The Analysis on Operational Risk Profile of Korean Banks
- Focusing on Internal Loss Data Analysis

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<Abstract>

The quantification of operational risk has received increased attention as an distinct capital charge under Basel Ⅱ. This paper compared current measurement methodologies of AMA targeting domestic banks, and illustrated main issues related to Op VaR calculation. The challenged problems, including a scanty of internal loss data, appropriateness of model assumptions, statistical robustness of Op VaR, still remain unsolved, however, banks with more structured approaches can find proper solutions at no distant date. Our analysis on collected loss data showed major operational risk characteristics of domestic banks compared with US banks loss data. In Korean banks, Internal & External fraud in Retail Banking had high operational risk exposures. But such risk event type as Clients, Products, and Business Practices, an weighty event type across US banks, should be monitored carefully because related business activities of domestic banks became increased. The AMA banks should make significant efforts to resolve some technical problems for complying with high standards of Basel Ⅱ requirements. By several empirical tests, we raised some important issues on GoF tests, distributional assumptions of severity and frequency, and conditional estimation. The results displayed that the measurement logics adopted by domestic banks required to be reviewed based on current developments of related researches. Although a long way to go, Korean banks might implement their effective operational risk frameworks successfully by considering operational risk management as a key component of business strategy sets.

***Key words** : Basel Ⅱ, Operational risk, Advanced Measurement Approach, Loss Distribution Approach, Goodness of Fit Test, Conditional Estimation

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1. Operational Risk in Basel Ⅱ

1.1. Backgrounds of Introducing Operational Risk

Basel Ⅱ, supposed to be launched by the year-end 2007 in Korea, has two main differences compared to the current Basel Ⅰ. First, by enabling banks to differentiate risk-weights according to the borrowers' credit ratings, it provides a significant degree of flexibility for banks to use internal model to measure the associated capital required for unexpected losses. Second, it includes operational risk in calculating the regulatory capital. This equivalent recognition of operational risk as a significant risk, like market and credit risk, will provide a opportunity for banks to make rapid progress in their managing capabilities for operational risk. This is because Basel Ⅱ requires banks not only to calculate the regulatory capital reflecting each bank's own risk profile, but also to establish their management frameworks in which banks can effectively assess and control operational risk.

Under Basel Ⅱ, operational risk (hereforth Op risk) is defined as "the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events". This definition includes legal risk, but excludes strategic and reputational risk.[3] The definition of Op risk under Basel Ⅱ is much narrower than traditional definition, in which all risks other than credit, market, interest rate and liquidity risk are included, for considering that the regulatory capital (Pillar 1) should be quantitatively measurable. As a result, while the capital charge for Op risk is calculated only in measurable risks stated on a bank's income statement, the related qualitative risks, like strategic and reputational risk, could be considered in the Internal Capital Adequacy Assessment Process (ICAAP) of Pillar 2.

Although some people have an skeptical view on reasonable Op VaR calculation, the imposition of regulatory capital for Op risk is to reflect recent experiences with serious impacts on banks' soundness as followings.

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[3] The definitions of each risk are as follows.

- Legal risk : losses arising from breaching laws, ethical standards, or contractual obligations, includes fines, penalties, or punitive damages resulted from supervisory actions, as well as the costs of a law suit.
- Strategic risk : losses arising from errors in decision-making of the management, improper implementation of a policy, absence of proper countermeasures to cope with the change in external business environments, etc.
- Reputational risk : losses arising from the deterioration in the opinion of stakeholders such as clients, shareholders due to the poor management or performance, financial loss events, or public criticism.

First, as in the Barings case(1995), naive internal control of a bank could cause the bankruptcy of such a big financial institution. In addition, Enron & Worldcom scandals brought heightened concerns of investors about the internal control and corporate governance related to Op risk. Second, like the example of LTCM(1998), the vulnerability of internal control within financial institutions was increasing due to the expansion of business operations and the treatment of complex financial products accompanied by recent financial deregulation. Banks could have unfamiliar risks from cross-over products (eg. bancassurance) and from trading derivatives for hedging market/credit risk. Third, the rapid growth of IT increased Op risk exposure of banks. The automation in business activities by IT system can do considerable impacts on Op risk profile. For example, some events with high frequency-low impact characteristics might be transformed into low frequency-high severity major risk owing to IT automation.

Under Basel Ⅱ framework, the inclusion of the Op risk in the regulatory capital calculation is evaluated as a marked change in bank's risk management history in that it enables banks to identify and control related risks systematically from all banking activities.

1.2. The Measurement of Operational Risk

The natures of Op risk are different from market/credit risk in several aspects, which lead to some difficulties in managing and measuring of Op risk. First, on the contrary that market/credit risk are regarded as direct costs of profit, Op risk is not directly linked to profit (or revenue). Second, Op risk is hard to identify its exposure due to the fact that it is naturally inherent in the whole business process, people, system. As a result, Op risk heavily relies on subjective approaches for identifying risk, however, market/credit risk can be recognized using objective data such as market volatilities, or changes in the exposure. Third, regarding the control ownership of Op risk, more efficient coordination with related functions such as internal audit, compliance should be emphasized, unlike that market/credit risk were mainly controlled by risk management team as a centralized function. Finally, compared to market/credit risk, the quantification of Op risk is more difficult due to the paucity of internal loss data.

Basel Ⅱ proposed three methods for calculating capital charge against Op risk. These are (ⅰ) Basic Indicator Approach (BIA), (ⅱ) The Standardized Approach (TSA), and (ⅲ) Advanced Measurement Approach (AMA). Among these, the BIA and TSA are difficult to reflect each bank's peculiar Op risk profile (i.e. control effectiveness), because these two approaches use a certain ratio of annual gross income for the calculation of Op risk regulatory capital charge. On the other hand, the AMA approach calculates basic Op risk capital by a statistical model such as LDA, and then adjust basic capital by qualitatively evaluation of business environments and internal controls. That is, the AMA is more sophisticated approach than other two methods, and also offers banks some incentives to manage and control Op risk more actively.

In addition, by requiring banks to consider Op risk in allocating internal capital and measuring business performance of each business unit, banks would be eagerly involved in internal control activities for sound risk management.

(1) Basic Indicator Approach (BIA)

Under BIA, gross income (= net interest income + non-interest income) of each bank was as a proxy that represents bank's Op risk exposure, and the required capital charge is calculated as 15% of a bank's three year average gross income. Differently from the TSA and AMA, no specific requirements should be met for a bank to adopt the BIA method, although, Basel committee encourages banks to comply with proposed principles in the Basel document, "Sound Practices for the Management and Supervision of Operational Risk(2003)", regardless of the selected method.

The BIA method considers only positive gross income among those of previous three years to prevent plausible distortions in regulatory capital due to 0 or negative value of gross income. In despite of its simplicity, there is a critical defect that BIA banks can have lower Op risk capital charge compared to those of similar banks in size and Op risk profile. For avoiding this problem, local regulator can require banks to hold some buffer capital under Pillar 2.

<Op Risk Capital Calculation Under BIA〉

$$K_{BIA} = [\Sigma(GI_{1 \ldots n} \times \alpha)]/n$$

K_{BIA} : Capital charge under BIA
GI : Annual positive gross income, over the previous three years
n : The number of the previous three years for which gross income is positive

(2) The Standardized Approach (TSA)

The regulatory capital for Op risk under TSA can be calculated through three-step procedures. First, a bank maps its previous gross incomes during three years to the 8 Business Lines (BL) prescribed in Basel Ⅱ. Second, in each BL, a required capital is calculated by multiplying the gross income of each BL by the percentage (β) assigned to individual BL, which the β's range from 12% to 18% according to Basel Ⅱ. Finally, the total required capital for Op risk is the sum of individual capital calculated in each BL.

Though the TSA does not require the regulator's approval as well as BIA, TSA banks should conduct an one-year intial monitoring period beforehand with local regulator's review. During such a monitoring period, banks can show they can meet the TSA minimum requirements of Basel Ⅱ. After reviewing the monitoring result, supervisor might require individual bank to delay an implementation of TSA. For the use of TSA, banks must comply with some primary requirements as followings. First, board Of directors and senior management should perform a material oversight on Op risk management activities via an appropriate reporting channels. Second, individual bank must have its sound ORM system with integrity. Finally, sufficient resources (human/physical resources) of a bank must be invested for controlling and managing of Op risk.

The regulatory capital charge is calculated as the three-year average of the simple summation of the capital charges across BLs. In any given year, negative capital charge (resulting from negative gross income) in any BL may offset positive capital charges in other BLs without any limitation. Yet, provided that the average capital charges of all BLs for a given year is negative, then the input to the numerator for that year will be zero.

〈Op Risk Capital Calculation Under TSA〉

$$K_{TSA} = \{\Sigma_{years 1-3} \max[\Sigma(GI_{1-8} \times \beta_{1-8}), 0]\}/3$$

K_{TSA} : Capital charge under TSA

GI_{1-8} : Annual gross income in a given year for 8 BLs

β_{1-8} : a fixed percentage for individual BL

(3) Advanced Measurement Approaches (AMA)

Under AMA, the regulatory capital is calculated based on a statistical model designed by a bank's own measurement methodology. The AMA targeting banks (hereafter AMA banks) should conform to both qualitative and quantitative requirements of Basel Ⅱ.[4]

In addition to 8 BLs classified under TSA, the AMA banks are required to categorize 7 Loss Event Types (LET), and thus they can do measure and manage Op risk for 56 cells (OR matrix : 7 LET x 8 BL).[5] The risk factors (severity, frequency) for each cell of OR matrix are estimated, and then banks generate loss distributions per each cell. The AMA banks should also conduct a initial monitoring for more than two years before regulator's approval. Then, if monitoring results are not satisfactory, regulator can require the bank to modify some calculation methodologies or to delay an implementation of AMA. As Basel Ⅱ presents only basics of qualitative and quantitative requirements, banks are allowed a significant degree of flexibility in actual implementation. This seems to reflect the fact that if regulator provides some specific methods for measuring and managing Op risk, it may discourage banks' efforts to develop more creative approaches.

Referring to the qualitative requirements under AMA, firstly, Op risk governance should be established based on the principle of checks & balances among board of directors, senior management, business units, Op risk management, audit function. Second, individual bank should construct systematic processes that identify, assess, measure, monitor and control Op risk as in credit and market risk. Third, some significant parts related to Op risk management and measurement should be documented to ensure an feasible implementation. Fourth, the results of Op risk measurement should be put to practical use in day-to-day business decision-making through timely reporting to board of directors and senior management. One of the main differences under Basel Ⅱ is that it has a strong understanding that the results of measurement should be utilized for business line activities.

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[4] In Korea, six domestic banks are planning to adopt AMA at the end of 2007.

[5] Basel Ⅱ classified Op risk event into 7 loss event types as followings : Internal Fraud (IF), External Fraud (EF), Employment Practices & Workplace Safety (EPWS), Clients, Products & Business Practices (CPBP), Damage to Physical Assets (DPA), Business Disruption & System Failures (BDSF), Execution, Delivery & Process Management (EDPM).

Next, the quantitative requirements under AMA are as follows. First, a bank must demonstrate that its Op risk measuring system meets the statistical criteria comparable to that of IRB approach for credit risk, (i.e. one-year holding period and a 99.9% confidence level). Second, four fundamental elements (internal/external loss data, scenario analysis, business environments & internal controls) should be combined in the Op VaR calculation, and the weights of those elements must be determined in a reasonable way. Among those elements, external loss data may serve not only as a calculation input but also a tool for identifying extreme loss events that may not be discovered in internal loss data set of individual bank. Scenario analysis has a valuable piece of information in that it has forward-looking evaluations of specific risk events by experienced business line managers.

Unlike market/credit risk, Op risk can consider not only quantitative elements but also qualitative one possibly under AMA. The AMA banks calculate a basic Op VaR using three elements (internal/external data, and scenario analysis) quantitatively, and then can adjust it qualitatively by reflecting the business environment and internal control factors for regulatory capital charge. Through such a qualitative adjustment, the AMA method intends to give banks more incentives to actively manage and reduce Op risk exposures.

Below, we will examine main requirements of Basel Ⅱ concerning four fundamental elements one by one. As for internal loss data, AMA banks should collect more than five years for Op VaR calculation, and exploit those data basically for constructing loss distributions.[6] Basel Ⅱ provides the standard framework in which a bank should collect and allocate the internal loss data according to 8 BLs by 7 LETs, namely 7x8 matrix. Besides, banks are advised to collect "risk event data" with potential loss for managing Op risk as well as financially recorded loss data. The BIA or TSA banks are also recommended to collect internal loss data for managing & controling Op risk.

The second element, external loss data (loss experiences of other banks or financial institutions) is used for complementing the scanty of internal loss data, or used for the identifying some catastrophic loss events. However, relevant external loss data needs to be scaled by proper method for being used in Op risk measurement since the eternal loss data could have some bias in terms of size or control level of the bank in which the data was originated.

The third element, scenario analysis with forward-looking characteristics, can be used to reflect the plausible future losses. By this, the limitation of backward-looking loss data can be overcome. However, the subjectivity of scenario analysis is inevitably involved,

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[6] According to Basel Ⅱ interim provision, a three-year period for internal loss data collection will be applied to domestic banks for initial launch of AMA in 2007.

therefore, if some subjective bias would be excessive, it is difficult to accept calculated Op VaR as regulatory capital.

Finally, as mentioned before, the factors reflecting business environments and internal control are used for qualitatively adjusting a basic Op VaR calculated by loss data (internal, external) and scenario analysis. For such adjustment of Op VaR, a bank can consider some following factors ; the phase of economic cycle, the level of competition in banking industry, internal control effectiveness etc. Individual bank can exploit Risk & Control Self-Assessment (RCSA), Key Risk Indicator (KRI) and Audit Score for the adjustment of Op VaR. Furthermore, a bank can reduce its Op risk capital charge by use of insurance products (banker's blanket bond, D&B etc). For possible reductions of regulatory capital by insurance, individual bank should meet relevant complicated requirements under Basel Ⅱ, and the level of capital reduction by insurance can not exceed more than 20% of total Op risk capital charge.

2. The Comparisons of Measurement Methodologies

2.1. The Comparative Analysis of Measurement Logics across Domestic Banks

Basically, the calculation of Op risk capital charge under AMA must be based on the internal loss data because of its direct relevance with each bank's Op risk profile rather than external loss data. Also, the internal loss data is more objective input than scenario data. Accordingly, the AMA banks should collect and classify internal loss data into 7 LETs and 8 BLs (7x8 OR matrix), and derive aggregated loss distributions via statistical techniques. However, even international banks can not have enough internal loss data for constructing loss distributions at each cell in 7x8 matrix, so all domestic banks do.

There are some opinions that the cells not having experienced loss event might be excluded from Op risk measurement because the likelihood of loss occurrences in those cells would be nearly zero. Yet, banks must check if related business activities or external loss data exist, and if any, potential risks of those cells must be measured.

Most of domestic AMA banks have intented to use external loss data and/or scenario data to supplement insufficient internal loss data. The use of external data can mainly provide two advantages for AMA banks. One is to infer distributional parameters of cells with the paucity of internal loss data by using Relative Relation (RR) approach. The other is to supplement some data points in the tail areas of distributions.[7] Banks to use external data for tail data points would apply Extreme Value Theory (EVT) after scaling external data by size, revenue etc.

If internally collected loss data of individual bank is assigned to 56 cells respectively, the cells below 5 have possible data to derive loss distributions statistically.[8] For statistically significant loss distributions, most banks used to set 10 data points as a minimum threshold. A few banks generated loss distributions by statistical techniques for each cell with even 4~5 data points. In case of assuming probability distributions ex ante due to the insufficiency of internal loss data, most banks used to utilize log-normal distribution for severity and Poisson distribution for frequency, but a few banks assumed severity distribution as log-normal gamma distribution.[9]

If the number of internal loss data exceeds the prearranged threshold, they can choose

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[7] Relative Relation (RR) approach is to infer unknown parameters of distribution using relative values of moments (mean, variance) between internal and external loss data in case of cells with lacking in internal loss data.

[8] The cells with above 10 data points are only 11 even though loss data of AMA domestic banks is pooled. Refer to the next chapter 3 for more detailed explanation.

[9] The reason why log-normal gamma distribution is assumed seems uncleared, a possible explanation can be presented in that the distribution has relatively fat-tailed.

the most proper distribution among many candidate distributions through ‘Goodness of Fit’ (GoF) test.[10] Among various GoF tests, Kolmogorov-Smirnov test, Anderson-Darling test, Cramer-Von Mises test, Akaike Information Criterion (AIC), Schwartz Bayesian Criterion (SBC), log-likelihood are frequently used. The test statistics from several distinct GoF tests might display confused results, therefore, it is required for banks to develop logical procedures, which are suited for the statistical properties of loss data in each cell.

While most banks assumed Poisson as frequency distribution without GoF test, some banks used to choose more proper distribution between Poisson and negative binomial distribution by mean-variance comparison. Poisson distribution can be selected provided that estimated mean is equal to or larger than variance, otherwise negative binomial distribution be selected. Regarding the selection of proper frequency distribution, it is more important to resolve a data shortage problem than to include negative binomial distribution into candidate distributions. By yearly base, the data points for the estimation of frequency distribution are no more than 3 or 4, there could be serious biases in estimation with a few number of data points regardless of distribution types.

When using scenario analysis to supplement the deficiency of internal loss data, related inquiries on expected severity, maximum severity (at a 95% or 99.9% confidence level) and expected frequency were presented to the appraisers, business experts. In some banks, business experts are required to provide direct assessments on related probabilities of mean & maximum severity as well as loss amount. Most of AMA banks assumed that severity followed log-normal distribution, while some banks used Weibull, Pareto, inverse Gaussian distribution as assumptional distributions for scenario data. With no exceptions, all AMA banks assumed that frequency for scenario data followed Poisson distribution.

Most banks used Maximum Likelihood Estimation (MLE) as a estimation method for parameters of distributions, however, 2~3 banks have planned to use Method of Moments (MM) as well as MLE. When estimating the parameters of EVT, some banks intended to use more sophisticated techniques such as (modified) Hill estimator. From the statistical criteria, the prerequisites for using MLE are that data must satisfy normality condition and sample size for estimation must be large enough. Also, the estimators by MM are likely to contain some biases due to asymmetry and fat-tailed properties of true distributions. Therefore, there is no estimation method that satisfies all desired properties of estimator (i.e. unbiasedness, efficiency) among currently available methods.

Therefore, with considering data availability and main characteristics of distributions, banks

[10] In Korea, the measurement systems of most AMA banks are equipped partly with SAS package, and all candidate distributions for severity provided in the measurement module of SAS package are 11 types.

should select most appropriate estimation method that can obtain more stable estimates over sample or time changes. In addition, since most banks used loss data above a specific threshold (i.e. one million won) for measurement, they must consider conditional estimation techniques in order for more accurate estimation.

When there exist the distributions derived from both internal loss data and scenario data, a method for integrating the two distributions are required. Generally, bayesian integration and credibility theory are known to be the most popular methods, so most banks consider to use these kinds of integration methods. However, a few banks adopt a more conservative manner in which they select higher value between Op VaR value of internal loss data and that of scenario data.[11]

It is widely known that the distribution of Op risk loss data shows fat-tailed property. Basel Committee also emphasized that extreme loss should be captured in the Op risk measurement system. Accordingly, most of domestic banks are considering positively to apply EVT. However, the paucity of data in the tail area and absence of objective methods for setting a threshold still remain to be solved regarding the EVT application.

The AMA targeting banks should derive an aggregated loss distribution per cell along the LDA procedures, and then calculate Op VaR at 99.9% confidence level. They need to aggregate those VaRs across cells in order to calculate the regulatory capital charge for Op risk.[12] Individual bank can use simple sum method based on perfect correlation assumption or copula function, that is a useful technique for generating a multivariate distribution, for statistically considering true correlations. Most banks are going to use elliptical copula such as normal and t-copula for aggregation of Op VaRs.

Below [Table 1] compares the measurement methodologies adopted by AMA domestic banks.

[Table 1] Comparison of Domestic Banks' Op Risk Measurement Approaches

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[11] Some banks used to put weights according to the number of internal loss data or predetermined weights, instead of directly applying Bayesian integration techniques.

[12] Before the aggregation of Op VaRs, capital charge adjustment by business environments & internal control factors and risk mitigation by insurance can be applied.

	Majority	Minority
Inputs	- Based Internal data and scenario - External data mainly used for RR	- External data used for estimating tail parts of distributions
Minimum requirement of data points for fitting distribution	- Fitting : over 10 - Assuming : less than 10	- Fitting : over 4~5
Assumptions of distribution of internal data	- Severity : Log-normal - Frequency : Poisson	- Log-normal gamma for severity distribution
Estimation Method	- MLE	- Option for Method of moments
Assumptions of scenario based distribution	- Severity : Log-normal - Frequency : Poisson	- Including Weibull, Pareto, Inverse gaussian for severity
Integration method	- Bayesian integration	- Selecting higher Op VaR value - Applying weights according to the number of internal data
EVT	- Being considered for external data	- Applying for scenario data
Correlation	- Elliptical copula to be expected	- Option for Archemedian copula

2.2. Main Issues for Implementation of AMA

The FSS and AMA banks have composed of a joint task force team since 2002 to facilitate valuable discussions on raised issues related to AMA implementation. Reflecting the discussion results, FSS established fundamental principles in「Basel Ⅱ Established Standards for Capital Charge Calculation (draft)」in October, 2004. Consecutively, to support the practical implementation of AMA banks, FSS published 「Detailed Guidelines on the AMA (1st draft)」 in May, 2005, and the 2nd draft of detailed guidelines in October of same year. The Second Draft provided many detailed guidances relating to overall Op risk management framework ; clarifying Op risk governance structure, setting clear indications on partial use (a combination of approaches), presenting scopes and criteria of initial monitoring.

In addition, the AMA banks initiated "Korea Operational Riskdata Exchange Committee" (KOREC) for pooling internal loss data since January, 2006, which could be helpful to supplement insufficient internal loss data of individual bank.

Although these efforts of FSS & AMA banks, there exist some critical problems to be resolved for successful AMA implementation. The AMA Banks should make an more effort to find out suitable solutions step-by-step after prioritizing according to their importance and emergency. The common challenging issues that domestic banks face can be summarized as follows.

① Lack of internal loss data

As mentioned above, individual bank did not have enough internal loss data for statistically significant measures. At the current state of individual bank, the cells with above 10 data points are less than 5 of total 56 cells, thus, banks do mostly depend on scenario analysis for Op VaR calculation. To overcome this problem, six banks organized data consortium, KOREC (supposed to enlist two more banks within this year) for data pooling. The use of consortium data via KOREC might help banks partially to solve data shortage problem. If required, KOREC may consider to expand its membership to insurance or securities institutions.

② Subjective bias of scenario analysis

The scenario data evaluated from business experts could be used for deriving loss distributions. The experts might present their opinions on frequency and severity of plausible risk events as forms of specific numbers or ranges. However, the scenario analysis could be polluted inherently by an subjectivity of appraisers. Furthermore, such factors as the number of generated scenario, evaluation method, and analysis procedure might cause considerable variations in Op risk measure of individual bank. Therefore, it is important for individual bank to establish objective processes and validation scheme based on internal/external loss data to minimize the subjective bias of scenario analysis.[13]

③ Suitable assumptions on related distributions

Most banks assume the type of distribution for cells with insufficient internal loss data or for the scenario data. In that case, some structural errors may be involved due to improper distribution assumption. To alleviate these errors on distributional assumptions,

[13] Among available tools to minimize the subjectivity of scenario data, for example, offering objective referential information (internal/external loss data, RCSA, KRI value), evaluating the same scenario by other experts group, using mean (or median) value of multiple valuations. The AMA Banks should develop more reliable methods and procedures which are appropriate to their specific scenario analysis methodology.

banks can utilize relevant studies such as LDCE(2004) and de Fontnouvell et al.(2004) with the analysis on data characteristics of foreign banks. According to their analysis, CPBP among LETs demonstrated the most strong fat-tail property, otherwise, EPWS and EF showed thin tails relatively. Although those cases of foreign banks may be useful for references, the different risk characteristics between foreign and domestic banks should be considered. Accordingly, it is advisable for individual bank to validate its assumptions based on data set collected from other domestic banks, especially those of peer banks which are similar in business environments and internal control level.

④ Validation methods on Op VaR model

There are nearly few credible validation techniques on Op VaR model even across world-wide banks at present. Despite of its difficulties, individual bank must receive objective validation by an independent team, regarding the statistical robustness of its Op VaR model for regulatory capital. To achieve this goal, banks should do reasonable reviews on the completeness of the input data, reliability of the assumptions, consistency of calculation logic and stability of the results. If required, the following assessments could be included in an validation process.

- To check if small changes in input data cause significant variations of bank-wide Op VaR.
- To evaluate the appropriateness of measurement logics by the comparison of the results from loss data with those from scenario data.

As a popular tool, stress testing could be used to enhance and validate models. The aim of the stress test is to observe how the model would behave under unusual circumstances or in the event that key assumptions in the model break down.

In addition to above mentioned problems, there are still several issues raised on Op risk measurement system ; the conditional estimation for avoiding some bias owing to setting a threshold for loss data collection, scaling methods for relevant external loss data, integrating way of internal loss data with scenario data, reflecting correlations across cells, applicability of EVT, and reducing calculation errors with Monte Carlo simulations. Although those problems are difficult to find best practices at this stage, more realistic solutions may be presented by learning-by-doing as banks accumulate data and experiences.

3. Results of Loss Data Analysis in Korean Banks

This chapter provides the analysis of collected loss data to understand Op risk profile of domestic AMA banks. The analysis includes some statistical tests to obtain the implications for reasonable Op VaR, specially we would conduct several GoF tests on pooled data to figure out distributional characteristics of each cell. The sample data for our analysis was the internal loss data collected by 6 Korean banks, and the sample was composed under the following data requirements for consistency of empirical tests.

- Sample period : 2003.1.1 ~ 2005.12.31
- Threshold : more than 1 million Korean won on basis of gross loss amount[14]

To understand the distributional properties of collected data, the descriptive statistics were described after being log-transformation of loss amount. [Figure 1] showed that the kurtosis of collected data was '17', however, it is significantly different from the '3' of kurtosis implied in case of normal distribution.[15] This means that loss data before log transformation do not follow log-normal distribution because log-transformed data do not follow normal distribution.

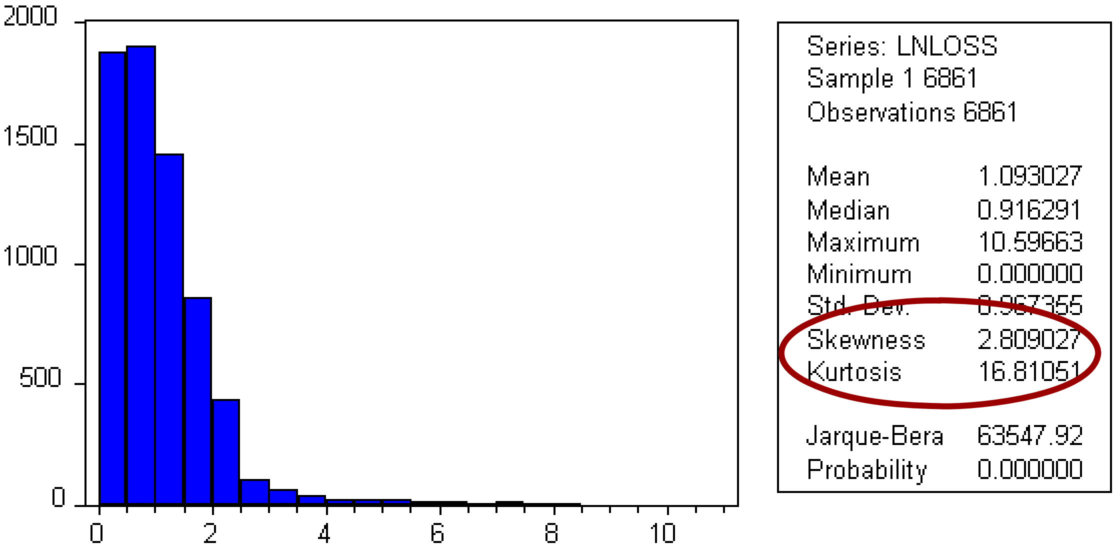
If log-transformed data follows normal distribution, theoretically, 99.7% of data would be observed in the range of 'mean ± 3× standard deviation'. In our data set, this critical value actually corresponded to about 4, the counted number of data over 4 was all 131, which is approximately 2% of total data points. This result implies that there are more data in right tail area in comparison with log-normal distribution. Therefore, after considering both higher kurtosis value and the number of data points in tail area, we might deduce the collected loss data of Korean banks had the fat-tail property.[16]

[Figure 1] Descriptive Statistics

[14] Loss amount is calculated by the gross loss amount basis (before insurance recovery and others recovery), and it is directly reflected financial loss of each bank. For the confidentiality, the characteristics of individual bank are excluded from the scope of analysis.

[15] The kurtosis of a distribution is very crucial moment due that it is related with the tail shape of distribution.

[16] The result of this analysis could be changed with individual banks, because the current data analysis of this paper is focusing on aggregated loss data regardless of banks, BLs and LETs.



For more concreteness, we mapped loss frequencies into the predetermined ranges of loss amount, the number of extreme losses above 10 billion won is just 3 during sample period.

Loss amount (Billion won)	Less than 0.1	0.1 ~ 1	1 ~ 10	More than 10
Frequency of Losses	6,760	75	21	**3**

Moreover, the results of percentile analysis below indicate the loss amount of 3.5 billion won at the level of 99.9 percentile. Accordingly, if only internal loss data would be used for Op risk measurement, calculated capital charge could be highly underestimated.

Percentile	90	95	99	99.9
Loss Amount (Million won)	8	12.1	200	3,550

This result implies that the internal loss data is not enough to reflect fat-tailed properties, one of the key characteristics in Op risk, therefore, banks need to use external loss data or scenario analysis to capture plausible extreme losses as prescribed in Basel Ⅱ.[17]

[17] In the case of Op risk model of Citi Group, the power law distribution is applied to reflect the fat-tails, on the condition of above 50 data points and more than 0.1 million dollars.

3.1. Analysis on Characteristics of Op Risk in Korean Banks

(1) Time series properties of Op risk loss data

The total number of collected loss data across AMA targeting banks is 6,861 and the total amount is 182.3 billion won during the sample period of 3 years.[18]

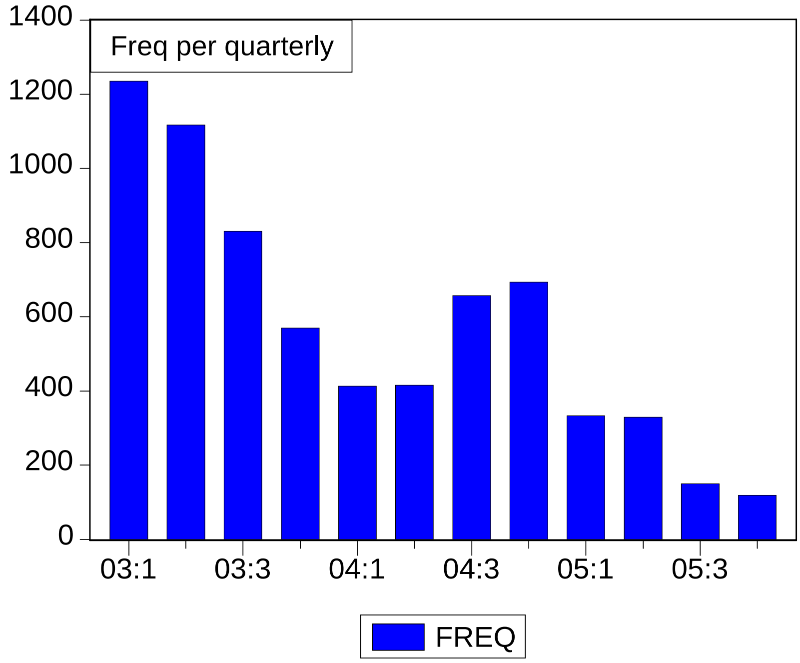
According to the result of analysing the time-varying properties of loss data through quarterly windows, the frequency of happened losses has decreased since 2003, but the individual loss amount per event has increased drastically since 2005. [Figure 2] shows that the frequency of operational losses decreased from 1,235 in the first quarter of 2003 to 119 in the fourth quarter of 2005, but the average loss amount of losses per event increased sharply from 10 million won in the first quarter of 2003 to 386 million won in the fourth quarter of 2005. Looking into more details, the frequency of loss events declined by virtue of the strengthened activities of internal and external controls, but Op risk exposure grew up due to some significant changes of business environment (i.e. keen competitions in banking industry, profits oriented risk culture etc).[19]

[Figure 2] Time-Varying Properties of Op Risk Loss Data

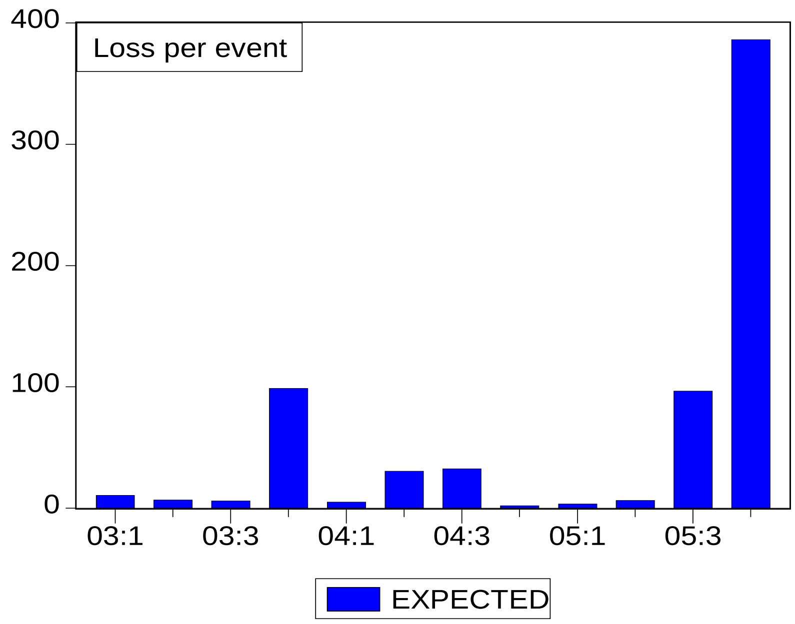
a. Frequency of loss event per quarterly

[18] Some of loss data are excluded because the loss amount is not confirmed finally, and particularly there could be some bias in the cell of Retail Banking/External Fraud because some banks did not submit related loss data on credit card fraud.

[19] If Op risk loss data have noticeable time-varying properties, the stationary assumption of LDA measurement logic should be reviewed. But, this sophisticated issue is beyond this paper's scope, and so follow-up researches are required.



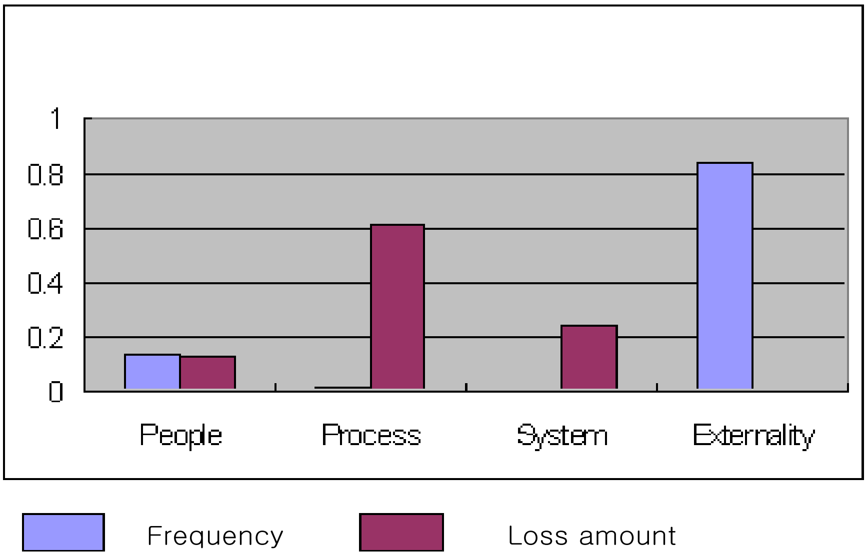
b. Average loss amount per event



In consultative papers, Basel Committee divided causes of Op risk losses into 4 categories (people, processes, systems and external factors). The causal analysis on Op risk is essential for identifying Key Risk Indicators (KRI) which are one of main tools for Op risk management, and is also helpful to design effective action plans for related Op risk events. As results of causal analysis on loss data, the 5,794 (corresponding to 84%

of total loss events) are caused by "external factors". But, if credit card frauds are excluded, main event type of external factors, "people" represent the next highest share (946 loss events, 14%) of causes. This means that most amount of Op risk losses in Korean banks are resulted from the event types of internal fraud such as embezzlement, misappropriation of assets etc. Also, Op risk events generated from inadequate processes contain higher loss impacts per event relatively to others. The average loss amount of this cause corresponds to more than 0.4 billion won per event. Therefore, the controlling effectiveness on relevant processes with high potential losses should be reviewed, for preventing against the occurrence of big loss. Specifically, in the case of tasks for redesigning of business processes such as Business Process Reengineering (BPR), banks should consider not only the enforcement of business competitive power but also potential impact on Op risk exposure.

[Figure 3] Proportions of 4 Op Risk Causes



**Note : The vertical axis represents the percentage basis.*

(2) 7x9 matrix analysis - Severity & Frequency

This section analyzes the Op risk profile of domestic banks through mapping pooled loss data by 7×9 matrix (8 BLs of Basel Ⅱ + staff functions).[20] This analysis is to figure out high-risk cells among the 63 cells.

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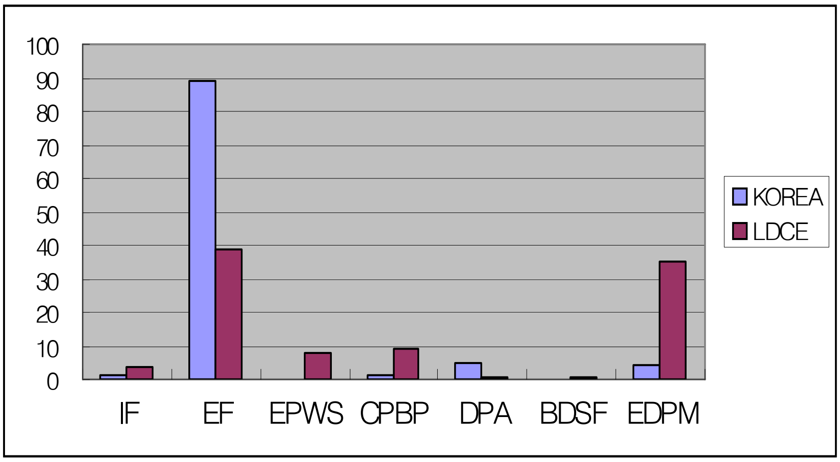
[20] This 7×9 matrix analysis is based on the assumption that bank allocated internal loss data into BLs and LETs properly. However, [Table 1] below shows that there seem some differences of BL mapping in the Damage to Physical Assets (DPA) & Business Disruption and System Failures (BDSF) across banks. Therefore, for more accurate analysis, the BL mapping criteria of banks need to be reviewed.

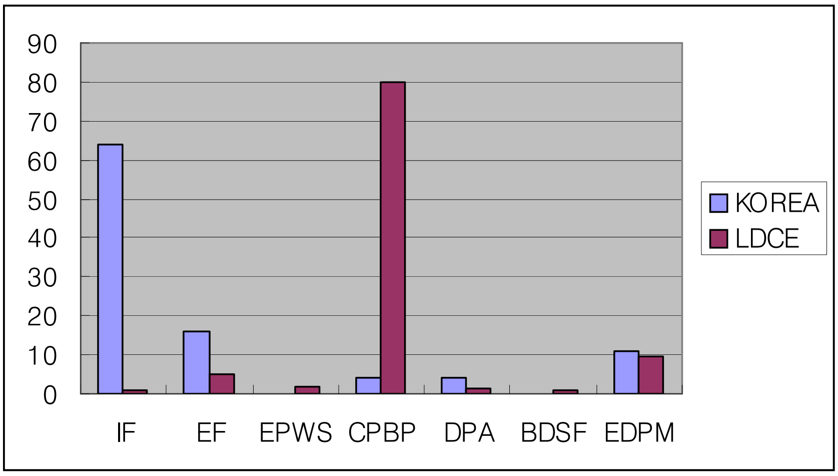
According to the results of LDCE (Loss Date Collection Exercise) which conducted in 2004 by US regulators (FRB, OCC, FDIC, OTS) on US banks, in frequency basis, Retail Banking (60.1%) among BLs and External Fraud (39.0%) and Execution, Delivery and Process Management (EDPM) (35.3%) among LETs took higher share of loss events. In loss amount basis, Others (70.8%) of BLs corresponding to staff functions and Clients, Products and Business Practices (CPBP) (79.8%) of LETs took higher share. [Figure 4] provides the comparison between loss data of Korean banks and LDCE(2004) data of US banks on basis of the number of losses and loss amount.[21]

[Figure 4] Comparisons of Loss Event Types : Korean Banks vs. LDCE(2004)

a. Frequency



b. Loss amounts



**Note : IF(Internal Fraud), EF(External Fraud), EPWS(Employment Practices and Workplace Safety), CPBP(Clients, Products and Business Practices), DPA(Damage to Physical Assets), BDSF(Business Disruption and System Failures), EDPM(Execution, Delivery and Process Management)*

**The vertical axis represents the percentage basis.*

21 For convenience, we denote 'Execution, Delivery and Process Management' as 'EDPM'.

Additionally, Korean banks data provided similar results with LDCE(2004) in that Retail Banking (96%) and External Fraud (89%) took higher share of the number of loss events. However, those ratios were much higher than those of LDCE results. This was resulted from relatively higher proportion of credit card fraud, but this kind of loss events is highest in view of frequency, not high loss amount per event. [Table 2] below provides the frequencies of loss events in 7x9 matrix.

[Table 2] The Number of Loss events

	IF	EF	EPWS	CPBP	DPA	BDSF	EDPM	Total
Corporate Finance	1	0	0	0	0	0	0	1
Trading & Sales	0	0	0	0	0	1	13	14
Retail Banking	73	6,114	5	21	190	3	186	**6,592**
Commercial Banking	20	6	0	4	0	1	20	51
Payment & Settlement	2	2	0	1	0	0	5	10
Agency Services	0	0	0	0	0	0	2	2
Asset Management	0	0	0	2	0	0	0	2
Retail Brokerage	1	0	0	6	0	0	3	10
Staff functions	2	5	22	1	128	7	14	179
Total	99	**6,127**	27	35	318	12	243	**6,861**

**The shadow parts among matrix represent the cells with above 100 loss events.*

On basis of loss amount, [Table 3] demonstrates that the data from Korean banks are allocated as Retail Banking (56%), Payment & Settlement (23%), Commercial Banking (10%), these appearances show some distinctive features unlike LDCE(2004) results, which are allocated as Others (70.8%), Retail Banking (12.3%), Trading & Sales (8.6%).

With regard to LETs, Internal Fraud had the highest share (64%) of total loss amount, followed by External Fraud (16%), EDPM (11%), however, LDCE(2004) had the highest share in CPBP (79.8%). Our analysis has found that US banks have serious Op risk exposure in CPBP, which was mainly caused from disputes with clients and product defects, but Korean banks have weighty Op risk exposure in illegal activities such as embezzlement. Although not significant in Korean banks at present, Op risk exposure in CPBP could ascend gradually due to active trading with more complex products, the newly introduction of class action etc. To prevent the potential loss from this type of risk events, preemptive activities of domestic banks should be carefully considered.

[Table 3] Loss Amount (unit : one million won)

	IF	EF	EPWS	CPBP	DPA	BDSF	EDPM	Total
Corporate Finance	28	0	0	0	0	0	0	28
Trading & Sales	0	0	0	0	0	26	5,406	5,432
Retail Banking	67,179	26,080	18	3,596	3,496	68	1,600	**102,037**
Commercial Banking	13,146	2,318	0	26	0	9	2,738	18,237
Payment & Settlement	36,859	13	0	5	0	0	4,737	41,615
Agency Services	0	0	0	0	0	0	2,091	2,091
Asset Management	0	0	0	4,468	0	0	0	4,468
Retail Brokerage	63	0	0	43	0	0	1,492	1,598
Staff functions	151	51	550	10	4,079	550	1,464	6,855
Total	**117,426**	28,462	568	8,148	7,575	653	19,528	**182,360**

**The shadow parts among matrix represent the cells with above 10 billion won.*

Generally, in Korean banks, Internal and External Fraud (LET) of Retail Banking and Commercial Banking (BL) have high Op risk exposure, and Payment & Settlement has relatively severe impacts with low-frequency. Specifically, Internal Fraud of Payment & Settlement shows an characteristic risk profile, namely, Low Frequency-High Impact (LFHI), which is very difficult to forecast owing to unexperienced risk events in a bank. However, this kind of risk has high potential impacts, so active controlling plans against this risk must be equipped within ORM framework. Also, External Fraud of Retail Banking has high frequency but low impact events, thus, it is possible to allocate operating costs for this risk because it could be expected to some degree.

3.1. Some Implications on Measurements

Basel Ⅱ required that Op risk be measured and managed for each cell of 7x8 matrix. Therefore, banks must generate a loss distribution per cell for Op VaR measurement in principle. We assigned pooled loss data of domestic banks into 7x9 matrix, and found that most cells did not have enough data for generating a loss distributions. Only 11 cells among 63 cells have more than 10 data points. (Refer to the [Table 4] below.)

Even though domestic banks would continue to do a data pooling via KOREC, they are still likely to face the problem of empty cells. Nevertheless, the task of data pooling is so important for Op VaR measurement in that it enables banks to elevate the accuracy of statistical estimation and provides some relevant information for proper utilization of scenario or external loss data.

[Table 4] Cells with 10 or more data points in 7x9 matrix

	IF	EF	EPWS	CPBP	DPA	BDSF	EDPM
Corporate Finance							
Trading & Sales							13
Retail Banking	73	**6,114**		21	190		186
Commercial Banking	20						20
Payment & Settlement							
Agency Services							
Asset Management							
Retail Brokerage							
Staff functions			22		128		14

[22] Losses with LFHI type have critical risk exposure, but are hard to be captured with only internal loss data. Therefore, this type of risk is required to be identified and evaluated through the external data or top-down view of internal experts group.

More specifically, pooled data of KOREC will help banks to reduce some bias in estimating parameters of distribution by MLE that require a large number of data, and to assess the appropriateness of assumed distributions in the case of using scenario or external loss data.

(1) Severity distribution

Most of domestic banks used various GoF tests such as KS test, AD test, AIC (SBC) test in order to choose optimal severity distribution. Because several test statistics might display some confused results, banks should have logical procedures for decision-making against this situation.[23]

In this chapter, we will present some considerations in finding a proper type of severity distribution through the statistical analysis of pooled loss data. We selected exponential, log-normal, gamma and Weibull distribution as candidate distributions, which are commonly adopted by domestic banks. Also, we used MLE as an parameter estimation method of distributions.[24]

The KS test statistics indicates a maximum distance between a hypothetical distribution and a true distribution of actual data. Therefore, the larger the KS test statistics is, the corresponding true distribution is more different from the hypothetical one. The KS test is more sensitive to differences in the body with a large number of observations than differences in the tails. Consequently, the KS test has a limitation in the context of Op risk, because the tail property is more important. As another GoF test, AD test is basically similar to KS test, but it supplements the shortcomings of KS test by placing more weights on the tails. The AIC and SBC are based both on likelihood function and the number of parameters estimated. It is generally said that the higher the value of log-likelihood is, the estimated distribution is better. But the estimation with too many parameters lowers degree of freedom, and accordingly statistical significances of estimators would decrease, so-called as "parsimony principle". Therefore, the fitness of a candidate distribution may be regarded as relatively good in the case of higher log-likelihood value and the estimator with parameters as few as possible.

As a result of performing several GoF tests on collected loss data, log-normal distribution is selected as the most appropriate one for every cell except ‘Corporate banking/EDPM’ cell among 11 cells with above 10 data points. The KS test, AD test and AIC (SBC) test

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[23] Some banks are known to use the calculated log-likelihood value for final decision, however, this seems to be too naive. For the selection of proper severity distribution, some critical characteristics of internal loss data (such as the number of data, tat-tail property etc) must be fully reflected.

[24] Please refer to Jo et. al.(2004) for detailed explanations about the characteristics of candidate distributions and GoF tests mentioned in this paper.

statistics showed the same result. However, for the ‘Corporate banking/EDPM’ cell, the KS test and AD test selected the log-normal, while the AIC (SBC) test chose Weibull distribution.

Though these GoF tests explained above are very popular in domestic banks, such approaches have two main problems. First, the power of test statistics could be different according to the number of data of tested cell because those approaches are based on MLE which assumed a large number of data points. Second, the predetermined threshold on data was not taken into consideration in estimating the parameters of distributions.

We performed an analysis to review the first problem using "Modified AD test" procedure. Specifically, the modified AD test is to exclude improper candidate distributions in view of data characteristics (especially, the number of actual data points) of the cell concerned. The test procedure includes simple simulations for generating distributions with the same number of data points in tested cell. The reason why we performed only AD test among various GoF tests is that the distributional features of the tails with extreme losses in Op VaR is so important that the AD test is more useful than the others.

<Modified AD test procedures>

a. Generating hypothetical data points as many as actual data points of tested cells
(eg.) Generating 20 data points for each candidate distribution by simulation if the number of the cell concerned is 20.

b. Examining the discriminatory power of AD test for candidate distributions
(eg.) Checking if null hypothesis that severity follows xxx distribution be accepted or not by AD test in case with the tested data is generated from xxx.

c. Excluding the candidate distributions if null hypothesis is rejected in the previous ‘b’ process
(eg.) Delete gamma distribution from candidate distributions list if hypothesis that severity follows gamma distribution is rejected in the previous test even though the true distribution is gamma.

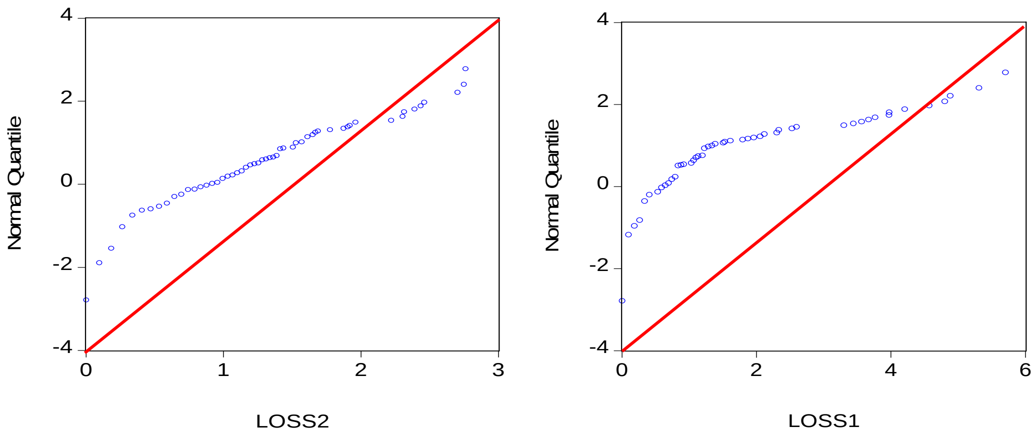
d. Selecting severity distribution among passed distributions in above test for each cell

The results of the modified AD test displayed "Gamma" distribution is selected for 10 cells except ‘Retail banking/EF’ with log-normal distribution. These consequences are somewhat unexpected because the modified AD test is just "modified" test with a simple simulation for considering the number of data points of tested cell. Accordingly, we can infer that popular GoF tests do not have high test power.

For clarification, we conducted Q-Q plot as a graphical test on ‘Retail Banking/IF’ cell with the most plentiful data – for which log-normal distribution is selected consistently regardless of AD test or modified AD test - and ‘Retail Banking/EDPM’ cell with the next most plentiful data, for which severity distribution is changed from log-normal from AD test to gamma from modified AD test.

[Figure 5] Results of Graphical Test : Q-Q plot

a. Retail Banking/EF   b. Retail Banking/EDPM



**Note : The above Q-Q plots were made against log-normal distributions, because the two cells had log-normal as severity distribution by statistical GoF tests.*

The log-normal distribution is selected for two cells according to the result of GoF tests, but Q-Q plot displays that the log-normal distribution can not fit the actual distribution of loss data well in ‘Retail Banking/EDPM’ cell. As a result, the power of the GoF tests, commonly used by domestic banks, are not high owing to the lack of data (especially, in the tail area). Thus, AMA banks need to make special efforts to develop statistically robust testing procedure, which could fully reflect the data characteristics of analyzed cell.

With regards to second problem, the setting of data threshold, Chernobai et al.(2006) pointed out that the parameters of distributions could be over/underestimate 40~50% by unconditional estimation. According to the results of Chernobai et. al.(2006), unconditional estimation of severity distribution caused mean value to be seriously overestimated and variance underestimated. Consequently, the underestimation of the variance of severity distribution led to lower capital charge. They insisted that such a bias might be amplified in the case of fat-tailed distribution, and thus it is necessary to apply conditional estimation techniques like Expectation-Maximization algorithm. Most domestic banks had a certain data threshold (usually, 1 million won) for considering data management costs. It can cause significant bias in the estimated parameters, and ultimately would influence calculated Op VaR value.

For deeply understanding the impact of various thresholds, we set thresholds at 0, 1 million and 10 million won respectively and analyzed the size of bias through the conditional estimation of ‘Retail Banking/EF’ cell. It turned out that the estimated means were significantly influenced while the estimated variances were not largely affected. As shown below, banks should pay a close attention to the fact that the mean estimate of severity distribution has a large deviation conditioned that data threshold is set at above 10 million won.

	0	**1 mil. won**	**10 mil. won**
Mean	0.98	0.76	**2.48**
Variance	0.70	0.84	0.91

(2) Frequency distribution

Usually, most domestic banks presumed Poisson as frequency distribution, otherwise a few banks selected more proper distribution by such a simple method as mean-variance comparison. The mean-variance comparison of 11 cells showed that Poisson was chosen for 7 cells and negative binomial was chosen for 4 cells respectively.

- Poisson distribution (Mean > Variance) : Commercial Banking/IF, EDPF, Retail Banking/EF, CPBP, DPA, Staff functions/DPA, EDPM.

- Negative binomial distribution (Mean < Variance) : Retail Banking/IF, EDPM, Staff functions/EPWS, Trading & Sales/EDPM

To some extent, the assumption of Poisson as frequency distribution appears to be reasonable judging from the result of mean-variance analysis. But these consequences are founded on the assumption that probability distribution is stationary, which implies main moments of distribution do not vary over time. Therefore, it might be inappropriate to estimate the parameter of frequency distribution under the stationarity assumption if the frequency of loss events is not stable over time, that is, mean frequency is time-varying as shown in [Figure 2]. According to Cavez-Demoulin et. al.(2005), operational loss events seemed to occur so irregularly, that they were not stationary. Regarding these characteristics of frequency distribution, some remarkable researches are under way across the academics and advanced international banks. Thus, domestic banks need to catch-up these trials for developing more sophisticated measurement methodology.[25]

As mentioned above, Op VaR models of domestic banks have some improper assumptions and logic, so more deep reviews about Op VaR model structures must be conducted by a bank itself.

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25 Referring to this issue, banks can consider the regression methods to fit expected frequency directly to asset size, revenue etc. Otherwise, heterogeneous Poisson distribution approach where parameter can change over time can be a possible alternatives.

4. Conclusions

Although Op risk management has such a long history as banking industry, much interest has not reached on it up to date owing to the difficulties in identification and measurements. But, the Op risk has become a matter of main concern on account of deregulation, globalization, newly introduced complex products, IT automation etc. It might be possible for banks to fall into insolvency in an extreme case because the failure of Op risk management could have serious impacts on soundness and profitability of banks. As such, the quantitative expansion and the qualitative changes of Op risk exposure could make the views of both banks and supervisors changed, consequently, Basel Ⅱ framework included Op risk in calculation of regulatory capital charge.

This paper compared the AMA modeling methods of domestic banks, and examined several main issues to be resolved for reasonable Op VaR. There are some realized problems as the paucity of internal loss data, the assumptions of distributions, the statistical robustness of Op VaR logics for banks to find a way out. These problems might be resolved in a near future on condition that banks would make more efforts for applicable practices. At an early stage of Basel Ⅱ framework, though many people had an skeptical view on possibility of quantification for Op risk, it could be recently observed for international banks to measure Op risk in a reasonable way. Besides, KOREC can provide pooled data set to partly solve data problem, and with regard to the AMA modeling issues, banks should facilitate greater consistency and reasonableness in model validation process. Accordingly, regulators are required to understand common difficulties of banks based on realistic perspectives, should provide more practical guidelines for feasible implementation of AMA.

By focusing on collected internal loss data of domestic banks, this study captures main properties of Op risk exposure, and presents some modeling issues like the poor test power of popular GoF tests and the necessity of conditional estimation etc. Most of all, the key finding of this analysis is to illustrate that some GoF tests can not fit loss data well, specially in the tail areas. If the GoF tests can not reflect fat-tailed properties of Op risk loss, it would lead to Op VaR underestimation. Therefore, banks must review and modify its current practices immediately for achieving higher standards of AMA.

The one of limitations of this paper is not to analyze fat-tailed properties of each cell by directly applying EVT technique because our sample data set is not sufficient for estimating fat-tail distribution per each cell.[26] Further analysis should be conducted for deriving more definitive conclusions after gaining enough data via KOREC.

[26] Although there is enough data in 'Retail Banking/EF' cell, we did not fit fat-tailed distribution because most events of the cell are credit card frauds, so the cell seemed not to display fat-tails.

This empirical study could be helpful for AMA banks to identify their modifications and upgrading issues on measurement module. More concretely, individual bank can refer to the results of this analysis for the distributional assumptions of scenario data. As banks have more extensive operational loss data, the ability to differentiate across alternative distributional assumptions should improve.

Most of domestic banks are highly depending on the advanced methodologies of European banks for measurement as well as risk management. The approaches has some strengths on AMA modeling, however, because it is naturally based on the risk culture of European banks, there are some points not to fit well to the reality of Korean banks. Regarding measurement module, this potential problems could be observed in scenario analysis. As for domestic banks are not familiar with collective discussions and group decision-making culture, the scenario analysis might be too subjective. Hence, scenarios should be reviewed by an independent party and re-assessment over time by comparing them with actual loss experience. The objective and independent reviewing procedure for scenario data must be implemented in AMA model.

There are still some critical issues for the AMA banks to meet the prescribed requirements of local regulator. However, banks are able to implement AMA approaches successfully if they consider Op risk framework as a necessary management program, rather than newly bothering regulations.

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