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IMPACT OF OPERATIONAL RISK TOWARD THE EFFICIENCY OF BANKING - EVIDENCE FROM TAIWAN'S BANKING INDUSTRY

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ABSTRACT

This study adopts a GARCH model to estimate the operational risk of Taiwan's banking industry by the Top-Down method. Based on the approach of Battese and Coelli (1995) we estimate the Trans-log cost model and the inefficient model simultaneously by the Maximum likelihood method. Our empirical result shows that the operational risks have a significantly positive impact on cost inefficiency - that is, regardless of which methods we use for calculation, operational risk drives down economic efficiency. Comparing with the basic index method, the multi-factor model of the Top-Down method is better at analyzing the relationship of operational risk and efficiency.

Contribution/ Originality: This study contributes in the existing literature by employing a multi-factor model of Top-Down method to quantify banking operational risk. Furthermore, this is one of the very few studies which examine the relationship between operational risk and "real" bank's performance – cost efficiency.

1. INTRODUCTION

The enactment of three great risks (credit risk, market risk, and operational risk) in Basel II has greatly influenced banking systems worldwide. Different from the cases of credit risk and market risk, information about operational risk is quite limited since financial institutions with great operational risk perhaps have already withdrawn from the markets. Because the exposure of operational risk information could induce a negative image or even punishment from the government financial authority, financial institutions do not have any incentive to reveal it. Therefore, while many financial institutions would like to charge their capital when internally considering market risk and credit risk, few banks would ever propose a precise method to estimate operational risk.

There are three methods suggested by Basel II to measure operational risk: Basic Index method, Standard method, and Advanced Internal method. For a bank that never had any operational risk or operates under a low frequency of loss incidents, if the Basic Index or Standard method is adopted to estimate the capital charge for operational risk, then it would be overestimated. If a Bottom-Up method (an advanced measurement approach) is employed, then it would charge less capital and obviously is comparatively more favorable. However, the bank then must face insufficient information. Many risk factors, like business nature and work force quality, and some external factors, like environment changes and industrial structure adjustment, need to be carefully considered. Since a Bottom-Up method would cost too much to establish the basic data, we propose a Top-Down approach to estimate the operational risk for Taiwan's banking industry.

Although there is no attached function of direct risk management like the Bottom-Up method, a Top-Down method offers a more efficient way to measure operational risk. A Top-Down method usually has higher sensitivity to large changes in the environment and industry. Therefore, this paper gives a real example to assess banks' operational risk by a Top-Down method and thus sheds light on the measurement of operational risk.

We apply the stochastic frontier approach, mostly based on the econometrics method proposed by Battese and Coelli (1995) to explore the impact of operational risk on the efficiency of Taiwan's banking industry. Taking banking as an intermediation of financial activities, we employ the intermediation method to select multiple inputs and outputs of the model. We then simultaneously set up a Trans-log cost function as well as an inefficiency model to estimate the cost frontier and impact of operational risks.

The research data are primarily from the database of Taiwan Economic Journal (TEJ) and the annual statistical reports of Taiwan's financial industry. In addition to operational risk, we also use other environmental variables to account for those factors that impact the inefficiency of the sample banks, including the ages of financial institutions and some key corporate governance variables.

This article consists of five sections. Following the introduction, the second section is the literature review about operational risk, economic efficiency, and their relationship. The third section shows procedures of estimating operational risk by a Top-Down method and includes the data source, theoretical foundations, model specification, and empirical results. The fourth section illustrates the model specification and empirical results of the Trans-log cost function as well as the inefficiency function. Finally, we offer some conclusions and policy suggestions in the fifth section.

2. LITERATURE REVIEW – OPERATIONAL RISK AND EFFICIENCY

Operational risk generally exists in every corner of financial institutions. Inside operational risk includes risks related to people, processes, and systems. Outside operational risk includes the impacts of politics, law, society, calamity, etc. Being unable to conceive operational risk and then manage it effectively could cause serious operational losses.

Research studies for operational risk have focused on two major trends. One discusses the method of assessing operational risk, including the Basic Index, Standard, and Advanced internal models suggested by Basel II. However, many studies point out that since there is a shortage of a suitable database, they can only concentrate on the theoretical parts, which are very difficult to apply to practical areas. Because the assessment of operational risk is still a new developing subject, most papers conduct a theoretical exploration. Another trend focuses on the risk management procedure, such as risk identification, recognition, assessment, tactics, and control of operational risk, in order to strengthen the full-fledged quality of banks and management of operational risk.

In theory, the risk profile confirmation, risk identification and its impact on profitability, earnings quality and its stability, risk-return optimization, and validation of other hidden factors are the key issues for evaluating operational information. Mori *et al.* (2000) pointed out that the merit of a bottom-up method is that banks can apply this quantitative method to directly manage operational information and performance evaluation.

De Fontnouvelle *et al.* (2003) found that the capital charge of operational risk is greater than the sum of market risk and credit risk. Jobst (2007) argued that, for modern banks, since the business is more complicated and the scale is getting larger, the negative impact of operational risk is more serious than that of other types of risk. The literature has also found that different loss information collected and different measurement methods used lead to quite inconsistent conclusions.

Yao *et al.* (2013) further developed a model, named Conditional Value-at-Risk (CVaR), based on the peak value of the extreme value theory (EVT) to measure operational risk. The results therein suggest that although the probability of huge losses and disastrous losses are relatively low and extremely low, respectively, banks' operational performance and reputation would be seriously negatively impacted if such losses actually happen. However, according to various settings of confidence interval, the estimated operational risk by EVT sometimes is not better than that by the Standard method or Basic Index method.

Regarding empirical research, Mitra *et al.* (2015) found that there is a significant difference of operational risk between emerging and developed markets. The industrial sector, which is basically linked to business operations, is also one of the factors influencing the level of operational risk. Nevertheless, this impact is not as significant as market development. Using data of 137 European banks from 2008 to 2010, Barakat and Hussainey (2013) indicated that banks with a higher proportion of outside board directors, lower executive ownership, concentrated outside non-government ownership, more active audit committee, and operating under regulations promoting bank competition provide operational risk disclosure of higher quality. They also found that the impact of bank supervisors toward operational risk disclosure quality depends on the ownership structure of the bank. To increase the risk reporting quality in banks, they suggested maintaining board independence, enhancing audit committee activity, easing entry to banking requirements, and promoting a more proactive role for bank supervisors.

Regarding the literature of efficiency, ever since Farrell (1957) proposed the Frontier Function to measure efficiency, many scholars have used this concept to estimate efficiency and productivity. Pitt and Lee (1981) and Schmidt and Sickles (1984) extended the stochastic frontier model to panel data, but they assumed that technical efficiency is invariant for individual firms. Cornwell *et al.* (1990) and Battese and Coelli (1992;1995) proposed the advanced model, which allows us to estimate time-varying efficiency levels.

Many researchers have tried to evaluate the exogenous factors that affect technical or economic (cost) inefficiency. Although some studies applied the two-stage approach (Kalirajan and Shand, 1989) this two-stage procedure consists of inconsistent assumptions in the two estimation stages regarding the identical distribution of efficiency effects. Wang and Schmidt (2002) indicated that there are serious estimation biases in both stages. Huang and Liu (1994) and Battese and Coelli (1995) proposed a single-stage approach to simultaneously estimate the stochastic frontier function and technical inefficiency model.

Aside from those mentioned approaches, the semiparametric technique has become popular for scholars in recent years for measuring productivity and efficiency. Using a generalized additive model approach, Ferrara and Vidoli (2017) overcame the curse of dimensionality and permits to obtain efficiencies that take into account the effect of contextual variables. The concept of flexibility in this model is appropriate in making a more accurate model selection. Concentrating on the errors-in-variables, Seo and Jeong (2016) succeeded in developing an innovative approach that does not require any parametric assumptions for the distribution of the latent covariates. However, the semiparametric approach has not been widely used in empirical studies due to the lack of user-friendly software.

Regarding the literature about the impact of various risks on banks' efficiency, Kaparakis *et al.* (1994) noted that the higher the risks are, the greater the banks' management inefficiency is. They indicated that the higher the ratio of non-performance loans to total loans and the lower the owner's equity ratio are, the lower the management efficiency is for bank performance. The empirical results of Mester (1996) show that the inefficiency ratio of U.S. banks is between 6% to 9%, which is primarily from allocative efficiency. Among inefficiency factors, the higher the capital adequacy ratio is, the more efficient a bank is, because the capital adequacy ratio can reduce the risk of moral hazard.

Altunbas *et al.* (2000) argued that, considering the factors of risk and quality, the optimal scale of Japanese banks should be small. Their empirical results show that scale efficiency is sensitive to risks and the quality factor. Becchetti and Sierra (2003) found that technical inefficiency is a good post-event variable for predicting the possibility of bankruptcy. Phan and Daly (2014) illustrated that for the Vietnamese banking industry, while credit risk and operational risk have a positive effect on cost efficiency, liquidity risk has a reverse relation. Therefore, many banks in emerging markets take on risks as a motivation to achieve higher efficiency.

3. ESTIMATING OPERATIONAL RISK: A TOP-DOWN METHOD

3.1. Methods of Estimating Operational Risk

The Top-Down and the Bottom-Up methods have different applications. The first method attempts to fully weigh the operational risk of all companies or the industry level from top to bottom and then assigns results to each business line. As for a Bottom-Up approach, it is initiated from each procedure or business line and then adds them in order to determine the risk profile of the head office. While the Bottom-Up method seems to be a perfect methodology, the shortage of information makes this method difficult to apply in practice. Applying a Top-Down method can also validate if any operational risk information is missing.

The steps for carrying on a Top-Down method can be roughly described as follows. First, we determine the target variable, which should be highly relevant with operational risk. The next step is to find out any risk factors that would influence this target variable. After that, we assess the relationship between these risk factors and the target variable. The analysis of this part generally uses regression analysis. In the fourth step, it is necessary to confirm the risk of the target variable and part of this target variable that we explained in step 2. The task in the next step is to deduct the risk explained by step 2 from the target variable. We then use the residual part to measure operational risk. Finally, we go on to the previous steps to subdivide the risk of the operation.

To estimate operational risk from the Top-Down method, we adopt the multi-factor model as follows:

$$R_{it} = \alpha_{it} + \beta_{1i}I_{1t} + \beta_{2i}I_{2t} + \beta_{3i}I_{3t} + \beta_{4i}I_{4t} + \varepsilon_{it}, \quad (1)$$

where R_{it} is the gross income rate for bank i in period t, which is also known as the target variable; I_{1t} is the non-performing loan rate, which represents credit risk; I_{2t} is the weighted loan interest rate; I_{3t} is the rate of return for the stock price index; and I_{4t} is the rate of return for the exchange rate. Here, I_{2t}, I_{3t}, and I_{4t} represent market risk.

One of the problems we may have with time series models is the existence of the ARCH effect. Therefore, we adopt the Lagrange Multiplier test of Engle (1982) for such an existence. For banks that an ARCH effect, we use the Generalized Autoregressive Conditionally Heteroskedastic (GARCH) model of Bollerslev (1986). In this case, the conditional heteroskedastic variance σ_{it}^2 is:

$$\sigma_{it}^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \delta_1\sigma_{t-1}^2. \quad (2)$$

Finally, we measure operational risk as:

$$\sigma_\varepsilon^2 = (1 - R^2)\,\sigma_i^2, \quad (3)$$

where R^2 is the regression's explanatory power, and σ_i^2 is the variance of the residual of each bank in regression (1).

3.2. Unit Root Test

It is well known that there is a spurious relationship between variables for time series data if variables are non-stationary. To check if variables are stationary in our regression, we adopt two types of a unit root test: Augmented Dickey Fuller (ADF) (Dickey and Fuller, 1979) test and Kwiatkowski, Phillips, Schmidt & Shin (KPSS) test (Kwiatkowski *et al.*, 1992).[1] The variables under testing include each bank's gross income rate and non-performing loan ratio. In addition, for our multifactor model, each bank shares the same market risk factors, including the weighted loan interest rate, the rate of return for the stock price index, and the rate of return for the exchange rate, which are also under inspection.

The unit root test for each bank's gross income rate shows that there are 20 I(0) series and 4 I(1) series at the 5% significance level in Table 1. As for the non-performing loan ratio, there are only 7 I(0) series and 17 I(1) series at the same significance level. For the common market risk factor-weighted loan interest rate, rate of return for the stock price index, and rate of return for the exchange rate, they are all stationary series at the 5% significance level.[2]

3.3. Model Selection, Estimation, and Diagnostic Checking

To conduct a GARCH estimation for the gross income rate equation, we have to make sure the error terms of each regression equation are independently and identically

[1] The null hypothesis of ADF is that the variable has a unit root, and hence we consider the variables as non-stationary series. The null hypothesis of KPSS is that the variable is stationary. Only when the null hypothesis of ADF is rejected or the null hypothesis of KPSS is not rejected can the variable claim to be stationary; otherwise, the variable will be considered to have a unit root and further unit root test of the differenced series will be conducted repeatedly until the stationary of differenced series is found.

[2] **Unit root test for market risk factors**

Market Risk Variables	ADF Statistic	KPSS Statistic
Weighted loan interest rate #	-2.3597	0.1350
Rate of return for stock price index	-6.1371**	0.0852
Rate of return for exchange rate	-6.8546**	0.0624

Note: 1. ** represents significant at the 5% significance level; 2. # represents the ADF test with intercept and trend; no # represents the ADF test with intercept only; 3. The critical value at the 5% significance level for ADF with intercept and trend is -3.5578; 4. The critical value at the 5% significance level for KPSS with intercept and trend is 0.1460.

Table-1. Unit Root Test for the Gross Income Rate

	Gross income rate		1st difference of gross income rate		NPL ratio		1st difference of NPL ratio rate	
	ADF	KPSS	ADF	KPSS	ADF	KPSS	ADF	KPSS
Chang Hwa Commercial Bank	-3.802026**	0.134898			-0.713346	0.532057**	-7.748459**	0.225228
First Commercial Bank	-4.907583**	0.398254			-0.823964	0.582226**	-5.379954**	0.141026
Hua-Nan Commercial Bank	-3.254662**	0.242659			-1.138396	0.611723**	-7.130956**	0.144098
China Development Bank	-3.440903**	0.140704			-3.229952**	0.746037**		
Mega International Commercial Bank	-1.180312	0.232228			-1.632158	0.717241**	-4.942928**	0.406913
Hsinchu Business Bank	-3.291732**	0.245648			-1.798443	0.580642**	-8.104029**	0.229812
King's Town Bank	-1.84544	0.634441**	-11.25684**	0.41052	-1.393213	0.470116**	-5.514309**	0.316903
Taichung Business Bank	-3.742675**	0.136161			-0.839279	0.398247		
Central Trust of China	-2.115319	0.29236			-2.90321	0.620205**	-8.361521**	0.279331
Cathay United Bank	-3.13271**	0.153694			-2.118181	0.525097**	-4.33876**	0.098404
Taipei Fubon Bank	-1.679621	0.208314			-2.850922	0.689206**	-12.89396**	0.316075
Taiwan Business Bank	-5.857142**	0.11151			-0.729788	0.319351		
Bank of Kaohsiung	-1.371912	0.592413**	-6.59887**	0.234249	-1.534703	0.685785**	-6.185081**	0.123266
Cosmos Bank	-0.549225	0.444834	-8.55729**	0.265769	-1.725832	0.560499**	-6.784333**	0.143499
Union Bank of Taiwan	-3.291703**	0.18063			-3.092672**	0.595493**		
Bank Sinopac	-0.51479	0.230115			-2.92809	0.47492		
E. Sun Bank	-2.882329	0.260783			-1.833422	0.73223**	-9.313336**	0.234388
Yuanta Bank	-3.969648**	0.144005			-1.187108	0.586985**	-7.932674**	0.253333
Taishin Bank	-3.596549**	0.147977			-2.200569	0.665032**	-9.221827**	0.315651
Far Easten Bank	-3.13455**	0.145735			-1.591784	0.518882**	-8.804773**	0.231075
Ta Chong Bank	-3.744644**	0.082722			-1.567356	0.700724**	-6.578699**	0.152549
En Tie Bank	-4.528331**	0.426653			-2.791045	0.29316		
Jih Sun Bank	-3.168368**	0.448258			-2.059857	0.413182		
Taiwan Cooperative Bank	-1.1343	0.550302**	-9.542237**	0.116416	-0.104279	0.590665**	-6.827823**	0.39788

Note: 1. ** represents significant at the 5% significance level. 2. The critical value at the 5% significance level for ADF with intercept and no trend is -2.9604. 3. The critical value at the 5% significance level for KPSS with intercept and no trend is 0.4.

distributed (iid) with conditional heteroscedastic variance. We first run the ordinary least squares (OLS) for each bank's gross income rate equation after executing the first difference for I (1) variables. To check if the error term is iid, we adopt Ljung-Box's Q(p) statistic.[3] According to Enders and Siklos (2004) the number of lag length p is set at one-fourth of observation numbers. For our research from 2000 to 2008, which is forty-five quarterly data-points, the number of lag length is set at eleven. The null hypothesis is that the error term is white noise (iid). The testing result shows that there are only four banks' error terms that follow white noise. The remaining twenty banks' error terms appear to be white noise after suitable ARMA (p, q) filtering in Table 2.

After suitable ARMA (p, q) filtering to let the error term be white noise, we then adopt the Lagrange Multiplier test for the existence of ARCH effect. From our results, there are six banks' errors terms that reject the null hypothesis and accept the alternative hypothesis of the ARCH effect at the 10% significance level. For these six banks, we select the GARCH (1,1) model for estimation. The remaining eighteen banks' gross income rate equations are estimated by the OLS method if there is no ARMA (p, q) for the error term; otherwise, we use feasible generalized least squares. Lastly, we adopt a similar Ljung-Box's Q(P) statistic and Engle's Lagrange Multiplier statistic to test each equation's error term. The results show that they are all white noise and have no ARCH effect.

3.4. Estimation of Operational Risk

Among the twenty-four banks in our sample, for eighteen banks' gross income rate whose equations are estimated by OLS or FGLS, the annually operational risk of each bank is estimated as $(1-R^2)\hat{\sigma}^2 = (1-R^2)SSE/3$, where SSE is the sum of squared

[3] $Q(p)=T(T+2)\sum_{k=1}^{p}\frac{r_k^2}{T-K}$, where r_k is the autocorrelation coefficients of residuals for lag k periods.

Table-2. Ljung-Box's Q(p) Test

		Q(1)	Q(2)	Q(3)	Q(4)	Q(5)	Q(6)	Q(7)	Q(8)	Q(9)	Q(10)	Q(11)
Chang Hwa Commercial Bank	AR(1)	2.1453	2.9258	6.9524	6.9567	6.9567	7.084	7.0841	7.2944	7.5961	7.6298	10.558
First Commercial Bank		0.2553	1.6442	3.6283	3.6306	3.8105	3.8406	5.09	5.2391	6.216	7.6441	7.7378
Hua-Nan Commercial Bank	AR(1)	1.5434	3.656	4.6405	5.1223	5.1235	5.1237	5.9403	6.185	6.5304	6.6254	8.3203
China Development Bank	ARMA(1,4)	0.0832	0.7283	5.6226	5.8317	5.8467	6.5891	6.8276	6.8527	7.0066	7.695	8.3478
Mega International Commercial Bank	ARMA(2,1)	0.0786	0.5526	1.1733	5.3833	5.3842	6.1761	8.1222	8.1222	13.187	13.314	13.338
Hsinchu Business Bank	AR(1)	1.388	2.778	4.8324	8.9542	9.0749	10.407	12.25	12.684	12.692	14.728	15.926
King's Town Bank	AR(1)	0.6339	3.157	3.1571	3.2249	3.2851	3.3091	3.3789	3.6063	3.8549	4.4059	5.3775
Taichung Business Bank	AR(1)	0.1786	0.2113	1.5204	1.5204	2.806	2.9571	3.813	3.8291	3.9925	4.0849	4.1252
Central Trust of China	AR(1)	0.1325	1.5216	3.2983	3.3223	7.459	8.1145	12.662	13.902	14.001	15.153	16.648
Cathay United Bank	AR(1)	0.1809	1.0395	4.3566	6.789	6.83	9.2801	10.88	10.882	11.135	11.139	11.345
Taipei Fubon Bank	ARMA(2,1)	3.6478	3.7339	3.7374	4.0079	4.0106	4.727	8.3224	8.5578	10.364	12.956	12.999
Taiwan Business Bank	ARMA(1,1)	0.3041	0.4389	0.4635	6.0852	6.5219	6.7244	7.697	7.7248	9.2208	9.9368	10.056
Bank of Kaohsiung		0.8825	4.1407	4.1487	5.3526	5.6931	6.0369	6.3185	6.4895	6.5117	6.6997	8.1465
Cosmos Bank		4.7655	4.7744	5.7502	5.8292	7.6522	9.2224	10.486	11.872	12.236	12.246	12.267
Union Bank of Taiwan	AR(1)	0.3483	0.7664	2.1978	2.7766	3.0502	3.7368	9.9441	10.457	13.434	13.77	14.18
Bank Sinopac	AR(1)	0.0022	0.034	0.0703	1.03	2.3601	2.8273	3.589	3.59	3.7613	4.793	4.9764
E. Sun Bank	AR(1)	2.0681	2.2653	2.9492	3.6478	5.7157	5.8094	5.8446	6.1298	6.5509	8.2928	8.9619
Yuanta Bank	AR(1)	0.3606	2.9184	5.8044	7.1886	7.4927	8.8014	8.9672	9.1219	9.1778	9.3355	9.434
Taishin Bank	AR(1)	0.0061	1.3499	1.5459	5.5507	6.2384	7.5684	7.5946	8.2448	8.6583	8.6628	8.7921
Far Easten Bank	AR(1)	1.5972	2.8356	3.0284	3.7782	3.7782	4.2067	4.4748	4.7569	5.0946	5.8941	10.571
Ta Chong Bank	AR(1)	0.0088	0.0522	0.0545	0.384	0.4061	0.4742	0.8072	5.6318	5.9721	6.0412	6.1666
En Tie Bank		1.3721	2.2413	3.9944	4.1555	5.2097	6.9401	8.1328	8.6064	9.3183	10.124	10.172
Jih Sun Bank	AR(1)	0.0338	1.8191	6.1718	6.1773	6.1924	6.1924	7.7623	7.8503	7.9996	8.0048	8.0345
Taiwan Cooperative Bank	AR(1)	0.3014	0.3014	2.8656	2.8831	3.0382	3.0553	3.0915	4.775	4.7762	5.1272	5.2445

Note: All Q(p) are less than their critical value at the 5% significant level ($\chi^2_{0.05}(p)$

residual for four quarters in each year. For the remaining six banks' gross income rate whose equations are estimated by the Maximum Likelihood of GARCH (1,1) model, the yearly operational risk is the sum of four quarters' estimated conditional variance from the GARCH (1,1) model multiplied with the part of the gross income rate, which is not explained by model 2. Table 3 shows the calculated yearly operational risk for each bank.

4. IMPACT OF OPERATIONAL RISK ON COST EFFICIENCY

Taking banking as an intermediation of financial activities, we employ the intermediation method to select multiple inputs and multiple outputs for the model. Based on Battese and Coelli (1995) a trans-log cost function is set to estimate the cost frontier and cost inefficiencies of banks. We then investigate the impact of the sample banks' operational risks associated with other environmental variables toward the cost inefficiency of these same banks.

$$\ln(TC_{it}/P_{1it}) = \alpha_0 + \alpha_1 \ln Y_{1it} + \alpha_2 \ln Y_{2it} + \beta_2 \ln(P_{2it}/P_{1it}) + \beta_3 \ln(P_{3it}/P_{1it})$$
$$+\frac{1}{2}\alpha_{11}(\ln Y_{1it})^2 + \frac{1}{2}\alpha_{22}(\ln Y_{2it})^2 + \frac{1}{2}\alpha_{12}\ln Y_{1it}\ln Y_{2it} + \frac{1}{2}\beta_{22}\ln(P_{2it}/P_{1it})^2 + \frac{1}{2}\beta_{33}\ln(P_{3it}/P_{1it})^2$$
$$+\frac{1}{2}\beta_{23}\ln(P_{2it}/P_{1it})\ln(P_{3it}/P_{1it}) + \rho_{12}\ln Y_1 \ln(P_{2it}/P_{1it}) + \rho_{13}\ln Y_1 \ln(P_{3it}/P_{1it})$$
$$+u_{it} + v_{it}, \qquad (4)$$

where $i = 1, 2..., 24$; $t = 1, 2,..., 9$; u_{it} and v_{it} are random error terms, which are assumed to be individually and mutually independent. In greater detail, their distribution functions are as follows:

$$v_{it} \sim N(0, \sigma_V^2); \qquad (5)$$
$$u_i \sim N^+(m_{it} = \delta' Z_{it}, \sigma_u^2); \qquad (6)$$

Table-3. Operational Risk for Each Bank by the Top-Down Method

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Chang Hwa Commercial Bank	129.50	585.71	56.22	12.39	601.08	211.16	11.37	843.61	1,346.73	11.04	2.54
First Commercial Bank	29.23	11.68	18.87	8.40	2,288.90	1,336.18	41.74	279.15	15.06	6.24	46.67
Hua-Nan Commercial Bank	59.97	222.66	98.17	66.62	1,508.04	1,342.69	55.29	85.47	25.50	47.38	9.85
China Development Bank	4,382.45	2,116.71	3,153.56	917.68	2,277.56	15,576.65	2,304.60	308.28	251.49	121.10	624.35
Mega International Commercial bank	5.32	0.51	10.12	0.37	12.47	32.55	2.72	27.91	13.63	10.28	84.43
Hsinchu Business Bank	12.45	46.43	33.33	27.86	151.69	159.16	34.88	69.64	563.29	-	-
King's Town Bank	228.28	250.82	364.11	251.66	263.91	553.04	249.58	259.70	392.97	257.31	255.89
Taichung Business Bank	295.88	17.38	26.69	127.17	1,627.22	375.79	213.54	119.98	1,970.59	385.91	86.20
Central Trust of China	10.44	4.38	22.38	16.25	114.94	138.23	62.34	46.94	177.16	281.18	15.16
Cathay United Bank	73.10	358.92	27.28	9.89	1,803.11	616.44	115.51	159.70	122.19	182.32	5.89
Taipei Fubon Bank	1.66	3.98	9.01	7.21	3.22	15.29	15.50	25.51	31.92	51.14	14.61
Taiwan Business Bank	90.96	146.22	197.34	596.81	1,238.71	216.90	106.40	946.57	2,581.80	145.18	266.85
Bank of Kaohsiung	0.30	96.66	66.32	10.66	36.31	82.17	13.32	3.48	0.84	4.69	29.50
Cosmos Bank	100.22	19.63	127.73	6,540.04	758.63	210.95	306.39	835.51	2,861.03	11,907.17	1,214.39
Union Bank of Taiwan	6.33	13.56	4.64	2.63	55.22	12.46	8.52	190.46	212.84	31.25	176.22
Bank Sinopac	0.60	2.71	25.16	3.42	20.65	8.37	7.05	15.13	23.05	32.08	41.20
E. Sun Bank	61.36	76.22	58.50	63.48	298.11	16,157.84	397.36	152.25	2,133.92	468.64	63.88
Yuanta Bank	35.51	150.62	126.18	111.66	2,215.14	268.35	42.13	26.01	109.08	297.28	175.26
Taishin Bank	42.11	45.24	51.52	86.93	354.76	217.12	138.09	414.05	9,357.69	11,748.44	165.50
Far Easten Bank	302.77	423.16	233.29	339.05	494.91	4,900.21	334.67	334.76	419.71	292.87	245.53
Ta Chong Bank	14.69	92.15	34.81	208.60	1,161.24	6.46	147.53	19.03	3,410.13	283.17	311.30
En Tie Bank	3.34	32.15	15.62	27.30	193.30	49.80	23.64	594.61	612.37	4,060.12	40.73
Jih Sun Bank	68.73	80.04	72.69	64.71	208.42	80.63	8.13	280.36	7,283.06	680.82	554.27
Taiwan Cooperative Bank	-	-	5.74	4.90	2.29	6.00	8.80	2.70	113.05	4.86	11.57

Source: This table is calculated as explained in the section 3.4

u_{it} is cost inefficiency, which it means is defined as:

$$m_{it} = \delta_0 + \delta_1 Z_{1it} + \delta_2 Z_{2it} + \delta_3 Z_{3it} + \delta_4 Z_{4it} + \delta_5 Z_{5it} + \delta_6 Z_{6it} + \varepsilon_{it}; \quad (7)$$

where $i = 1, 2, \ldots, 24$; and $t = 1, 2, \ldots, 9$.

4.1. Data Sources and Selection of Variables

Our research data are primarily from the database of Taiwan Economic Journal (TEJ) and the annual statistical reports of Taiwan's financial industry. The main variables used in our two models are defined as follows.

(I) Output Variables:

(1) Discount and net loans (Y_1).

(2) Short-run and long-run investments (Y_2).

(II) Input Variables and Their Prices:

(1) Labor (X_1): Total number of employees in a bank. The price of labor (P1) is labor costs divided by the total number of employees.

(2) Capital (X_2): We use the net value of fixed assets as capital. The price of capital (P_2) is capital costs divided by the net value of fixed assets. The capital costs consist of the total amount of rents plus depreciation.

(3) Fund (X_3): The amount of funds includes total deposits and borrowing. The price of funds (P_3) is the costs of funds divided by total deposits and total borrowing. The primary costs of funds are the interest for using the funds.

(III) Inefficiency Factors:

According to the literature, there are three kinds of factors that might affect the cost inefficiency of banks. First are the basic characteristics of a bank, such as its scale, monopolistic power, number of branches, and structure of corporate governance. Salim *et al.* (2016) for instant, found that board size and committee meetings have a significantly positive influence toward Australia's banking industry. Second are the profitability variables, such as return on assets, return on net capital, and so on Phan and Daly (2014). Finally, the last group reflects the risk variables, such as non-performing loan ratio, capital adequacy ratio, and so on Altunbas *et al.* (2000). It is also indicated that those three groups of variable may have the both-side effect toward bank's efficiency. In order to analyze which factors influence the cost inefficiency of Taiwan's banking industry, we choose a couple of variables from the above three categories, associated with our main inefficient factors - three great risks. In order to avoid the collinearity problem, we conduct correlation analysis first. According to our empirical results of correlation analysis, we delete some variables that are highly correlated with other variables. Finally, we select the following variables as our inefficient factors.

(1) Ratio of loans to total assets (Z_1): It equals net loans divided by total assets. Since loans are the main business of traditional banks, the higher the ratio is, the more specialization the bank exhibits. Therefore, we would expect the ratio to have a negative relation with cost inefficiency. However, a modern bank has to have a diversified business. If the ratio of loans to assets is too high, then it usually indicates that the bank is weak in diversification. Therefore, the relation of this variable with inefficiency is ambiguous (Kwan, 2006).

(2) Number of branches (Z_2): Since more branches of a bank should simultaneously increase its benefits and management costs, the relation of this variable to inefficiency is ambiguous.

(3) Age of the institution (Z_3): According to the leaning theory and surviving theory, older bank tends to have a relative higher efficiency (Mester, 1996). Therefore, we expect that the age of a bank has a positive relation with its cost efficiency.

(4) Effect of financial holding group (Z_4): A dummy variable that equals one if a bank belongs to a financial holding group, and zero otherwise. Since a financial holding group owns economies of scale and economies of scope, we expect that the effect of a financial holding group on cost inefficiency is negative (Vennet, 2002).

(5) Capital Adequacy Ratio (CAR): Measures the ability of a financial institution to meet its obligations by comparing its capital to its assets. The formula of CAR is

CAR = (1st-tier capital + 2nd-tier capital) / (Risk-weighted assets)

This index quantifies the ability to undertake credit risk and market risk through the qualified capital of the bank. When banks raise their capital adequacy ratio and the ability for managing capital and risk, capital utilization efficiency can be strengthened along with the sound management of bank operations. An improvement of capital adequacy regulation would reduce risk, raise efficiency, and suppress the emergence of the moral hazard (Mester, 1996). Therefore, we expect a negative relationship between the capital adequacy ratio and cost inefficiency.

(6) Operational Risk (Z_6): We use two methods to calculate the operational risk of Taiwan's banks. The operational risk of model one is calculated according to the basic index method suggested by Basel II. It is the gross income of each bank times a fixed ratio (15%). The operational risk measurement of model 2 suggested by this paper is from the top to bottom (Top-Down) view of the Multi-Factor Model. The operational risk comes from inadequate internal processes, persons, and systems or external events. Not like other financial risk (market risk or credit risk), when operational risk is increasing, a high reward is not accompanied as a trade-off and banks' business efficiency drops instead. We thus expect that the operational risks of the two models both have a positive correlation with cost inefficiency.

4.2. Empirical Results of the Cost Function

Based on the approach of Battese and Coelli (1995) we use the software Frontier 4.1 to estimate the Trans-log cost model and the inefficient model simultaneously by the Maximum likelihood method. We present the empirical results of the cost model in Table 4. Since $\sigma^2(=\sigma_v^2+\sigma_u{}^2)$ and γ ($=\sigma_u^2/\sigma^2$) are both significantly different from zero, this shows that it is suitable to set the inefficiency model to estimate the influence of environmental factors. Although Table 4 shows the estimated parameters of all combination terms of output and input variables, the effects of all variables towards the total costs must be inspected by marginal effects, which should be calculated and tested by the partial derivatives of each variable on the whole equation.

According to microeconomic theory, a typical cost function must fit the regularity conditions.[4] Since the Trans-log function is a second degree of approximation of a true cost structure, it is necessary to use the first derivative to inspect and test the theoretical attributes of each output and input variable. The results of the Wald test[5] illustrate that the marginal effects of outputs are monotonic and the marginal effects of input prices are non-decreasing.

[4] The formal conditions proposed by Varian (1992) are : (1) the cost function is a non-decreasing function of factor prices, (2) the cost function is homogeneous first-order of factor prices, (3) the cost function is a concave function of factor prices, and (4) the cost function and factor prices are a function of the continuous second derivative.

[5]

Null hypothesis	$H_0: \dfrac{\partial TC}{\partial Y_i}=0$	
Alternative hypothesis	$H_1: \dfrac{\partial TC}{\partial Y_i}>0$	$i=1,2;$
Null hypothesis	$H_0: \dfrac{\partial TC}{\partial P_i}=0$	
Alternative hypothesis	$H_1: \dfrac{\partial TC}{\partial P_i}>0$	$i=1,2,3;$

Table-4. Empirical Results of the Stochastic Frontier Cost Function

Variable	Model 1			Model 2		
	Parameter	Standard	t-	Parameter	Standard	t-value
Constant	-	4.9214	-	-	1.744899	-16.418
$\ln Y_1$	4.5358***	0.4760	9.5292	5.062244***	0.378933	13.3592
$\ln Y_2$	-1.4161***	0.2241	-	-	0.22982	-6.41149
$\ln(P_2/P_1)$	-1.2949***	0.4564	-	-1.23164**	0.528064	-2.33236
$\ln(P_3/P_1)$	2.0322***	0.5100	3.9846	1.88959***	0.473944	3.98695
$(½)(\ln Y_1)^2$	-0.2963***	0.0449	-	-	0.052541	-6.06353
$(½)(\ln Y_2)^2$	-0.0601***	0.0217	-	-	0.021513	-2.66958
$(½)(\ln Y_1)(\ln Y_2)$	0.2780***	0.0561	4.9524	0.278383***	0.05497	5.064255
$(½)[\ln(P_2/P_1)]^2$	0.0208	0.0445	0.4675	0.023727	0.041625	0.570025
$(½)[\ln(P_3/P_1)]^2$	0.2324***	0.0580	4.0066	0.240207***	0.054112	4.439072
$(½)[\ln(P_2/P_1)][\ln(P_3/P$	-0.1845***	0.0642	-	-	0.070757	-2.67751
$\ln Y_1 * \ln(P_2/P_1)$	-0.0104	0.0410	-	-0.0151	0.0472	-0.31997
$\ln Y_1 * \ln(P_3/P_1)$	0.0258	0.0341	0.7579	0.038536	0.036898	1.044396
$\ln Y_2 * \ln(P_2/P_1)$	0.0436*	0.0230	1.8923	0.045357	0.028416	1.596182
$\ln Y_3 * \ln(P_3/P_1)$	-0.0139	0.0211	-	-0.01633	0.023886	-0.68388
sigma-squared: σ^2	0.01□5***	0.0039	4.7762	0.015815***	0.002464	6.418331
Gamma: γ	0.8079***	0.0564	14.325	0.763228***	0.040106	19.03037
LR test	174.2503			174.8017		

Note: Operational risk in Model 1 and Model 2 is calculated by the Basic Indicator Approach and Top-Down Method, respectively; *** represents significance at the 1% level;** represents significance at the 5% level; * represents significance at the 10% level.

Combined with the result from Table 4, we find that relative to the prices of capital and fund, the price of labor will drive the total cost higher.[6]

4.3. Factors Influencing Cost Inefficiency

Table-5. Empirical Results of the Inefficiency Equation

Variable	Model 1			Model 2		
	Parameter	Std. error	t-value	Parameter	Std. error	t-value
Intercept (Z_0)	2.6850***	0.2990	8.9786	2.5443***	0.2896	8.7848
Z_1	-0.0311***	0.0039	-8.0167	-0.0301***	0.0039	-7.7759
Z_2	-0.0005***	0.0002	-2.6216	0.0012	0.0011	1.1814

[6] **The Result of the Wald Test (Accomplished by Limdep)**

Variable	Model 1			Model 2		
	Parameter	Standard error	Wald	Parameter	Standard error	Wald
$\partial TC/\partial Y_1$	0.147814***	0.019259	7.675	0.145766***	0.02012	7.245
$\partial TC/\partial Y_2$	0.460276***	0.086146	5.343	0.450343***	0.089593	5.027
$\partial TC/\partial P_1$	97858.29***	35320.6	2.771	100681.8***	35937.4	2.802
$\partial TC/\partial P_2$	.15D+09***	.52D+08	2.87	.15D+09***	.53D+08	2.911
$\partial TC/\partial P_3$	.11D+10***	.24D+09	4.649	.12D+10***	.24D+09	4.715

Note: **** represents significance at the 1% level; ** represents significance at the 5% level; * represents significance at the 10% level.*

Z_3	-0.0164***	0.0022	-7.5473	-0.0152***	0.0038	-4.0076
Z_4	-0.1643***	0.0489	-3.3613	-0.1680***	0.0467	-3.5999
Z_5	-0.0149***	0.0044	-3.3877	-0.0147***	0.0054	-2.7224
Z_6	3.97E-05***	1.42E-05	2.7981	1.24E-05**	5.78E-06	2.1447

Note: *** represents significance at the 1% level;** represents significance at the 5% level; * represents significance at the 10% level.

Risk Variables:

(1) Capital Adequacy Ratio (Z_1): This factor plays two roles in a banking risk management system. First, its "risk sharing function" will reduce the losses, therefore offering more protection for depositors as well as degrade the recourse to deposit insurance. Second, it limits the opportunity of moral hazard by stockholders who might aggressively take on excessive risk (Pessarossi and Weill, 2015). The empirical result shows that there is a significantly negative relationship between the capital adequacy ratio and cost inefficiency. This result is unsurprising and consistent with some reliable research (Fiordelisi *et al*., 2011; Chortareas *et al*., 2012; Berger and Bouwman, 2013).

(2) Operational Risk (Z_6): According to the Basel Committee for Banking Supervision (BIS), operational risk comes primarily from factors such as inappropriate staff, inappropriate internal operation procedures, errors in the operating system, and risk of loss from the environment. Therefore, its effect certainly differs from credit risk or market risk, which usually has a trade-off with return. Furthermore, high operational risk not only does not increase returns, but has a bad impact that results in low technical efficiency as well as poor allocative efficiency (Sun and Chang, 2011). The empirical result shows that, for both models, operation risk has a significantly positive impact on cost inefficiency, which, in general, is in line with Berger and Mester (1997) indicating that poor managers may be unfavorable to both cost and risk management. As Mitra *et al.* (2015) suggested, regardless of the calculation methods or industrial sector, operational risk will induce downward economic efficiency.

Comparing the magnitude of operation risk calculated from the two models, we find that the marginal effect of the operational effect on cost inefficiency in model 1 is about three times greater than the one in model 2. According to Apostolik and Donohue (2015) the Basic Indicator Approach is just an inferior alternative measurement for the magnitude of operational risk, in which banks may set up a greater capital charge than they really need to. Our result indeed supports the literature of overestimation in capital charge for operational risk by the Basic Indicator Approach, and also implies that the operational risk estimated by the multi-factor model of the Top-Down method would cut the degree of negative impact of operational risk toward cost efficiency. Therefore, compared with the basic index method in this situation, the multi-factor model of the Top-Down method is better in analyzing the relationship of operational risk and efficiency. Nevertheless, one interesting question that may arise is how the level of market development would influence operational risk and therefore drive economic efficiency (Mitra *et al*., 2015). Actually, the answer to this question is far beyond the information we have, however, it is a considerable suggestion for a research direction in the future.

Control Variables:

(1) The ratio of loans to total assets (Z_1): The relationship between the ratio of loans to total assets and cost inefficiency is significantly negative. From the balance sheets of Taiwan's aggregate financial industry from 2000 to 2008, we find that total loans are about four and half times the sum of long-run and short-run investments, indicating that loans are Taiwan banks' major business. Therefore, a bank with a higher ratio of loans to total assets means it is more specialized, which leads to high management efficiency.

(2) Number of branches (Z_2): Cost inefficiency is smaller when a bank has more branches in model 1. Nevertheless, the relationship between these variables is reverse but insignificant in model 2. This evidence suggests that banks operating in Taiwan may have good administrative management, which can increase efficiency.

(3) Age of bank (Z_3): In both models, the ages of bank have a negatively significant relation with cost inefficiency. This is just because of the learning effect, which brings valuable experience in doing business as well as running management. Therefore, older banks in Taiwan are more efficient than younger banks.

(4) Whether joining a financial holding company (Z_4): Our empirical result shows that a bank joining a financial holding company will raise its efficiency. This is because a financial holding company contains the advantage of economies of scale and economies of scope, when all bank businesses are becoming more complicated under the impact of globalization.

5. CONCLUSION

The measurement and management of operational risk in the banking industry have dramatically changed over the last decade due to changes in business lines and the environment. Starting from 1998, the Basel Committee on Banking Supervision has been developing the measurement of capital charge for operational risk. According to Basel II, there are three proposed approaches, and a bank might choose a specific approach depending on its own characteristics. The most simply approach, the Basic Indicator, apparently is not a good measurement, because using this method often means charging a higher capital requirement than what a bank really needs. Conversely, while the Advanced Measurement Approach seems to be most favorable, it requires some information that sometimes is very hard to access. Therefore, in this paper we develop a Top-Down method that requires much cheaper data information.

The Top-Down method we adopt herein derives from the idea that the capital requirement for operational risk is a variance of the regression of the gross income rate (a target variable that is highly relevant for all risks) with credit risk and market risk. In order to accomplish this process, we conduct a series of econometric tests before using a GARCH model. We also calculate the capital charge for operational risk using the Basic Indicator Approach in order to compare it with the Multifactor model in the Top-Down Method.

Using the Stochastic Frontier Approach proposed by Battese and Coelli (1995) the results we find are consistent with some studies in the literature. That is, regardless of the calculation method, operational risk has a significantly positive impact on cost inefficiency and therefore drives efficiency down (Berger and Mester, 1997; Sun and Chang, 2011; Mitra *et al.*, 2015). More interestingly, we find from the evidence of Taiwan's banking industry that the impact of operational risk calculated by the Basic Indicator toward cost efficiency is three times greater than that estimated by our Top-Down method. This result is strongly supported by the literature (Apostolik and Donohue, 2015) in that using the Basic Indicator Approach usually overestimates the capital requirement for operational risk. However, following the results of Mitra *et al.* (2015) we suggest that future research investigate the relationship between operational risk and efficiency under different levels of market development.

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