OPERATIONAL RISK ASSESEMENT TOOLS FOR QUALITY MANAGEMENT IN BANKING SERVICES

Alina Mihaela Dima
The Bucharest Academy of Economic Studies, Romania
E-mail: alinamihaeldima@yahoo.com

Abstract

Among all the different types of risks that can affect financial companies, the operational risk can be the most devastating and the most difficult to anticipate. The management of operational risk is a key component of financial and risk management discipline that drives net income results, 2capital management and customer satisfaction. The present paper contains a statistical analysis in order to determine the number of operational errors as quality based services determinants, depending on the number of transactions performed at the branch unit level. Regression model applied to a sample of 418 branches of a major Romanian bank is used to guide the decision taken by the bank, consistent with its priorities of minimizing the risk and enlarging the customer base ensuring high quality services. The analyisis reveals that the model can predict the quality of the transactions based on the number of operational errors. Under Basel II, this could be a very helpful instrument for banks in order to adjust the capital requirement to the losses due to operational errors, predicted by the model.

Keywords: quality management, operational risk, banking services, binary regression model

JEL Clasification: G32, C24

Introduction

Quality concerns are critical to many services and products, but especially in finance and banking area, where diversification and sophistication of financial technology are making the activities of banks and thus their risk profiles more complex. Developing banking practices suggest that risks other than credit, interest rate and market risk can be substantial (BIS, 2003). The risks associated with the provision of banking services differ by the type of service rendered. However, for the sector as a whole, the risks can be broken into six generic types: systematic or market risk, credit risk, counterparty risk, liquidity risk, operational risk, and legal risks (Santomeo, 1997). Bank regulators and researchers have long sought to understand the determinants of bank risk-taking (Kwan and Eisenbeis, 1997). The operational risk becomes a major constraint since it involves taking appropriate measures to ensure the qualitative transactions without processing errors in order to deliver the best services to the customers.

Although the operational risk is by itself not a new concept, it has by far not received the same amount of attention as credit and market risk until recent years. Fundamental changes in financial markets, increasing globalization and deregulation, as well as corporate restructuring had a large impact on the magnitude and nature of operational risks confronting banks. Following severe operational failures resulting in the restructuring of the affected financial institutions (e.g. Natwest, Allied Irish Bank, LTCM) or in the sale of the entity (e.g. Barings), the emphasis on operational risk within banks has increased, leading regulators, auditors, and rating agencies to expand their focus to include the operational risks as a separate entity besides market and credit risk (Helbok and Wagner, 2006).

The operational risk was for the first time treated as a self-contained regulatory issue in the "Operational Risk Management" document published by the Basel Committee on Banking Supervision in 1998. "The New Basel Capital Accord" was first formulated in a proposal in 1999, released in 2001 and became effective in 2007; within the framework, the operational risk was integrated in the so-called Pillar 1, which implies its inclusion in the calculation of a banks' overall capital charge. Along with revising the minimum capital standards already covering credit and market risk, Basel II sets a new minimum capital standard for the operational risk. While requiring capital to protect against the operational risk losses, the new framework is meant to encourage banks to improve their risk management techniques as to reduce the operational risk exposure and mitigate losses resulting from operational failures. The new capital accord provides incentives of lower capital requirements to those banks that demonstrate strengthened risk management practices and reduced risk exposures (Haubenstock and Andrews, 2001).

As one of the innovations proposed by the Basel II, the operational risk is defined by this institution as "the risk of direct or indirect loss resulting from inadequate or failed internal processes, people and systems or from external events". This approach is in accordance with other opinions (Santomero, 1997) that consider operational risk associated with the problems of accurately processing, settling, and taking or making delivery on trades in exchange for cash. Lippold and Vanini (2003) define the operational risk as the risk a bank faces in production and services for its clients. However, the operational risk is a term that has a variety of meanings within the banking industry, therefore for internal purposes banks may choose to adopt their own definitions. This internal definition should respect the individual situation of every bank, such as its size, and sophistication, its nature and complexity of its activities in an economic manner, considering the full range of material operational risks facing the bank and captures the most significant causes of severe operational losses. Broadly speaking, the operational risk contains losses that follow from acts undertaken (or neglected) in carring out business activities. The majority of operational losses are due to transaction processing errors (Harmanzis, 2002). Such losses result from human error, absence of proper procedures, failure to follow existing procedures, or inadequacies within the procedure when first established (Grody et al, 2005).

The management of operational risk is not a new practice; it has always been important for banks to try to prevent fraud, maintain the integrity of internal controls, reduce errors in transaction processing, and so on in order to preserve the best quality services for their customers, but also because errors can lead to huge losses. However, what is relatively new is the view of operational risk management as a comprehensive practice comparable to the management of credit and market risk in principle. In the past, banks relied almost exclusively upon internal control mechanisms within business lines, supplemented by the audit function, to manage the operational risk. While these remain important, recently there has been an emergence of specific structures and processes aimed at managing the operational risk.

1. Literature review

Following the widespread recognition of the importance of the operational risk in banking and the knowledge that the operational risk exhibits characteristics fundamentally different from those of other risks, an increasing amount of academic research has been devoted to this issue. Power (2005) or Harmanzis (2002) reviews the development of the operational risk in general; approaches to measure and manage the operational risk are presented by Ebnother, Vanini, McNeil, and Antolinez (2003) and surveys in Healy and Palepu (2001). Most research on the operational risk in recent past has focused either on the quality of quantitative measurement methods of the operational risk exposure (Makarov, 2006, Degen et al., 2006; Mignola and Ugoccioni, 2006 and 2005; Nešlehová et al., 2006; Grody et al, 2005; de Fontnouvelle et al., 2004; Moscadelli, 2004; Alexander, 2003; Coleman and Cruz, 1999; Cruz et al., 1998) or theoretical models of economic incentives for the management and insurance of operational risk (Leippold and Vanini, 2003: Crouhy et al., 2004; Banerjee and Banipal, 2005). Only little attention has been devoted to statistical issues of coherent and consistent operational risk reporting and measurement within and across banks (Dutta and Perry, 2006; Currie, 2004 and 2005) and operational risk reporting has remained to be an unexplored topic in academic research.

Harmantzis (2002) assumes that the correlation among risk type is zero, that is to say that all risk types are completely independent of each other. De Fontnouvelle et al. (2004) use publicly available data to quantify the operational risk and prove that capital charge for the operational risk will often exceed that of the market risk. Ebnoether et al (2003) present study-cases on operational risk measuring and show that for a production unit of a bank with well-defined workflows, the operational risk can be unambigously defined and modelled. Although quantitative models in the operational risk management have become more common in the last two decades, the measuring of the operational risk is not a trivial exercise. Today's turbulent financial markets, growing regulatory environments, and increasingly complex financial systems have led risk managers to realize the importance of measuring and managing the operational Risk (Harmantzis, 2002). However, the operational risk is not thought to be easily measured, since it covers various risks such as transactions processing errors and omissions including system failure, threft and fraud, rogue trade, lawsuits and loss or damage to assets (Mori, Hiwatashi and Ide, 2000).

Operating risk and/or system failure are a natural outgrowth of their business and banks usually employ standard risk avoidance techniques to mitigate them (Santomero, 1997). Self Risk Assessment method is one of the possible tools used by banks for identifying and assessing the operational risk used by a bank to assess its operations and activities against a menu of potential operational risk vulnerabilities. This process is internally driven and often incorporates checklists and/or workshops to identify the strengths and weaknesses of the operational risk environment. Scorecards, for example, provide a means of translating qualitative assessments into quantitative metrics that give a relative ranking of different types of operational risk exposures.

An accurate estimation of the operational risk, and its use in corporate or global financial risk models, could be translated into a more efficient use of resources. One important ingredient to accomplish this goal is to find accurate predictors of individual risk in the credit portfolios of institutions (Galindo and Tamayo, 2000). In the next part, we are analysing the tools used by a major Romanian bank to monitor and evaluate the operational risk in all its branches and we are proposing a model to assess the frequency of errors determined by the number of transactions made at the level of each branch unit.

2. Methodology

The basic assumption for the study is that transactions drive the largest components of the operational risk and the probability of operational losses increases as the volume and complexity of transactions increase. The errors have both a cause and effect on the performance of the process. As Ebnother at al (2002) noticed, an important issue in the operational risk is data availability, especially in Romania where the operational risk management is quite a new concept. We used a database from a Romanian major bank (due to confidentiality reasons, we could not give the real name), regarding the monthly operational errors centralization within 418 branches on the whole Romanian territory. The main objective is to correlate the number of transactions within a month at the branch level with the quality of transactions expressed on a 1 to 4 scale, ranked according to the number of operational errors. Errors of processing transactions are defined as deviations from quality standards of operational processes. We have chosen to analyse the last index (operational quality) of the seven indexes defining the Branch Quality Index, as the first six are defined in accordance with program quality standards and are assessed through the unity evaluation report.

Branch Quality Index

Table 1

Indexes	Percentage in the final score (%)
Image and organisation	10
Novelty and transparency	20
Service mobility	10
Selling process	20
Customer care	20
Supervision process	10
Operational quality	20

The evaluation of the operational quality is based on the monitorization of the following processes: 1). registration or administration of customers' information; 2). opening or administration or closing the accounts of the customers; 3). financial transactions involving customers'accounts or general book-keeping accounts; 4). registration or administration of services contracts (e.g. MultiCash).

Indexes of evaluation of operational errors

Table 2

Degree of accomplishment	**Quality rating**	**Mark**
Above 0,05%	Under expectations	1
Between 0,05% si 0,03%	According to the expectations	2
Between 0,029% si 0,02%	Over the expectations	3
Below 0,02%	Exceptional	4

- Number of processed errors is reported to the number of transactions processed in the banking unit
- The level over the expectations corresponds to a value of the ratio of maximum 1 error to 5.000 transactions processed (within the interval 0.029% and 0,02 %).

The methods of assessing quality services are the following: the evaluation made by the regional quality officer, evaluation through Mystery Shopping and evaluation through operational reports.

3. Data analysis

Using SPSS 16 program, we made the correlation between the number of transactions (the independent variable) and the number of operational errors (the dependent variable), defined by a rating that expresses the degree of accomplishment. As we applied logistic binary regression (where we denied the nule hypothesis, and we accepted the alternative hypothesis), we have used a binary system of codification of expectations related to the transactions' quality such as: 1- quality conforming (the corresponding quality alternative redefined the values "over expectations" and "exceptional" in the banking quality classification index) and 0 - quality non-conforming (the corresponding quality alternative redefined the values "under expectations" and "according to the expectations").

Determinat Coefficients

Table 3

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.676[a]	.457	.455	18.695
a. Predictors: (Constant), number of transactions				

In table 3, we can notice that determinat coefficient (R square value is 0.455) indicates the proportion (45%) in which the dependent variable (operational errors number) is explained by the variation of the independent variable (the transactions number). In addition, the model shows that there is a positive and significant correlation of 0.676 between the number of transactions and the number of operational errors as one can notice in table 4:

Regression Model

Table 4

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	11.627	1.260		9.227	.000
	no of transactions	.000	.000	.676	18.671	.000
a. Dependent Variable: number of operational errors						

Beta value of 0.676, which expresses the level of correlation betwen the dependent variable and the independent one, shows that every unit increase of the transaction number increases the probablility of operational errors with 0.676. This value of correlation means that 67% of operational errors are due to the high number of transactions, meaning the overhitting of the system. An optimisation system should involve tailoring the right number of transactions. The regression model presented in table no 6 is a realistic one, which predicts the number of errors depending on the number of the transactions and it can be used in banking system for quality evaluation proccess.

In the following part, we made a logistic binary regression, where we applied the test $\chi 2$ to determine the significant level of the variables. As one can notice in table 5, the model is significant (.000) at this level.

Omnibus Test of Model Coefficients

Table 5

		Chi-square	df	Sig.
Step 1	Step	106.846	2	.000
	Block	106.846	2	.000
	Model	106.846	2	.000

We have used two hypothesis, namely nule hypothesis H0: ”*the increase in the number of transactions will not increase the number of errors*” and alternative hypothesis H1:*”the increase in the number of transactions will increase the number of errors*”. We have tested the two hypothesis and we rejected the nule one.

Classification Table[a]

Table 6

	Observed		Predicted		
			nota		Percentage Correct
			0	1	
Step 1	nota	0	278	7	97.5
		1	73	59	44.7
	Overall Percentage				80.8
a. The cut value is .500					

In table 6, we can notice that the model can predict with 97%, the probability that the transactions with high level of complexity have a non-corresponding quality. This model is a precautionary one, as it can predict with high probability only the transactions with many errors (”bad transactions”), while for transactions with low level of errors („good transactions”), the probability is only 44.7%.

Variables in the Equation

Table 7

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	nrtranz	.017	.003	43.568	1	.000	1.017
	nrerr	-.063	.009	44.504	1	.000	.939
	Constant	-.540	.183	8.685	1	.003	.583
a. Variable(s) entered on step 1: nrtranz, nrerr.							

In table 7, one can notice that there is a low correlation (0.017) between the mark (quality) of the transactions with the number of transactions. This means the variable is quite independent (the quality of the transaction ”good” or ”bad” does not depend on the number of transactions performed in the bank). The correlation between the transaction mark (quality) and the number of errors is negativelly significant (-0.063), meaning that the high number of errors determines the low quality of the transaction. The constant (-0.540) expresses the contributions of other variables to the transaction quality, meaning that there are other factors that can influence the high quality of the transactions (such as qualification of the personnel working in the banking environment, the experience of the management team, the transaction type - internal/external, transactions made between two subsidiaries or more than two etc).

Conclusions

The regression model presented might be considered a decision support tool for a bank willing to reduce the losses based on operational errors, an important element for risk management to provide the best quality services for its customers. An effective way of risk assessement is to establish a framework for systematically tracking and recording the frequency, severity and other relevant information on individual loss events. Promptly detecting and addressing these deficiencies can substantially reduce the potential frequency and/or severity of a loss event. Thus, an efficient monitoring process is essential for adequately managing the operational risk, but sometimes is very costly. A large number of banking transaction will determine a higher number of operational errors, that will involve higher costs for reducing the negative effects.

The regression model presented can be extended in further research to predict the probability of failure of a transaction determined by its complexity and the influence of other relevant factors (type of transaction: internal or external, the number of subsidiaries involved: within the same branch/subsidiary or between two or more than two, the level of qualification of the personnel involved in transaction process, the management experience, etc). The advantages and benefits of using such a prediction model are in reducing costs per transaction unit, increasing the profit and optimising processes. Thus, the system has to be standardised and consistent on a bank wide level for identification, recording data for quantification, qualification, controls and measurement, analysing and managing operational risk based on well-defined requirements by the management.

Low-quality branches could result in loss of valuable customers and reduced profitability over time, a result that bank managers should take into consideration. Hence, if we seek high-quality low-cost best-practice benchmark branches, quality needs to be considered. In operational risk termes, quality is seen as minimum level of errors per unit of transaction. Their early assessement through predictive models could save time and loss of important resources for the banking management that can be used more efficiently for orher purposes.

References

1. Alexander, C. (ed.) (2003). *Operational Risk: Regulation, Analysis and Management,* Financial Times - Prentice Hall.
2. Bank for International Settlements (2003). *Sound Practices for the Management and Supervision of Operational Risk,* Risk Management Group of the Basel Committee on Banking Supervision (February).
3. Banerjee, S. and Banipal, K. (2005). *Managing Operational Risk: Framework for Financial Institutions*, Working paper, A.B Freeman School of Business, Tulane University (November).
4. Coleman, R. and Cruz M. (1999). *Operational Risk Measurement and Pricing*, Derivatives Week, Vol. 8, No. 30 (26 July), 5f.
5. Cruz, M., Coleman, R. and Salkin, G. (1998). *Modeling and Measuring Operational Risk*, Journal of Risk, Vol. 1, No. 1, 63-72.
6. Crouhy, M., Galai, D. and Robert, M. (2004). *Insuring versus Self-insuring Operational Risk: Viewpoints of Depositors and Shareholders,* Journal of Derivatives (Winter), 51-5.
7. Currie, C. V. (2005). A *Test of the Strategic Effect of Basel II Operational Risk Requirements on Banks*, School of Finance and Economics, Working Paper No. 143 (Sept), University of Technology, Sydney.
8. Currie, C. V. (2004). *Basel II and Operational Risk - Overview of Key Concerns*, School of Finance and Economics Working Paper No. 134 (March), University of Technology, Sydney.
9. Daniels, K. and Ramirez, G.G. (2008). *Information, Credit Risk, Lender Specialization and Loan Pricing: Evidence from the DIP Financing Market,* Journal of Financial Services Research, 34:35–59.
10. Springer Science de Fontnouvelle, P., Rosengren, E. S. and Jordan, J. S. (2004), *Implications of Alternative Operational Risk Modeling Techniques,* SSRN Working Paper (June).
11. Degen, M., Embrechts, P. and Lambrigger, D. D. (2006). *The Quantitative Modeling of Operational Risk: Between g-and-h and EVT,* Working paper, ETH Preprint, Zurich (19 December).
12. Dutta, A. and Perry, J. (2006). *A Tale of Tails: An Empirical Analysis of Loss Distribution Models for Estimating Operational Risk Capital*, Working paper No. 06-13, Federal Reserve Bank of Boston (July).
13. Ebnother, S., P. Vanini, A. McNeil, and Antolinez, P. (2003). *Operational Risk: A Practicioner's View*, Journal of Risk, 5.

14. Harmantzis, F. (2002). *Operational Risk Management in Financial Services and the New Basel Acco*rd, working paper, Stevens Institute of Technology.

15. Healy, P., and Palepu, K. (2001). *Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature*, Journal of Accounting and Economics, 31, 405-440.

16. Hauswald, R. and Marquez, R. (2006). *Competition and strategic information acquisition in credit markets*, Journal of Financial Studies 19(3):967–1000.

17. Helbok, G and Wagner, H. (2006). *Determinants of operational risk reporting in the banking industry*, Journal of Risk, July 11.

18. Galindo, J. and Tamayo, P. (2000). *Credit Risk Assessment Using Statistical and Machine Learning: Basic Methodology and Risk Modeling Applications*, Computational Economics 15**:** 107–143, 2000., Netherlands.

19. Grody, A. D., Harmantzis, F. C. and Kaple, G. J. (2005). *Operational Risk and Reference Data: Exploring Costs, Capital Requirements and Risk Mitigation*, Stevens Institute of Technology, Hoboken, NJ.

20. Kwan, S. and Eisenbeis, R. A. (1997). *Bank Risk, Capitalization, and Operating Efficiency*, Journal of Financial Services Research 12:2/3 117±131 Kluwer Academic Publishers.

21. Leippold, M., and Vanini, P. (2003). *The quantification of operational risk*, Journal of Risk 8, November 3, p. 1.

22. Makarov, M. (2006). *Extreme Value Theory and High Quantile Convergence*, Journal of Operational Risk, Vol.1, No. 2.

23. Mignola, G. and Ugoccioni, R. (2006). *Sources of Uncertainty in Modeling Operational Risk Losses*, Journal of Operational Risk, Vol. 1, No. 2 (Summer).

24. Mignola, G. and Ugoccioni R. (2005). *Tests of Extreme Value Theory*, Operational Risk, Vol. 6, Issue 10.

25. Moscadelli, M. (2004). *The Modelling of Operational Risk: Experience with the Data Collected by the Basel Committee*, Discussion paper.

26. Mori, T., Hiwatashi, J. and Ide, K. (2000). *Measuring Operational Risk in Japanese Major Banks*, July 14, Bank of Japan Working Paper Series.

27. Power, M. (2005). *The Invention of Operational Risk*, Review of International Political Economy 12, 577-599.

28. Santomero, A. (1997). *Commercial Bank Risk Management: An Analysis of the Process*, Journal of Financial Services Research 12:2/3 83-115 Kluwer Academic Publishers.