CENTRAL BANK &
FINANCIAL SERVICES
AUTHORITY OF IRELAND

3/RT/05 **May 2005**

Research Technical Paper

Measuring Bank Profit Efficiency

Trevor Fitzpatrick * **Kieran McQuinn** †

Economic Analysis and Research Department
Central Bank and Financial Services Authority of Ireland
P.O. Box 559, Dame Street
Dublin 2
Ireland
http://www.centralbank.ie

*European Central Bank. E-Mail: trevor.fitzpatrick@ecb.int.

†E-Mail: kmcquinn@centralbank.ie. The views expressed in this paper are the personal responsibility of the authors. They are not necessarily held either by the CBFSAI or the ECB. The authors would like to thank Karl Whelan (CBFSAI) for his comments on an earlier draft of the paper. Any errors are the sole responsibility of the authors.

Abstract

This paper proposes that a variant of the Battese and Coelli (1995) inefficiency model be applied as a unified and consistent framework in exploring the determinants of credit institutions' profit inefficiency scores. To date, work concerned with the potential determinants of credit institutions' inefficiency levels has addressed the issue in either a single-step or multi-step process. In the former, inefficiency scores are conditioned by region and bank-specific indicators, while in the latter, generated inefficiency scores are subsequently regressed on a set of indicators. The approach proposed here allows these issues to be explored jointly in a statistically consistent manner. The model is applied to a sample of banks from Ireland, the UK, Canada and Australia.

1 Introduction

One prominent feature of studies of credit institution profit inefficiency has been an attempt to delineate the effects on inefficiency measures due to institution-specific (i.e. bad management) or environment-specific (i.e. bad luck) factors. Credit institutions in country Y may have a relatively greater inefficiency level vis-à-vis a credit institution in country X because of factors specific to the local economy (say risk of problem loans, lower economic growth etc.) or because of factors germane to the institution itself (poor managerial practices). The potential of both of these factors to impinge on inefficiency levels is not in question. However, the manner in which the issue is explored empirically is.

A brief review of the literature addressing this issue reveals two main approaches (so called one-step and multi-step approaches). In the one-step approach, the initial generation of the inefficiency score is conditioned by the inclusion of both bad luck and bad management variables. Berger and Mester (1997), for example, included both a bad luck and a bad management variable in their estimated cost and profit functions. Their evidence, generally, tended to support the bad management hypothesis i.e., having controlled for bad luck, credit institutions with loan performance problems also tended to have high costs and low profits "consistent with the bad management hypothesis." This approach is not just confined to parametric applications, Lozano-Vivas et al. (2002) consider 10 environmental variables in the non-parametric data envelopment analysis (DEA) model and found that relatively weak macroeconomic performance as suggested by the country-specific environmental indicator coincided with a greater change in the inefficiency score of the institution in question. Thus, they argue that, in order to achieve a cross-country comparison of inefficiency scores on an "equal footing", one needed to include these country-specific variables in the original determination of the score.

In contrast to this first-stage approach, Maudos et al. (2002), adopt a multi-stage approach whereby, inefficiency scores are initially estimated parametrically and the resulting scores are then regressed on a series of variables deemed "potential correlates" of inefficiency. These potential correlates include, size variables, specialisation variables, other characteristics specific to the bank and characteristics of the markets in which the banks operates. Maudos et al. (2002) found that certain scale variables, loan to asset ratios, market concentration, higher risk and market growth indicators had significant and the expected signed impact on inefficiency scores. Using different panel data estimators, Fitzpatrick and McQuinn (2005) found evidence of a significant negative relationship between cost inefficiency scores and loan loss reserves in the same second stage manner.

Significant drawbacks can be identified with both approaches. In the first instance, inefficiency scores are not directly related to potential correlates of inefficiency. One cannot, for instance, directly estimate the individual effects of either bad management or bad luck on inefficiency levels. In the two-stage approach, the first stage involves the specification and estimation of the stochastic frontier function and the prediction of inefficiency effects. This estimation is carried out under the assumption that these inefficiency effects are identically distributed with one-sided error terms. However, the second stage involves the specification of a regression model for predicted inefficiency effects, which contradicts the assumption of an identically distributed one-sided error term in the stochastic frontier.

As a means of addressing this issue within a unified and consistent framework, we propose a variant of the increasingly popular Battese and Coelli (1995) model.[1] In short, we believe this stochastic model enables the generation of profit inefficiency levels for a sample of credit institutions, while simultaneously enabling these scores to be related to a set of explanatory variables.

In the next section we present the Battese and Coelli (1995) inefficiency model. Section three outlines the results of the empirical application and a final section offers some concluding comments.

2 A Stochastic Model of Profit Inefficiency

The Battese and Coelli (1995) model simultaneously allows for the generation of inefficiency scores and the regression of these scores on a series of potential explanatory variables. The model constitutes an improvement, in consistency terms, on previous models of inefficiency where inefficiency scores were estimated in a first-step and subsequently regressed on a series of explanatory variables. The model was postulated in the context of a stochastic production function. However, we follow Rahman (2003) and assume that a profit function behaves in a manner con-

[1] A similar application in an agricultural context was proposed by Rahman (2003).

sistent with the stochastic frontier concept. Profit efficiency, sometimes referred to as 'total' efficiency, differs from, cost efficiency in that it not only requires technical efficiency and both input and output allocative efficiency, it also requires that technical efficiency and both types of allocative efficiency be achieved at the proper *scale*. Therefore, a credit institution may not be operating on the profit frontier due to scale inefficiency.

For the purposes of this paper we use the alternative profit function specified by Berger and Mester (1997).[2] Combining the Berger and Mester (1997) profit function and the Battese and Coelli (1995) inefficiency model we get the following

$$\pi_{it} = f\left(Y_{it}, W_{it}, E_i\right) e^{(\eta_{it} - A_{it})}, \tag{1}$$

$$A_{it} = I_{it}\rho_1 + \psi_{it} \tag{2}$$

where

π_{it} = institution $i's$ profit in period t,

Y_{it} = vector of outputs,

W_{it} = vector of input prices,

E_i = country or region-specific variable,

η_{it} = independent and identically distributed errors i.e. $\eta \sim N\left(0, \sigma_\eta^2\right)$,

A_{it} = non-negative random variable (inefficiency) which is assumed to be independently distributed, such that A_i is obtained by truncation at zero of the normal distribution with mean $I_{it}\rho_1$ and variance σ_A^2,

ρ = vector of parameters to be estimated,

I_{it} = vector of variables which may influence the profit inefficiency of a credit institution,

ψ_i is defined as the truncation of the normal distribution with zero mean and variance σ^2 such that the point of truncation is $-I_{it}\rho_1$. Therefore $\psi_i \geq -I_{it}\rho_1$. As noted by Battese and Coelli (1995), these assumptions are consistent with A_i being a non-negative truncation of the $N\left(I_{it}\rho_1, \sigma_A^2\right)$ distribution.

(1) and (2) are estimated simultaneously using maximum likelihood estimation. The likelihood function and its partial derivatives are presented in Battese and

[2] See Vander-Vennet (2002) for a discussion of the merits of the alternative profit function versus the standard specification in the context of credit institutions.

Coelli (1993) where the likelihood function is expressed in terms of the variance parameters $\sigma^2 = \sigma_\psi^2 + \sigma_A^2$ and $\theta = \sigma_A^2/(\sigma_\psi^2 + \sigma_A^2)$

The key aspect of this system is that both (1) and (2) are estimated simultaneously. Therefore, the inefficiency model given by (2) will impact on the parameter estimates obtained in the profit function (1).

2.1 Data

The bank level data used are consolidated data from large commercial banks and are all sourced from Bankscope[3]. The data are deflated with the relevant consumer price index (CPI) for each country. We use commercial banks to minimise the risk that differences in profit efficiency may be due to different production technologies or other effects from being a non-commercial bank. Any institutions with missing data or implausible values were omitted. In addition, any non-domestic subsidiaries reporting consolidated accounts from any of the remaining three countries were also removed to prevent double counting. In countries where mergers had occurred during the sample period, the institutions concerned were dropped in order not to bias the results. The institutions used are banks headquartered in four different countries - Canada, the UK, Ireland and Australia. We focus on institutions from these countries (frequently labelled as 'Anglo-Saxon') because of the relatively similar nature of the financial systems in operation there.[4] We are attempting to focus on cross-country differentials which are due to exogenous economic conditions and internal managerial performance rather than on the potential effects on inefficiency levels of inherently different banking systems. This left a seven year (1996-2002) balanced panel of 55 different banks - 11 each from Canada and Australia, 5 from Ireland and 28 from the UK.[5]

In choosing the inputs, outputs and profits of a credit institution we follow the approaches of Berger and Mester (1997), Maudos et al. (2002) and Vander-Vennet (2002). Profits are defined as the difference between interest plus non-

[3]Produced by Bureau Van Dijk (BVD).

[4]International financial systems are frequently distingushed between the Anglo-Saxon model (i.e., the UK, north America, Canada, Australia, and New Zealand etc.) and the continental European model. The difference between these models lies in the manner in which ownership, control, and regulation are organised. For more on this see Franks and Mayer (1994).

[5]The complete list of institutions used is available, upon request, from the authors.

interest income minus interest and non-interest expenses. We specify two outputs, (Y_1 = total loans Y_2 = total other earning assets)[6], and three inputs (W_3 = price of labour (total personnel expenses/total assets),[7] W_4 = price of physical capital (non-interest expenses - personnel expenses / corrected fixed assets) and W_5 = price of financial capital (total interest expenses / total deposits)). We also specify the dependent variable as $\ln(\pi^*) = \ln(\pi + |\pi^{min}| + 1)$, where $|\pi^{min}|$ is the absolute value of the minimum value of profits in the sample. Some credit institutions report a negative profit. Given our log-linear specification, we adjust the profit levels in the sample such that the profit level for the institution with the largest negative amount corresponds to $\log(0+1) = 0$. We also seek to minimise the effects of large scale differentials amongst the institutions in the sample by normalising both output variables by an institution's total assets. Macroeconomic data used in the analysis are taken from the OECD[8]. In particular we use the GDP growth rate and the standardised unemployment rate (the percentage of the civilian labour force). Sample means for each variable are presented in Table 1 (insert Table 1 here).

3 Empirical Model and Results

The model given by (1) and (2) is estimated by maximum likelihood using FRONTIER 4.1 (Coelli (1996)). In specifying a functional form for (1), we adopt the flexible functional translog profit function for each institution i. The system estimated is as follows

[6]We also explored the use of off-balance sheet assets as the second output, however, these indicators were not avilable for all of the institutions in the sample.

[7]We use total assets instead of total employees as the relevant denominator owing to the absence of employee data for many credit institutions in the sample. As noted by Maudos et al. (2002) this definition can be interpreted as labour cost per worker adjusted for differences in labour productivity as $PE/TA = PE/NE \times NE/TA$ where PE is personnel expenses, NE is number of employees and TA is total assets.

[8]OECD Economic Outlook Number 75 - Statistical Annex Tables.

$$
\begin{aligned}
ln(\pi^*_{it}) &= \beta_0 + \sum_{j=1}^{2} \beta_j \; lnY_{ijt} + 1/2 \sum_{j=1}^{2}\sum_{k=1}^{2} \beta_{jk} \; lnY_{ijt} \; lnY_{ikt} + \sum_{j=3}^{5} \beta_j \; lnW_{ijt} \\
&\quad + 1/2 \sum_{j=3}^{5}\sum_{k=3}^{5} \beta_{jk} \; lnW_{ijt} \; lnW_{ikt} + \sum_{j=1}^{2}\sum_{k=3}^{5} \beta_{jk} \; lnY_{ijt} \; lnW_{ikt} + \\
&\quad \sum_{j=1}^{3} \alpha_j E_j + \psi_{it} - A_{it} \qquad (3) \\
A_{it} &= \sum_{j=1}^{59} I_{jt}\rho_1 + \psi_{it} \qquad (4)
\end{aligned}
$$

Along with the standard inputs and outputs in the profit function we also include three country-specific dummies, (E_j), for Canada, Ireland and the UK. Thus, we are allowing for cross-country differences in the profit levels of the different institutions. Turning to the inefficiency model (4), we follow Schmalensee (1985) in adopting dummy-variables as indicators of firm-specific or managerial performance variables. While others have used the ratio of a credit institution's loan loss provisions to its total assets as a proxy for such influences, we believe the use of firm-specific dummies is preferable, particularly, given the panel nature of the data.[9] We include 54 dummies, $(\sum_{j=1}^{54} I_i)$, and exclude the credit institution which had the nearest average efficiency score to the sample average in an earlier run of the model. In order to capture the potential impact of adverse macroeconomic conditions within a country we include, in the 'I' vector, both the GDP growth rate and the standardised unemployment rate for each country $(\sum_{j=55}^{56} I_j)$.[10] Finally, we also include country-specific dummies in the inefficiency model $(\sum_{j=57}^{59} I_j)$. Thus, we are allowing for potential differences in both the level and efficiency of profits across countries for the credit institutions concerned. Consequently, we have 59 variables in the inefficiency model.

[9] The definition of specific and general provisions varies across countries as do banks discretion in provisions for loans. Provisions tend to be based on historical averages of the institutions, consequently, they do not exhibit much within-group temporal variation. In addition loss provisions were not available for all institutions which would have reduced the size of the sample further.

[10] We also explored the use of output gap estimates for each country. The correlation coefficient between the GDP and unemployment rates was -0.02 per cent suggesting that multi-collinearity between these variables was not a potential problem.

Tables 2 (insert Table 2 here) and 3 (insert Table 3 here) present the results for the profit function and the inefficiency model respectively. For the profit function, 58 per cent of the variables are significant at the 5 per cent level. This compares quite favourably with other similar-type applications. Results for the three country dummies suggest that credit institutions from Canada have significantly lower profit levels than those of Australian institutions while UK institutions have significantly *higher* profit levels. Of interest also in Table 2 is the result for the variance parameters - θ in particular. We note that the estimated value of the variance parameter θ is greater than 0.5 which suggests that efficiency effects are likely to be significant in the analysis of institutions' profit levels across countries.

Table 3 reports the results of the inefficiency model. As the dependent variable is the level of *inefficiency*, a positive coefficient suggests that the variable in question increases the level of inefficiency. We suppress the results for the bank level dummies.[11] In total 43 per cent of the dummies are significant at the 10 per cent level. Of these coefficients 30 are positively signed while 24 are negative. Both the 'bad luck' variables have the hypothesised effect. An increase in the GDP growth rate for a particular country decreases the profit inefficiency of a credit institution. Conversely, an increase in the unemployment rate in a country increases the level of inefficiency. Table 3 also reports the results of six likelihood ratio tests conducted on the model. The first null hypothesis examines whether inefficiency effects are absent from the model. This is strongly rejected by the data. Tests 4 and 5 examine whether the inefficiency model can be restricted to exclude the bank-level dummies and the macro variables respectively. In both cases we can reject the null hypothesis at even the one per cent level. Therefore, our model offers quantitative evidence of the effects of both of these potential influences on the level of profit inefficiency within credit institutions. The second likelhood ratio test rejects the null hypothesis of a Cobb-Douglas specification for the profit function vis-à-vis the more flexible translog.

In terms of profit efficiency levels we also find evidence of significant cross-country differentials. UK credit institutions appear to be significantly more inefficient than their Australian counterparts. A possible explanation for this result is that the average price of labour is higher for UK institutions than the other

[11] They are available from the authors upon request.

countries considered[12] The UK component of the sample contains a relatively large number of institutions with significant capital market, private banking, and asset management operations. This may entail higher profit levels achieved with relatively higher labour input costs. Both sets of country-level impacts for the profit function and the inefficiency model are supported by the results of likelihood ratio tests 3 and 6 in Table 3.[13]

A statistical summary of the profit inefficiency scores is presented in Table 4 (insert Table 4 here). We split the sample of credit institutions into 'big', 'medium' and 'small' sizes based on the sample averages of the total assets series for each credit institution.[14] As might be expected we find that the large category reports the lowest average size of profit inefficiency at 21 per cent of profits, with the medium and small category reporting similar average scores of 46 and 41 per cent respectively. Overall, it is evident that a sizeable portion of profits (21 - 46 per cent on average) is being lost across the sample due to sub-optimal technical, allocative and scale efficiency. The range of results is largest for the small category with an almost 70 per cent difference between the largest and the smallest inefficiency level.

In terms of comparing our results with previous work, most of the empirical efficiency work on European, (Altunbas et al. (2001)), Australian, (Sturm and Williams (2004)) and UK institutions, has tended to concentrate on cost efficiency. Amel et al. (2004), provide a comparative review of profit efficiency in their discussion of consolidation within the financial sector. They find an average level of profit efficiency of about 50 per cent but, these estimates are very sensitive to specification and estimation methods. A comprehensive study for the US (Clark and Siems (2002)), using stochastic frontier analysis among other techniques, finds profit efficiency scores ranging from 58 per cent to 69 per cent depending on the measurement of inputs and outputs.

[12]The price of labour in UK institutions is, on average, 58 per cent, 20 per cent and 2 per cent greater than the relative figures for Irish, Australian and Canadian banks for the sample.

[13]The significance of the country-specific dummies, particularly in the profit function, may suggest evidence of different production technologies across the different countries.

[14]This results in 18 credit institutions in both the big and small category and 19 in the medium group.

4 Conclusions

In this paper, we have presented a variation of the Battese and Coelli (1995) model of inefficiency as a means of exploring the profit inefficiency of credit institutions. We believe this approach has the specific advantage of statistical consistency in that the stochastic profit function and the inefficiency model used are estimated simultaneously.

Our results suggest that both the commonly hypothesised 'bad management' and 'bad luck' factors appear to have some influence on inefficiency levels for the present sample. We differ from previous studies by using institution-specific dummies as a means of capturing managerial influences on efficiency. Evidence is also found of significant cross-country differentials in both the levels and inefficiency of profits. This is an interesting result given that the financial systems in the countries are relatively similar; though doubtlessly differing in terms of magnitude. We also note that a sample-wide average of 36 per cent of profits is lost due to inefficiencies.

Many additional factors can be explored within the 'I' vector in the inefficiency model. These include various indicators of market structure such as branch density, concentration, the presence of non-domestic banks and overall domestic banking performance. Our application here serves to highlight the potential usefulness of the model, while paving the way for future work.

References

[1] Altunbas, Y., Gardener, E., Moyneux, P. and Moore B. (2001). “Efficiency in European banking,” *European Economic Review*, 45, 1931-1955.

[2] Amel, D., Barnes, C., Panetta, F. and Salleo, C. (2004). “Consolidation and efficiency in the financial sector: A review of the international evidence,” *Journal of Banking and Finance*, 28, 2493-2519.

[3] Battese, G. and Coelli, T. (1993). A stochastic frontier production function incorporating a model for technical inefficiency effects, Working Paper 69, Department of Econometrics, University of New England.

[4] Battese, G. and Coelli, T. (1995). “A model for technical inefficiency effects in a stochastic frontier production function for panel data,” *Empirical Economics*, 20, 325-332.

[5] Berger, A. and Mester, L. (1997). Inside the black box: What explains differences in the efficiencies of financial institutions, Working Paper 97-1, Federal Reserve Bank of Philadelphia.

[6] Clark, J. and Siems, T. (2002). “X-efficiency in banking: Looking beyond the balance sheet,” *Journal of Money Credit and Banking*, 34, 987-1013.

[7] Coelli, T. (1996). A computer program for stochastic frontier production and cost function estimation, Working Paper 96/07, Centre for Efficiency and Productivity Analysis (CEPA).

[8] Fitzpatrick, T. and McQuinn, K. (2005). “Cost effieincy in UK and Irish credit institutions,” *The Economic and Social Review*, 36, 45-66.

[9] Franks, J. and Mayer, C. (1994). Corporate control: A synthesis of the international evidence, IFA Working Paper 165-92, London Business School.

[10] Lorenzo-Vivas, A., Pastor, J. and Pastor, J. (2002). “An efficiency comparison of banking systems operating under different environmental conditions,” *Journal of Productivity Analysis*, 18, 59-77.

[11] Maudos, J., Pastor, J., Perez, F. and Quesada, J. (2002). “Cost and profit efficiency in European banks,” *Journal of International Financial Markets Institutions and Money*, 12, 33-58.

[12] Rahman, S. (2003). “Profit efficiency among Bangladeshi Rice farmers,” *Food Policy*, 28, 487-503.

[13] Schmalensee, R. (1985). “Do markets differ much?,” *American Economic Review*, 75, 341-351.

[14] Sturm, J. and Williams, B. (2004). “Foreign bank entry deregulation and bank efficiency: Lessons from the Australian experience,” *Journal of Banking and Finance*, 28, 1775-1799.

[15] Vander-Vennet, R. (2002). “Cost and profit efficiency of financial conglomerates and universal banking in Europe,” *Journal of Money Credit and Banking*, 34, 254-282.

Table 1: Sample Mean of Variables

Variable	Level	Unit
Profits	495,231	$ Million
Total Loans	0.1418	Ratio
Other Earning Assets	0.0116	Ratio
Price of Labour	0.0120	Ratio
Price of Physical Capital	0.0465	Ratio
Price of Financial Capital	3.485	Ratio
Inefficiency Variables		
GDP Growth Rate	3.728	%
Unemployment Rate	6.753	%

Note: N = 385 (55 Institutions × 7 years.) All data is in real terms and is deflated by the relevant country consumer price index, 1995 = 1.

Table 2: Profit Function Estimates

Dependent Variable: $ln(\pi^*)$			
Parameter	Variable	Estimate	T-Stat
β_0	Constant	19.868	19.828
β_1	Total Loans	0.523	0.627
β_2	Earning Assets	1.177	2.846
β_3	Labour	0.441	1.898
β_4	Financial Capital	2.312	4.700
β_5	Physical Capital	0.162	0.863
β_{11}	(T. Loans)^2	-0.450	-2.335
β_{12}	T. Loans $\times$ E. Assets	0.497	2.606
β_{13}	T. Loans $\times$ Labour	0.025	0.241
β_{14}	T. Loans $\times$ F. Capital	0.409	2.255
β_{15}	T. Loans $\times$ P. Capital	-0.065	-0.986
β_{22}	(E. Assets)^2	0.030	0.721
β_{23}	E. Assets $\times$ Labour	0.059	1.035
β_{24}	E. Assets $\times$ F. Capital	0.234	2.306
β_{25}	E. Assets $\times$ P. Capital	-0.038	-1.044
β_{33}	(Labour)^2	-0.001	-0.096
β_{34}	Labour $\times$ F. Capital	0.168	2.919
β_{35}	Labour $\times$ P. Capital	0.047	2.220
β_{44}	(F. Capital)^2	0.157	2.407
β_{45}	F. Capital $\times$ P. Capital	0.034	0.772
β_{55}	(P. Capital)^2	0.018	1.768
α_1	Canada Dummy	-0.127	-2.708
α_2	Ireland Dummy	0.077	0.833
α_3	UK Dummy	0.503	8.757
Variance Parameters			
σ^2		0.020	10.308
θ		0.624	22.397

Note: N = 385 (55 Institutions $\times$ 7 years.)

Table 3: Inefficiency Model Estimates

Dependent Variable: A_{it}			
Parameter	Variable	Estimate	T-Stat
$\rho_1 - \rho_{54}$	Individual Bank Dummies		
ρ_{55}	GDP Growth Rate	-0.006	-1.022
ρ_{56}	Unemployment Rate	0.0002	0.023
ρ_{57}	Canada Dummy	-0.373	-0.989
ρ_{58}	Ireland Dummy	0.258	0.548
ρ_{59}	UK Dummy	0.484	1.776
Hypothesis Tests			
Test	Hypothesis	λ	Decision
1	$H_0 : \theta = \rho_0 = \ldots = \rho_{59} = 0$	148.261	Reject H_0
2	$H_0 : \beta_{11} = \beta_{12} = \ldots = \beta_{55} = 0$	469.300	Reject H_0
3	$H_0 : \alpha_1 = \alpha_2 = \alpha_3 = 0$	81.878	Reject H_0
4	$H_0 : \rho_1 = \rho_2 = \ldots = \rho_{54} = 0$	373.752	Reject H_0
5	$H_0 : \rho_{55} = \rho_{56} = 0$	19.430	Reject H_0
6	$H_0 : \rho_{57} = \rho_{58} = \rho_{59} = 0$	256.179	Reject H_0

Note: N = 385 (55 Institutions $\times$ 7 years.) Bank level dummies are suppressed but are available from authors upon request. λ is a likelihood ratio statistic calculated as -2[log(likelihood(H_0))-log(likelihood(H_1))]. It has an approximate chi-squared distribution with degrees of freedom equal to the number of independent constraints under the H_0 hypothesis. All tests are at the 1 per cent level.

Table 4: Profit Inefficiency Estimates: Statistical Summary

	Big	Medium	Small
Maximum	0.549	0.715	0.708
Minimum	0.022	0.116	0.012
Mean	0.207	0.457	0.406
Range	0.527	0.599	0.696
St. Deviation	0.175	0.183	0.262
Skewness	0.617	-0.559	-0.250
C. of Variation*	0.843	0.339	0.645
N	126	133	126

Note: * C. = *Coefficient* of Variation = Standard Deviation / Mean, Range is between Maximum and Minimum values for each size category.