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AN ANALYSIS OF PRODUCTIVITY CHANGES OF CHARTERED ACCOUNTING FIRMS IN THE U.K., 2009-2012

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ABSTRACT

In this paper we examine the productivity growth as well as efficiency and technical changes in a sample of 43 UK accounting firms between 2009 and 2012. Data Envelopment analysis and the Malmquist index are used to, respectively evaluate performance measures for the firms for each of the 4 periods and then to compute the Malmquist productivity index along with efficiency and frontiers shifts (or technology) changes over the four periods. The findings indicate first that except for the big four accounting firms (KPMG, Deloitte, PwC and Ernst & Young), the other firms performed poorly over the 4 years and the overall average efficiency index is only 0.58, which suggests a suboptimal use of resources (inputs) by these firms. However, the big four firms perform much better than the rest of the firms with an overall average efficiency score of 0.97. Results also show that although not substantial, there is an average productivity growth of 0.85% of the accounting firms between 2009 and 2012 and an average gain of 1.38% in productivity for the big four firms. Moreover, the productivity growth for all firms is due to technological progress while that of the big four firms is mainly due to improvement in efficiency.

INTRODUCTION

Many researchers have tried to use different criteria to measure the productivity and efficiency of CPA firms. However, in most of the papers published authors used a set of ratios to assess performance. Jerris and Pearson (1996) tried to link revenues to the resources used to generate them in order to produce a more meaningful basis for evaluating the CPA firms' performance. They argued that CPA firms can benchmark and evaluate firm-wide performance relative to other firms by using ratios of firms' revenue to resources such as revenue per partner, revenue per professional, revenue per employee, revenue per office, etc. To Jerris and Pearson, these ratios provide measures of average productivity and efficiency of resources within each firm. Jerris and Pearson further concluded that when reviewing revenue per office they found that size alone does not result in more effective use of office capacity.

Jerris and Pearson updated their findings in 1997. They found that the top performing CPA firms for both 1994 and 1995 had significantly higher percentages of revenue from MAS and significantly lower percentages of revenue from tax. Based on the results of their updated study, Jerris and Pearson concluded that even though CPA firm rankings are often determined by total revenue, this is not a complete picture of firm performance. Total revenue rankings ignore how well the firms managed their resources. Franz and Jerris (2005) used the same ratios introduced by Jarris and Pearson (1996) to evaluate the performance of the ten largest CPA firms. They calculated those ratios for two sample groups. The first for 1994 consisted of 92 CPA firms and the second for 2004 consisted of 93 CPA firms. The results of their research indicated that when revenues were the sole measure of productivity and efficiency, the Big Six in 1994 and the Big Four in 2004 were the top revenue producers and occupied the top spots of the list of largest CPA firms ranked in descending order. However, when the ratios of revenues per partner, per professional, per employee and per office were applied, the Big Six in 1994 and the Big Four in 2004 were not consistently in the top of the list of the largest ten CPA firms listed in descending order. The difficulty encountered by managers in obtaining a comprehensive measure of efficiency and productivity resides in the fact that firms have multiple inputs and multiple outputs. Djerdjouri and Djema (2012) state that the traditional evaluation methods are centered on calculation of simple ratios and productivity indicators. Partial productivity calculates the ratio of one type of input (or one input) and relates it to a single output. This approach provides only a limited vision of efficiency. Total ratio of productivity takes into account all outputs and inputs to obtain a single ratio. However, there is an aggregation problem such as choosing the weights to be used in order to obtain a single ratio. Furthermore, this approach requires quantity and price information. Then, the productivity changes for each weight of an input or output. Thus, the total ratio of productivity is very sensitive to the fluctuation of prices. All these drawbacks do not allow a comprehensive measure of efficiency and performance. The DEA technique addresses the above mentioned drawbacks by substantially improving on the weaknesses of productivity ratios. It is the dominant non-parametric technique in productivity analysis. The technique has many advantages some of which are mentioned in section 2.1 below. It enjoyed a rapid growth in empirical applications in diverse fields. Chang and Cunningham (2003) examine whether or not the input-output efficiency depends on the share of compensation given to partners and to other professionals (i.e., the inputs). Their study was based on a dataset of 64 CPA firms published by Accounting Today during the years 1995–1999, and include measures of output including the net revenues generated from three sources: Accounting and Auditing, Tax Services, and Management Advisory Services. They find that partners, on average, are not over-compensated when compared to professionals and other type of employees. Banker, Chang, and Natarajan (2007) addressed Data Envelopment Analysis (DEA) as it relates to the evaluation of efficiency when aggregate cost or revenue data is available. They tried to relate the use of aggregate revenue (or cost) data to the measurement of technical and allocative inefficiency using DEA when the information about prices is not available, except for the aggregate revenue (or cost). Specifically, they tried to show that the DEA technical inefficiency measure using a single aggregate output (input) variable constructed from multiple outputs weighted by their market prices reflects the aggregate technical and allocative inefficiency. The results of their study indicated that the public accounting industry operated under significant allocative inefficiency. This finding implies that US public accounting firms had not fully realigned their resources in response to a changing market and that they could generate significant cost savings by better utilizing their human resources. They argued that the application of their methods should also enable policy analysts and researchers to interpret the results of their efficiency analysis models when using aggregate revenue or cost data in terms of technical and allocative inefficiencies. In Gregoriou, Kandiel, and Read's study (2011), they focused on public accounting firms in the United Kingdom that offer services in the following three areas: Accounting and Auditing, Tax Services, and Management Advisory Services during the five-year period from 2004 to 2008. They excluded those firms that did not disclose total revenues, number of partners, number of offices and number of professionals during this time period. Gregoriou, Kandiel and Read applied the Data Envelopment Analysis approach in order to analyze the input-output efficiency of the United Kingdom public accounting firms and the empirical results demonstrate that DEA can provide consistent results in the ranking of CPA firms. They concluded that the DEA methodology provides users with meaningful insights, is supplemental when reviewing various other performance measures and is an overall valuable measure in analyzing the efficiency of CPA firms. Many other studies reported DEA applications in manufacturing, banking, healthcare and many other industries to assess technical as well as scale efficiency of firms and organizations. Regarding the assessment of productivity changes, the same drawbacks are encountered with existing ratio methods. Another important shortcoming pointed to by Chen et al. (2004) is that the ordinary index of productivity does not reflect the productive efficiency opportunities. In this paper we use the DEA-based Malmquist productivity index to assess productivity changes of the accounting firms. The index was first introduced by Caves et (1982) and then extended by Fare et al. (1992) to use the DEA efficiency measures of the firms obtained by the DEA technique to compute the productivity growth for each firm from one period to the next. Furthermore, the two components of the Malmquist index are computed, namely, the efficiency change and the technical or frontier shift change in order to have a better idea as to what influences the productivity gain or loss in the firm. Many studies have reported on the successful application of the Malmquist productivity index to examine productivity growth by firms in different industries (Fare et al., 1992; Fare el al., 1994; Liu, S.T., 2010; Gonzalez, E., 2004; Liu, F., 2008; Chen, Y., 2004). In this paper, we employ the DEA technique to assess the operating efficiency of the 43 UK accounting firms for each of the 4 years between 2009 and 2012; as well the Malmquist productivity index approach to investigate productivity change of 43 accounting firms in the UK over the period 2009-2012. The rest of the paper contains a brief description of the methodology, followed by a discussion of the inputs and outputs used to measure the efficiency and the productivity changes of the accounting firms. Next, the findings are presented and discussed, followed by a conclusion.

METHODOLOGY

DEA method: Data Envelopment Analysis (DEA) is a non-parametric technique that measures the relative efficiency of a set of Decision Making Units (DMU) with multiple inputs/outputs using a linear programming based model. More precisely, given a set of decision making units (DMUs) with multiple inputs and outputs, DEA determines a best-practice or efficient frontier. The DEA frontier DMUs are those with maximum output levels given input levels or with minimum input levels given output levels. DEA provides efficiency scores for individual units as their technical efficiency measure, with a score of one assigned to the frontier (efficient) units and a score of less than one to the inefficient units. The technique was first proposed by Charnes et al. (1978). Given a set of n DMUs, each with m inputs x_{jr} (observed input j at DMU r) and k outputs y_{ir} (observed output i at DMU r), the original DEA mathematical model is formulated as follows:

$$\text{Maximize E0} = \frac{\sum_{i=1}^{k} u_i y_{i0}}{\sum_{j=1}^{m} v_j x_{j0}} \qquad (1)$$

Subject to:

$$\frac{\sum_{i=1}^{k} u_i y_{ir}}{\sum_{j=1}^{m} v_j x_{jr}} \leq 1 \qquad \text{for } r = 1,\ldots,n \qquad (2)$$

$$u_i , v_j > 0 \quad \text{for } i = 1,\ldots, k \text{ and } j = 1,\ldots,m \qquad (3)$$

where E_0= Efficiency index of the DMU being assessed from the set of r =1,…,n.

The model searches for the best set of weights (u_i, v_j) that maximizes the efficiency ratio of the DMU being evaluated subject to the condition that the no ratio be greater than 1 for any DMU in the sample. An efficiency index equal to one indicates that the DMU is relatively efficient and is on the efficiency frontier. For ease of mathematical manipulation, Charnes et al. (1978) transformed the above fractional programming model into the following easier to solve linear programming model, known as the [CCR] model:

$$\text{[CCR]:} \qquad \text{Maximize } \Theta \qquad (4)$$

Subject to:

$\sum_{j=1}^{n} \lambda_j y_{rj} \geq \Theta y_{r0}$; for r =1,…,k (5)

$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0}$; for i =1,….,m (6)

$\lambda_j \geq 0$; for j=1,…,n (7)

Furthermore, efficiency can either be characterized with an input orientation or an output orientation. DEA can handle multiple inputs and multiple outputs. It does not require the knowledge of prices of inputs and outputs. Moreover, it does not require a specification of the functional form that relates inputs and outputs

Malmquist productivity index: The Malmquist productivity index measures the productivity changes over time. It was introduced by Calves et a.l (1982) and then extended by Fare et al. (1992) using DEA to compute output distances and construct the index directly from the multiple inputs and outputs data. This DEA-based Malmquist productivity index is an excellent tool for measuring the productivity change of DMUs between time periods. If the above [CCR] model is solved for firm k in period t and if we denote the optimal objective function value by Θ_{kt}^{t*} and $D_k^t(x_k^t, y_k^t) = 1/_{\Theta_{kt}^{t*}}$ then

$0 \leq D_k^t(x_k^t, y_k^t) \leq 1$ is a measure of efficiency of firm k in period t. It represents the amount by which inputs can be proportionally reduced and while not reducing the produced output level, and it is referred to as the distance function value. Solving the [CCR] model for (t+1), we will get the efficiency measure for the same firm for the next time period of (t+1) denoted by $D_k^{t+1}(x_k^{t+1}, y_k^{t+1})$. For the Malmquist index we also need to compute the mixed period measures $D_k^t(x_k^{t+1}, y_k^{t+1})$ and $D_k^{t+1}(x_k^t, y_k^t)$.

The Malmquist productivity index is computed as:

$$\mathrm{MPI}_k = \sqrt{\frac{D_k^t(x_k^{t+1}, y_k^{t+1}) D_k^{t+1}(x_k^{t+1}, y_k^{t+1})}{D_k^t(x_k^t, y_k^t) D_k^{t+1}(x_k^t, y_k^t)}} \quad (8)$$

and it measures the productivity change of firm k from period t to period t+1. Also, $\mathrm{MPI}_k > 1$ means that there is a gain in productivity for firm k in period t+1. If $\mathrm{MPI}_k < 1$, then there is productivity loss for firm k and if $\mathrm{MPI}_k = 1$, then there is no change in productivity for the firm from period t to period t+1. Fare and al. (1992) further decomposed the Malmquist index into two main components as:

$\mathrm{MPI}_k = \mathrm{EIC}_k \mathrm{x} \mathrm{TIC}_k$ where

$\mathrm{EIC}_k = \frac{D_k^{t+1}(x_k^{t+1}, y_k^{t+1})}{D_k^t(x_k^t, y_k^t)}$ represents the change in efficiency and

$$TIC_k = \sqrt{\frac{D_k^t(x_k^{t+1}, y_k^{t+1}) D_k^t(x_k^t, y_k^t)}{D_k^{t+1}(x_k^{t+1}, y_k^{t+1}) D_k^{t+1}(x_k^t, y_k^t)}}$$ represents a shift in the technology frontier

If $EIC_k > 1$ then there is a gain in technical efficiency for firm k whereas, $EIC_k < 1$ indicates a loss. And if $EIC_k = 1$ there is no change. The same interpretation is valid for the shift in technology frontier. $TIC_k>1$ indicates that there is technical progress for the firm k, whereas a value $TIC_k<1$ indicates a technical regress. And if $TIC_k=1$ there is no technical change. This component reflects movements of the best practice frontier, not the movements of the firm towards the frontier, and thus it shows the progress of the production of the firm allowed by the technology. Furthermore, technical change principally occurs when innovation takes place and new technology or processes are introduced in the firm.

DATA

The three inputs considered include (i) the number of offices, (ii) the number of partners, and (iii) and the number of professionals. These professionals represent the other professionally qualified staff who are not partners. The inputs represent the different categories of human resources which are the main revenue generators for accounting firms. And the only output used in this study is revenue expressed in millions of dollars. The data on the three inputs and one output for the public accounting firms referenced in this study were obtained from the United Kingdom publication, Accountancy Age as well as from the Accountancy Magazine.com website. In order to ensure consistency, our dataset consisted of only CPA firms that offered services in the following three areas: Accounting and Auditing (A & A), Tax Services (Tax), and Management Advisory Services (MAS). We excluded those firms that did not disclose their total revenues, number of partners, number of offices and number of professionals available each year. These exclusions reduced the number of chartered accounting firms to 43. The Accounting firms included in our study are ranked by revenue in descending order from largest to smallest and are tracked during the entire investigative period from 2009 to 2012. Descriptive input and output statistics for the sample data are provided in table 1 below:

Table 1. Summary Statistics of inputs and outputs (2009-2012)

	2009	**2010**	**2011**	**2012**
Inputs:				
1) Number of offices				
-Mean	13	14	13	13
-Standard Dev.	12.8	13.9	13.86	12.59
-Minimum	1	1	1	1
-Maximum	45	50	52	51
2) Number of partners				
-Mean	120	120	127	128
-Standard Dev.	188.87	188.74	212.23	218.38
-Minimum	8	11	11	10
-Maximum	853	858	953	991

3) Number of				
professionals	1273	1324	1420	1372
-Mean	2560.03	2777.74	3173.66	2993.55
-Standard Dev.	86	89	85	83
-Minimum	10529	13306	16533	14973
-Maximum				
<u>**Outputs**</u>:				
1) Revenue				
- Mean	222551860.5	225136744.2	225485348.8	235967441.9
-Standard Dev.	526992256.8	529393449.2	532372458.1	567799222.8
-Minimum	11700000	11720000	11600000	1350000
-Maximum	2244000000	2248000000	2331000000	2461000000

We can see from table 1 that the values of the standard deviation are relatively high for all inputs and outputs. This clearly indicates that the firms that constitute the sample vary greatly in size and that the sample is heterogeneous. However, the stable mean values of inputs indicate that there is no substantial increase in inputs for each firm from period to period.

RESULTS

Table 2. Efficiency scores per year (2009-2012) for all the firms

	2009	2010	2011	2012
Mean	0.577	0.584	0.591	0.577
Stdev	0.176	0.189	0.193	0.205
Min	0.3203	0.3067	0.253	0.047
Max	1.00	1.00	1.00	1.00

When all the 43 firms are considered together, the mean efficiency score per period between 2009 and 2012 is low with a mean of 0.582 over the four years. This clearly shows that the firms are not performing at an optimal level and that there is ample room for improvement in efficiency. The results indicate that on average the firms can obtain the same revenues while cutting their inputs by around 42% across the board.

Table 3. Efficiency distribution

	2009	2010	2011	2012
Efficiency = 1	2	3	3	4
$0.7 \leq$ Efficiency < 1	6	7	8	5
Efficiency < 0.7	35	33	32	34

Table 3 above shows that 81% of the firms in 2009, 77% in 2010, 74% in 2011 and 79% in 2012 have efficiency scores that are less than 0.70. This is a very large percentage of highly inefficient firms. Moreover, only 5% of the firms in 2009, 7% in both 2010 and 2011, and 9% of the firms in 2012 are relatively efficient, that is optimizing the use of their resources in obtaining the revenues they achieved during each year between 2009 and 2012.

Table 4. Efficiency scores per year (2009-2012) for the big four firms

	2009	2010	2011	2012
Mean	0.947	0.961	0.961	0.986
Stdev	0.063	0.047	0.05	0.028

Min	0.87	0.91	0.89	0.943
Max	1.0	1.0	1.0	1.0

Results in table 4 clearly indicate that the big four firms, namely KPMG, Deloitte, Ernst & Young, and Pricewater house Coopers (PwC) perform at much higher level of efficiency than the rest of the firms. The mean efficiency score in each period is very close to 1, with an average score of 0.964 over the four periods. However, even for the big four firms there is room for about 3.6% improvement in performance.

Table 5. Efficiency distribution for the big four firms

	2009	**2010**	**2011**	**2012**
Efficiency = 1	1	2	2	3
0.7 ≤ Efficiency < 1	3	2	2	1
Efficiency < 0.7	0	0	0	0

Table 4 and table 5 above show that in 2009, only one firm (Deloitte) is efficient while the three others have efficiency scores between 0.87 and 1. In 2010, two firms (KPMG and Deloitte) obtain an efficiency score of 1, while the two others (Ernst-Young and PwC) have a core 0.91 and 1. In 2011, the same two firms, that is Deloitte and KPMG again are relatively efficient (Efficiency Index =1) and the two other firms obtain an efficiency score between 0.89 and 1. And finally in 2012, PwC joins KPMG and Deloitte in obtaining a perfect efficiency score of 1, and only Ernst & Young is relatively inefficient with a score 0.943. We note that the firm Deloitte achieves a perfect efficiency score for each of the four years, indicating a consistency of Deloitte's very good performance over the 2009-2012 time period. Table 6 shows the mean productivity changes in all the 43 accounting firms, as represented by the Malmquist input based productivity index in section 2.1. As stated previously in section 2.2, the Malmquist index (MPI) is a combination of the efficiency (EC) and technical (TC) change components.

Table 6. Productivity changes (MPI) for all the 43 firms

	2009/2010	**2010/2011**	**2011/2012**	**2009/2012**
MPI*	1.0077	1.0283	0.9873	1.0085
EC	1.0157	1.0173	0.9763	0.9972
TC	0.9919	1.0106	1.0111	1.0108

**MPI=EC x TC*

Results show that there was on average productivity gains in 2 periods, namely a 0.77 % growth from 2009 to 20120 and a 2.83 % increase from 2010 to 2011 and a slight 1.27% productivity loss from 2011 to 2012. Moreover, there was an overall average increase of 0.85% in productivity from 2009 to 2012.

Table 7. MPI distribution

	2009/2010	**2010/2011**	**2011/2012**	**2009/2012**
MPI > 1	25	28	28	24
MPI = 1	0	0	0	0
MPI < 1	18	15	15	19

As table 7 indicates, we found that there were more productivity gains than losses for all periods. From 2009 to 2010, there were productivity gains in

25 firms and productivity losses in 18 firms, i.e. progress in 58% of the firms. And in the next two periods, from 2010 to 2011 and from 2011 to 2012, there were productivity gains in 65% of the firms. And overall the period 2009 to 2012 we found progress in 56% of the firms. We also note that on average, progress in productivity during this period is mainly explained by positive shifts of the frontier, that is, in technical efficiency.

Table 8. Productivity changes (MPI) for the big four firms

	2009/2010	2010/2011	2011/2012	2009/2012
MPI	0.9711	1.0061	1.0492	1.0138
EC	1.0177	1.0011	1.0266	1.0433
TC	0.9544	1.005	1.0222	0.9713

As expected and as was the case for the efficiency analysis, the big four accounting firms do better in terms of productivity than the other firms in the sample. On average, from 2009 to 2010 there was a 2.89% loss in productivity, which was due mainly to a loss in technical efficiency (frontier change). In this same period there was a gain of 1.77% in efficiency. For the period 2010 to 2011, there was a 0.61% gain productivity due to a 0.11% gain in efficiency and a gain of 0.5% in technical change. The improvement continued between 2001 and 2012 with a considerable 4.92% gain in productivity due to increases in both managerial efficiency (+2.66%) and technology change(+2.22). And overall, between 2009 and 2012 there was an average increase of 1.38% in productivity in the four accounting firms due essentially to a considerable increase in efficiency (+ 4.33%). However, in this period there was a decrease in technical change (-2.87%).

Table 9. MPI distribution for the big four firms

	2009/2010	2010/2011	2011/2012	2009/2012
MPI > 1	2	2	4	2
MPI = 1	0	0	0	0
MPI < 1	2	2	0	2

From 2009 to 2010, KPMG and Ernst&Young saw a gain in productivity while Pricewater House Coopers and Deloitte have a loss in productivity, thus we saw a progress of 50%. The same progress of 50% was observed between 2010 and 2011 where Price Water House Coopers and Deloitte achieved a gain in productivity while KPMG and Ernst & Young had a loss. However, between 2011 and 2012 there was a 100% progress. In fact all the four big firms achieved a gain in productivity (+4.89% on average), a gain in efficiency (+2.66%) and a gain in technical change (+2.22%). And for the overall period between 2009 and 2012, there was progress in 50% of the big firms (KPMG and Ernst &Young).

CONCLUSION

In this paper, we assess the performance of the top UK accounting firms as well as their productivity. To this end, we selected a sample 43 UK top accounting firms. Data for the firms was obtained for the 2009-2012 period. First, for each period, a nonparametric mathematical technique, an input oriented DEA, was used to compute the technical efficiency of each firm. The results showed clearly that the big four firms were relatively efficient with an overall mean efficiency score of 0.96 over the four years, whereas the majority of the firms were relatively inefficient with an overall a mean efficiency index of around 0.58 for each period and an overall mean efficiency score of 0.582 over the 4 year period. This suggests that there is plenty of room for improvement. The results indicate that the firms can obtain much more revenue given the inputs level they are currently using or they can obtain the same level of output (revenue) with an average reduction of 41.8% of the inputs across the board. Firms are not optimizing the use of their resources. Also, the firm Deloitte showed superior performance, being relatively efficient for each of the 4 years. In the second stage of the analysis, we assess the productivity of the firms.

The technique we use is the input-based Malmquist productivity index introduced by Caves et al. (1982) and expanded by Fare et al. (1992) using DEA to compute output distances and construct the index directly from the multiple inputs and outputs data. The index is further decomposed into two components, efficiency change and technical change. The findings show first that there were productivity gains in two out of three periods (2009-2010, 2010-2011) and a slight decrease in 2011-2012. However, there was an average growth of 0.85% in productivity from 2009 to 2012. This suggests that even though the firms do not perform at their optimal level, there is improvement in the productivity from 2009 to 2012. This is a good sign for the firms however there is still a lot to do in order to optimize the use of their resources. The results also show again that the big four accounting firms do much better in terms of productivity than the other firms in the sample. There was a productivity gain in two out of three periods (2010-2011 and 2011-2012) with a considerable gain of 4.92% from 2011 to 2012. And overall, there was an average increase of 1.38% in productivity from 2009 to 2012 for the big four firms. And this growth was due essentially to an average increase of 4.33% in technical efficiency.

Finally, in this paper we have shown how an application of operations research methods can help managers improve their analysis of the firm performance. The DEA method provides a wealth of information that can be used by managers of the accounting firms in making important and strategic decisions. More specifically, it provides guidance on how to improve the efficiency of the firms by identifying a set of reference sets along with target input and output levels. The Malmquist index provides managers with in depth information about the overall productivity of the firm as well as the specific components of technical efficiency changes and technological shifts, which further explain the determinants of the productivity growth. This type of rigorous analysis is very crucial if we want to comprehensively capture the firm’s performance. Managers can obtain very valuable information to make better decisions. Moreover, the DEA and the Malmquist models’ results can help managers focus on the operating aspects of the firms rather than on the profitability measures already in use. What is important from a managerial perspective is how inefficient firms should orient strategies to become better performers. The results of the analysis can be used by managers to provide prescriptive guidance to accounting firms to improve their operational efficiency.

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