counterparty default, payment uncertainty and delayed payment. The insurance policy is always characterized by deductible and policy limit for each loss, overall limit for all payment amounts as well. On the premise that the overall limit M is not exhausted, the recovery according to the policy is given by

$$r = \begin{cases} 0 & \text{for } x \le d \\ x - d & \text{for } d < x \le m + d \\ m & \text{for } x > m + d \end{cases} \tag{1}$$

where r is the recovery, d and m represent the deductible and policy limit for each loss, respectively. Then, the loss amount of x given the insurance policy could be modified as $\tilde{x}$ which is give by

$$\tilde{x} = x - r = \begin{cases} x & \text{for } x \leq d \\ d & \text{for } d < x \leq m + d \\ x - m & \text{for } x > m + d \end{cases} \tag{2}$$

Once the overall limit is exhausted, all the subsequent losses will receive no compensation. By clearly examining the liability of the insurance policy to individual loss, the net losses $\tilde{x}$ are aggregated to reflect the total operational risk loss for the given year. Given the recovery might be affected by counterparty default, payment uncertainty and delayed payment, modelling the random recovery amount by taking these factors into consideration seems necessary.

2.1. Counterparty default

Counterparty default in this paper can be defined as that the insurer is unable to fulfill its payment obligations instead of being intend to evade its responsibility. In this paper, we impose three hypotheses: first, the default only happens when the insurance provider runs out of its solvency and faces a danger of bankruptcy. Therefore, we model the counterparty default from the perspective of the insurance provider's ruin probability. Second, the insurance provider has no default preference which means the provider may be intend to default directed towards some significant payment obligations. Third, all the insured operational losses incurred after the default date will receive no recovery any more. Upon, it is very important to determine the exact occurrence time of all the insured operational losses incurred and the definite date of the default, through which we can find out which losses are covered by insurance policy and which are not due to the counterparty default.

The occurrence time of the operational risk losses is given as follow. Once a number of annual losses $N(x)$ is taken from the frequency distribution, the time intervals between adjacent events are assumed to follow a *Poisson distribution* with a parameter λ_{int}. To specify the exact date of each loss, a random draw is taken from the given *Poisson distribution*, and the date of τth loss is given by

$$d_\tau = \sum_{j=1}^{\tau-1} I_j \tag{3}$$

where I_j is the interval time between loss jth and $(j+1)th$.

Once the exact date of each loss is determined, what we would do next is to simulate the default date, after which the operational loss events would have no recovery any more. We define $\lambda(t)$ as the default intensity at time t, so that $\lambda(t)\Delta t$ is the probability of default between time t and $t + \Delta t$ conditional on no earlier default. If $V(t)$ is the cumulative probability of the company surviving to time t, then

$$V(t + \Delta t) - V(t) = -\lambda(t)V(t)\Delta t$$

By taking limits

$$\frac{dV(t)}{dt} = -\lambda(t)V(t)$$

From which we get

$$V(t) = e^{-\int_0^t \lambda(s)ds}$$

where t is defined as the default time. More details can be seen in Hull (2009) [14]. As known, if variable Z follows an exponential distribution with parameter$\lambda = 1$, it is easy to get

$$P(Z > z) = e^{-z}.$$

By assuming

$$z = \int_0^t \lambda(s)ds \tag{4}$$

where z representing the cumulative default intensity, the cumulative probability of the company surviving to time t is given by

$$P(Z > \int_0^t \lambda(s)ds) = e^{-\int_0^t \lambda(s)ds}.$$

Therefore, we can simulate the default date by first generating a random number from the exponential distribution and solve the equation (4). More details in Duffie and J. Singleton (2003) [15].

2.2. Payment uncertainty

Payment uncertainty is defined as the risk that the insurer does not pay the guaranteed amount specified ex ante in the policy or just grants part of it, thus cause a deviation from the guaranteed recovery. Deviations from guaranteed recovery can be calibrated by discounting payment amount specified in the policy using a discount factor defined as recovery rate β which could be given as

$$\beta = \frac{actually\ recovery}{guaranteed\ recovery} \tag{5}$$

As β is likely to be a function of the loss severity, thus β could be set as non-increasing function $\beta = f(x)$ which satisfies $f^{'}(x) \leq 0$ or a piecewise function as follow [4]:

$$\beta = \begin{cases} \beta_1 & \text{for } d < x \leq u_1 \\ \beta_2 & \text{for } u_1 < x \leq u_2 \\ \cdots\cdots & \\ \beta_k & \text{for } u_{k-1} < x \leq u_k \end{cases} \tag{6}$$

where $\beta_1 \geq \beta_2 \geq \cdots \geq \beta_k, \beta_j \neq 0, j = 1, 2, \cdots, k$. Thus, the net loss of each operational risk loss event without being defaulted could be modified as

$$\tilde{x} = x - \beta r = \begin{cases} x & \text{for } x \leq d \\ x - \beta(x-d) & \text{for } d < x \leq m+d \\ x - \beta m & \text{for } x > m+d \end{cases} \tag{7}$$

All the insurance payments without default are multiplied by β to reflect the partial overall reimbursement observed in reality.

2.3. Liquidity risk

Liquidity risk in this paper is limited to the payment delay which may lead to an extra financing and incur a financing cost to the bank only if the bank runs out of its liquidity. In many cases, there may not be an immediate liquidity shortage when experiencing an operational risk loss because banks intend to hold enough capital reserves. On the contrary, if a bank is running out of its liquidity, the cost of financing and financing itself should be included in the capital charged. Therefore, from the perspective of banks' own liquidity, the liquidity need will be satisfied only if bank hold enough capital reserves and the liquidity concern becomes parts of a capital charge problem. In order to evaluate the mitigation impact of insurance in operational risk management of a bank, the delayed payment will not matter and could be ignored in our evaluation if we assume that a bank has adequate liquidity.

3. Empirical results

In this section, we are going to estimate the economical capital concerning the insurance. First, we are going to specify some parameters. Given a bank whose specific kind of operational risk loss severity distribution as *Lognormal distribution* with $\mu = 9$ and $\sigma = 2$, while loss frequency follows a *Poisson distribution* with parameter $\lambda = 200$ which may lead to the average interval time between losses is about 1 day, so $\lambda_{int} = 1$. For simplicity, we suppose that the insurance policy is provided by just one insurance company which may ignore the diversification benefits if we consider several insurance providers. Suppose that the insurance policy with parameters $d = 1,000,000$; $m = 15,000,000$ and $M = 30,000,000$ [4]. We set insurance companies with different default intensities. Though LDCE (2008) [16] notes that "a small proportion of losses with the typical bank reporting insurance recoveries for 2.1% of losses", the Basel Committee on Banking Supervision (2010) recently release a report which points out "the Banks and insurance companies are collaborating to expand the use of insurance to take advantage of an improved understanding of operational losses and to evolve products in line with the mitigation expectations outlined in the Basel II Framework" [8]. Therefore, in order to explore the potential of insurance in operational risk management, we suppose that each loss of a specific kind of operational risk is covered by the policy, we consider three different cases:

Case 1: no insurance available in the capital calibration process and the result is set as a benchmark;

Case 2: Insurance available and no counterparty default happens. Due to it is lack of data reflecting the recovery rate associated with loss severity, the recovery rate reflecting payment uncertainty is set as 74.6% for all losses, and the figure is according to the empirical data of the 2008 Loss Data Collection Exercise [16];

Case 3: Insurance available and counterparty default is modeled as a stochastic factor while recovery rate reflecting payment uncertainty keeps the same as previous case.

So far, we have finally introduced all the elements necessary for the estimation. Before we present the results of our study, it is necessary to detail the whole computation process. First, we simulate series of samples up to 50,000 via Monte Carlo simulation which will generate 50,000 sample years and each sample contains the loss events in a sample year. We calculate the capital without insurance by sorting the annual loss in an ascending order. Second, all the guaranteed payment are multiplied by β which reflects the payment uncertainty and the losses in each sample year would be deducted by the actually recovery amounts. And the $\tilde{x}$ are aggregated into the annual loss, by sorting we can obtain the capital. Third, we simultaneously determined the date of loss events and the default time, from which we can filter the losses without any recovery, and calculate the capital similarly as before.

Table 1 and 2 provide the necessary information to gauge the implied benefit of insurance regarding to the different cases. With reference to table 1, when insurance is not ready for operational risk management, the capital requirement is the highest among the cases in terms of all the capital measures including EL, UL, $VaR_{99.9\%}$ and $CVaR_{99.9\%}$.

Table 2 shows the mitigation impact of insurance. When referred to insurance, we first calculate the capital without considering the factor of counterparty default, and then the capital by taking counterparty default into account, in which several default intensities are considered. Clearly from table 2, it is immediately recognizable that the insurance mitigation of reducing the capital which is required to cover the potential loss. For all the capital measures, the capital savings range from 13.59% to 19.70% which are significant and imply that the insurance is a valuable tool to transfer or financing operational risk.

Regarding to the impact of the counterparty default, we might think the capital would be lager than that of without considering default due to the reason that the default behaves as a negative factor. As presented in table 2, observe that there are certain differences between the $VaR_{99.9\%}$ and $CVaR_{99.9\%}$, respectively. However, these differences do not seem to be significant, and this might imply that the factor of counterparty default does not matter a lot in term of capital reservation. Further, under different default intensity hypothesis, the variation of capital is also limited. As presented in table 2, when intensity is 0.04~0.06, the reduced percentage of $VaR_{99.9\%}$ and $CVaR_{99.9\%}$ are equal to those of no default situation. On the other side, when intensity is 0.07~0.10, the reduced percentage of $VaR_{99.9\%}$ and $CVaR_{99.9\%}$ starts to fall but no so much, and this is consistent with BCBS (2010) imposing a rating constraint to insurer [8]. The $VaR_{99.9\%}$ and $CVaR_{99.9\%}$ present kind of stability regarded to the variation of default intensity. Therefore, based on the variation trends of $VaR_{99.9\%}$ and $CVaR_{99.9\%}$, with increasing intensity together, we can come to a conclusion that the factor of counterparty default is not as important as expected in term of capital charge especially when the counterparty of a bank is with an acceptable credit rating. The reason attributing to this could be extracted from table 3. Under the counterparty default model and intensity assumptions, there are at most 2.67% of 50,000 sample years which experience default incident and this is fewer than necessary to drastically change the annual loss distribution. So we are not surprised at that the $VaR_{99.9\%}$ and $CVaR_{99.9\%}$ do not vary too much by taking the default into account.

Table 1 Capital Results under Different Measures

	No insurance	Insurance without default	Insurance with default						
			0.04	0.05	0.06	0.07	0.08	0.09	0.10
EL	11959154	10254566	10272966	10276940	10281336	10287023	10292461	10298146	10302352
UL	56549157	45437917	45419517	45415543	45411147	45408502	45852153	45846469	45842262
$VaR_{99.9\%}$	68508311	55692483	55692483	55692483	55692483	55695525	56144615	56144615	56144615
$CVaR_{99.9\%}$	96572072	83074114	83074114	83074114	83074114	83112246	83223055	83446855	83446855

Table 2 The Mitigation Impact of Insurance

	No insurance	Insurance without default	Insurance with different default intensity						
			0.04	0.05	0.06	0.07	0.08	0.09	0.10
EL	--	14.25%	14.10%	14.07%	14.03%	13.98%	13.94%	13.89%	13.85%
UL	--	19.65%	19.68%	19.69%	19.70%	19.70%	18.92%	18.93%	18.93%
$VaR_{99.9\%}$	--	18.71%	18.71%	18.71%	18.71%	18.70%	18.05%	18.05%	18.05%
$CVaR_{99.9\%}$	--	13.98%	13.98%	13.98%	13.98%	13.94%	13.82%	13.59%	13.59%

Note: '--' represent that the case of no insurance is set as a benchmark.

Table 3 The loss given default and no. of defaulted sample years

	Default intensity						
	0.04	0.05	0.06	0.07	0.08	0.09	0.10
Maximum Extra loss if default	17858905						
Percent of $VaR_{99.9\%}$ in case 2	32.07%						
No. of defaulted sample years	544	680	816	936	1080	1214	1336
Percent of 50,000 sample years	1.08%	1.36%	1.63%	1.87%	2.16%	2.43%	2.67%

Although the counterparty default seems to impose little impact on capital calibration, we still find that in term of operational risk management, the extra loss incurred by default is up to 17858905 which consists of 32.07% of $VaR_{99.9\%}$ in case 2 which does not take the factor of counterparty default into account and is larger than all series of EL. Upon, we come to another conclusion that though counterparty default does not impact the capital calibration too much, it should be embedded in operational risk management as it may incur significant extra loss. That may be why the BCBS (2010) impose the criteria that the insurance provider should have a minimum claims paying ability rating of A or equivalent [8].

4. Concluding Remarks

This paper is another shot toward recognising the risk mitigation effect of insurance in operational risk modelling. In this paper, we model the insurance benefit by explicitly modeling the uncertainties as counterparty default and payment uncertainty under LDA. The results show that insurance benefits are significant which is encouraging to use the insurance to transfer parts of operational risks. The modelling method is advantageous in that it successfully models the counterparty default and determines which loss is given no recovery. When referring to liquidity risk problem limited to payment delayed, we attribute it to the liquidity condition of a bank. We find that the factor of counterparty default does not have significant impacts on the calibration of capital, especially when the insurer has with an acceptable credit rating. However, it can not be ignored in operational risk management because it might incur a big liability loss in a specified year. Given the increasing interest in exploring the potential of insurance in operational management, further investigation is needed and the future extensions should shed light on the tactics of applying insurance under comprehensive understanding of bank risk profile (e.g. insurance portfolios) and design of exclusive insurance products.

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