J Prod Anal (2015) 44:337–349
DOI 10.1007/s11123-014-0397-8

A comparison of the technical efficiency of accounting firms among the US, China, and Taiwan under the framework of a stochastic metafrontier production function

Bao-Guang Chang · Tai-Hsin Huang · Chun-Yi Kuo

Published online: 20 June 2014

Abstract This study employs the newly developed stochastic metafrontier production function by Huang et al. (A new approach to estimating the metafrontier production function based on a stochastic frontier framework. Working paper, Vanderbilt University, National Cheng-chi University, Taiwan, 2012) to compare the technical efficiencies of accounting firms (AFs) among the US, China, and Taiwan, operating under different technologies. Although AFs play an important role in a nation's capital market, the accounting industry has not attracted much attention to academic researchers. The main difference between the stochastic metafrontier function and the one proposed by Battese et al. (J Prod Anal 21:91–103, 2004) and O'Donnell et al. (Empir Econ 34:231–255, 2008) lies in the second step, where the stochastic frontier approach (SFA) is recommended instead of programming techniques. Taiwan's AFs are found to have the highest average metafrontier technical efficiency (MTE) and AFs in the US have the highest technology gap ratio (TGR). Nonetheless, the average TGR and MTE values of American AFs are closer to those of Taiwan. The low performance of Chinese AFs may be attributed to government regulations and the lack of market competition. However, the programming technique suggests reverse results for AFs in Taiwan and the US and larger variances for TGR and MTE. Then these three countries' AFs show decreasing returns to scale, indicating that mergers and acquisitions may not be advantageous for expanding their production scale.

Keywords Accounting firms · Technical efficiency · TGR · Stochastic metafrontier approach

JEL Classification M41 · C51 · D24

1 Introduction

The economic development of a country is influenced by the health of its capital market, which is determined by governmental policy, the business environment, investors, and the accountants who audit and attest to the financial statements of listed companies. Accountants are important behind-the-scenes players facilitating the economic development of a nation. Nevertheless, Greenwood et al. (2005) and Bröcheler et al. (2004) point out that factors related to the performance of accounting firms are seldom addressed in academic literature and many of the existing studies deal only with the accounting firm in a single country.

Banker et al. (2005), Chang et al. (2009a, b) and Knechel et al. (2009) explore the operating efficiency of the top 100 accounting firms in the US. Chang et al. (2011) studies 51 accounting firms in Taiwan to determine how IT capital and human capital affect the productivity of the firm. Although the Chinese government releases input and

B.-G. Chang
Department of Accounting, Tamkang University, No. 151, Yingzhuan Rd., Tamsui District, New Taipei City 25137, Taiwan, ROC
e-mail: baog@mail.tku.edu.tw

T.-H. Huang
Department of Money and Banking, National Cheng-Chi University, No. 64, Sec. 2, ZhiNan Rd., Wenshan District, Taipei City 11605, Taiwan, ROC
e-mail: thuang@nccu.edu.tw

C.-Y. Kuo (✉)
Graduate Institute of Management Sciences, Accounting, Tamkang University, No. 151, Yingzhuan Rd., Tamsui District, New Taipei City 25137, Taiwan, ROC
e-mail: 136514@mail.tku.edu.tw

output data of the top 100 Chinese accounting firms, the performance of that industry with regard to efficiency and scale economies has yet to be examined in-depth. Put simply, most previous studies have employed data envelopment analysis (DEA) to measure the operating efficiency of the accounting firms in a single country. Collecting data on the accounting firms in multiple nations to compare differences in production efficiencies, could compensate for the insufficiencies in existing research and provide businesses and government agencies with information valuable for future improvement.

Investment in human capital is essential to building people-oriented due to accounting firms are professional service firms, much like law firms and consulting firms. These kinds of professional service firms are characterized by knowledge intensity, low capital stock, and a highly professionalized workforce (Greenwood et al. 2005 and Nordenflycht 2010). Differences with regard to economic environment, market scale, organization type, auditing costs, and industry regulations can cause accounting firms in different countries to adopt different production techniques. In terms of the economic environment, a survey conducted by the Heritage Foundation on the Index of Economic Freedom in major countries around the world respectively ranked the US, Taiwan, and China at 10th, 20th, and 140th. This implies that the governments exert varying degrees of control on their accounting industries. In market scale, a survey by Select USA indicated that altogether, the accounting industry in the US generated a total revenue of USD 116.1 billion in 2010, which is significantly higher than that in China (USD 2.45 billion) and in Taiwan (USD 0.69 billion). In organization type, the accounting firms in the US and China may be partnerships, limited liability companies, or limited liability partnerships, whereas partnerships are the mainstream in Taiwan.

In auditing costs, China adopts international accounting standards for financial reporting in listed companies since 2006. In contrast, Taiwan and the US have their own accounting standards. This means different auditing standards among the three countries and leads to certain differences in the auditing programs for financial statements and the amount of manpower invested. With regard to regulations specific to the accounting industry, the US has added new internal control audits and restricted the types of businesses the firms can do due to independence considerations (Chang et al. 2009b). Generally speaking, the interaction effects of the aforementioned factors result in heterogeneous production technologies undertaken by these accounting industries. Such technological differences can be gauged by the gap between the metafrontier and group-specific frontiers, i.e., the technology gap ratio (TGR). The purpose of this study is to evaluate and compare the production efficiencies of accounting firms in the US, China, and Taiwan, under the framework of the stochastic metafrontier production function proposed by Huang et al. (2012).

Metafrontier production function was first proposed by Hayami (1969) and Hayami and Ruttan (1970, 1971). Recently, Battese et al. (2004) and O'Donnell et al. (2008) proposed a two-step approach to estimate and compare technical efficiency among firms from different technology groups. Huang et al. (2012) proposed a new two-step stochastic metafrontier (SMF) production function that differs from Battese et al. (2004) and O'Donnell et al. (2008) mainly in the second step, in which a stochastic frontier approach (SFA) is used to avoid the need for programming techniques. In this approach, corresponding parameter estimates have the desirable statistical properties and the estimated technology gap ratio is less affected by random shocks, compared to estimates obtained from DEA.

Our empirical results show that the average TGR and MTE measures of Chinese accounting firms from the SMF and QP models proposed by Battese et al. (2004) and O'Donnell et al. (2008) lag behind those of the US and Taiwan. Based on the SMF approach, accounting firms in Taiwan have the highest average MTE values, followed by those in the US and China. American accounting firms have the highest average TGR values, followed by Taiwan and China. Nonetheless, the mean TGR and MTE values of American accounting firms are closer to those of Taiwan. However, based on the QP model, American accounting firms have the highest average TGR and MTE values, followed by Taiwanese accounting firms.

The remainder of the paper is organized as follows. Section 2 briefly reviews previous literature regarding the measurement of efficiency in the accounting firms and the metafrontier approach. Section 3 derives the SMF. Section 4 describes the data sources and descriptive statistics of the output and inputs for the three countries. Section 5 analyzes the empirical results and Sect. 6 presents our conclusions.

2 Literature review

2.1 Efficiencies of the accounting firms

Continuing the seminal research of Simunic (1980), many researchers began exploring the production process of auditing services provided by accounting firms. O'Keefe et al. (1994) proposed an auditing production model based on firm inputs and outputs. Using the internal data of a large representative accounting firm in the US, regression analysis was used to assess the relationship between the number of hours invested by employee at various levels (such as partner, manager, senior, and staffs) and output.

Some recent studies have extended the auditing production model to measure the operating efficiency and productivity of accounting firms.

Banker et al. (2003) employ a translog revenue function to estimate the top 100 public accounting firms in the US. They compile balanced panel data, including 64 large accounting firms over the period from 1995 to 1999, and find that the sample firms exhibit continuing improvements in productivity over those 5 years. In addition, merger and acquisition activities among these firms are justified by the existence of scale economies. Their study, however, does not compare and analyze production techniques or technical efficiency; it only uses the revenue function to decompose scale economies and explore changes in productivity. Nonetheless, the variables they used for human resources and firm revenue provides an important context for subsequent related studies on efficiency and productivity.

Banker et al. (2005) analyze this shift in the production function and the cross-sectional distribution of firm productivity by using revenue and human resource data available for the period from 1995 to 1999. The sample firms comprise 64 of the top 100 public accounting firms in the US. The productivity of an average firm is shown to improve by 9.5 % during this period, due primarily to technical progress, which contributes 12 % to production in the industry, but is partially offset by a decline in technical efficiency changes. Banker et al. (2007) use DEA to measure technical efficiency, in which total revenue is treated as a single output. Using data for the top 100 US public accounting firms for the period from 1995 to 1998, they conclude that the public accounting industry operates under significant allocative inefficiency. This finding implies that the sample firms have not fully realigned their resources in response to a changing market for their services, which would have generated considerable cost savings through the reallocation of human resources.

Lastly, Chang et al. (2009b) use DEA and the Malmquist Index to compare the efficiency, productivity and technological advancement of 56 US accounting firms before and after the passing of the Sarbanes–Oxley Act in the US. They find that after this Act was passed, the overall increase in productivity is attributable mainly to technological progress rather than improved efficiency. This outcome is particularly evident in the Big-4 firms. Next, Chang et al. (2009a) studies data from 62 US accounting firms and found that after the passing of the Sarbanes–Oxley Act, increased industry productivity is driven by revenue growth from management and consulting fees.

The literature on efficiency and productivity in accounting industry has barely been analyzed outside the US. Although the auditing market of Taiwan differs from that of the US in relation to market scale and litigation risk, Taiwan's firms are otherwise similar to US firms in terms of partner qualifications, organizational model, and issues related to professional ethics (Parker and Morris 2001). According to Chang et al. (2011), the overall revenue growth rate of accounting firms in the US and Taiwan from 1995 to 1999 was 80 and 78.9 %, respectively. Cheng et al. (2000a) use two-stage DEA to evaluate the technical efficiency of Taiwan's accounting firms in 1994 and apply the Tobit model to estimate the impact factors. They find that in 1994 firms reduced input by an average 27.8 % but were still able to maintain service standards, indicating that production efficiency had been improved. Factors such as the scale and age of the firm, scope of services and expenditure on staff training were found to positively influence the overall efficiency of a firm. Cheng et al. (2000b) conduct empirical analysis of accounting data from the same year and find that auditing, tax, management and consulting services have economies of scale, and that the latter three show significant economies of scope. Chang et al. (2011) employ DEA to study annual data from Taiwan's accounting firms from 1993 to 2003 and point that IT and human capital significantly affect the production efficiency and productivity of a firm.

Although the Chinese government releases input and output data of the top 100 Chinese accounting firms, this industry has not attracted very much attention among researchers. It should also be noted that most previous works on accounting firms focused primarily on a single country using the nonparametric approach, i.e., the DEA.

2.2 Literature review of metafrontier approach

The metafrontier production function was first proposed by Hayami (1969) and Hayami and Ruttan (1970, 1971). This function assumes that all firms in different production groups have potential access to the same technology; however, differences in the political systems, government regulations, and economic environment often affect their adoption of these resources.

Battese et al. (2004) and O'Donnell et al. (2008) proposed a mixed approach with a two-step procedure for estimating the metafrontier. This approach combines the stochastic frontier regression in the first step to estimate the group-specific frontier with the mathematical programming techniques in the second step in order to estimate the metafrontier. One potential difficulty with this approach lies in its estimation in the second step, in which the metafrontier estimators are void of statistical properties, due to the deterministic nature of the mathematical programming techniques employed. Furthermore, programming techniques are unable to isolate idiosyncratic shocks, such that the estimation results are susceptible to random shocks.

Huang et al. (2012) proposed the stochastic metafrontier model using SFA to estimate the metafrontier parameters in the second step. In the second step, maximum likelihood (ML) is still used to estimate the metafrontier parameters, which allows researchers to engage directly in statistical inference and test without the need to rely on simulations or bootstrapping methods. Secondly, SMF can distinguish between random factors of interference and inefficiency and thereby directly estimate TGR. Compared to the results of Huang et al. (2012), the TGR estimated using the two-step approach of Battese et al. (2004) and O'Donnell et al. (2008) was underestimated and showed greater variance.

Most recent studies have employed the two-step mixed approach developed by Battese et al. (2004) and O'Donnell et al. (2008). Examples of such studies include Bos and Schmiedel (2007) who estimate the cost and profit metafrontier function as well as compared the technical efficiency of the banking industry in 15 Western European nations. Moreira and Bravo-Ureta (2010) compare the metafrontier technical efficiency of the dairy farms in three South American countries (Argentina, Chile and Uruguay).

Chen (2012) inputs risk factors into an input-oriented generalized metafrontier Malmquist productivity index to compare the cost efficiency and productivity of 42 banks in Taiwan from 1999 to 2007. Few previous studies have applied the metafrontier production approach to compare and analyze the accounting firms across multiple nations. Considering its function in facilitating direct testing and analysis of second step metafrontier estimating results, we use the SMF developed by Huang et al. (2012) to compare production efficiency in the accounting firms of the US, China, and Taiwan.

3 Methodology

3.1 Stochastic metafrontier approach

The metafrontier production function model for firms of different groups adopting heterogeneous technologies is estimated by a two-step procedure, as suggested by Battese et al. (2004) and O'Donnell et al. (2008). In the first step the group-specific stochastic frontier is estimated for each group and the mathematical programming technique is applied to estimate the metafrontier in the second step. A stochastic group-specific production frontier is formulated as

$$y_{jit} = f_t^j(x_{1jit}, x_{2jit}, \ldots, x_{Mjit}; \beta^j)\, e^{V_{jit}-U_{jit}},$$
$$j = 1, 2, \ldots, J; \quad i = 1, 2, \ldots, N_j; \quad t = 1, 2, \ldots, T \tag{1}$$

where y_{jit} denotes the output of the ith firm in the jth group at the tth period; x_{mjit} denotes the mth input quantity; β^j is an unknown vector of technology parameters associated with the jth group. Note that the production function $f_t^j(.)$ is both subscripted by t and superscripted by j, characterizing that the individual group-specific production function can vary across groups and over time. The random errors V_{jit}s represent statistical noise and are assumed to be independently and identically distributed as $N(0, \sigma_v^{j2})$; U_{jit}s represent technical inefficiency and are assumed to be $U_{jit} \sim u_i^j e^{-\eta_j(t-T)}$, where $u_i^j \sim |N(0, \sigma_u^{j2})|$ is a half-normal random variable with a zero mean and a constant variance of σ_u^{j2}.[1] Technical efficiency increases, decreases, or constant over time depending upon whether $\eta_j > 0$, $\eta_j < 0$, or $\eta_j = 0$, respectively. After taking the natural logarithm on the both sides of (1), the transformed regression model can be estimated by the ML. A firm's technical efficiency (TE) is defined as:

$$TE_{it}^j = \frac{y_{jit}}{f_t^j(X_{jit})\, e^{V_{jit}}} = e^{-U_{jit}}, \tag{2}$$

where X_{jit} denotes the input vector of the ith firm in the jth group at the tth period.

The common underlying metafrontier production function for all groups in the tth period is defined as $f_t^M(X_{jit})$, $j = 1, 2, \ldots, J$. The metafrontier $f_t^M(X_{jit})$ by definition envelops all individual group's frontier $f_t^j(X_{jit})$. Their relationship is formulated as follows.

$$f_t^j(X_{jit}) = f_t^M(X_{jit})\, e^{-U_{jit}^M}, \quad \forall\, j, \ i, \ t \tag{3}$$

where $U_{jit}^M \geq 0$, implying that $f_t^M(.) \geq f_t^j(.)$ and the ratio of the jth group's production function to the metafrontier is defined as the technology gap ratio (TGR),[2] i.e.,

$$TGR_{it}^j = \frac{f_t^j(X_{jit})}{f_t^M(X_{jit})} = e^{-U_{jit}^M} \leq 1. \tag{4}$$

which gauges the gap between the metafrontier and group frontier. A TGR value equaling unity implies that a firm has adopted the most advanced technology to produce outputs. A TGR value less than unity means that this firm has failed to do so perhaps due to economic and/or non-economic environmental restrictions faced by the firm. The technology gap component of U_{jit}^M in (4) is thus group, firm, and time specific and depends on the accessibility and adoption of available metafrontier production technology.

[1] This specification is in line with Battese and Coelli (1992). Note that the assumption that u_i^j is a half-normal random variable for all groups of j, instead of a truncated-normal, allows us to compare the technical efficiency of accounting firms in different countries under the same standard, i.e., the distribution of u_i^j in each group is kept by the same portion of the right-half.

[2] Readers are suggested to refer to Battese and Rao (2002), Battese et al. (2004), O'Donnell et al. (2008) and Huang et al. (2012) for the detailed formulation and interpretation of the TGR.

At any given input level X_{jit}, the gap between a firm's observed output y_{jit} and the metafrontier $f_t^M(X_{jit})$ can be decomposed into three components, i.e.,

$$\frac{y_{jit}}{f_t^M(X_{jit})} = TGR_{it}^j \times TE_{it}^j \times e^{V_{jit}}. \tag{5}$$

The three components are referred to as the ith firm's TGR_{it}^j, technical efficiency, and random noise $e^{V_{jit}}$.

It should be emphasized that, although both the technology gap ratio TGR_{it}^j and the firm's production efficiency TE_{it}^j are bounded between zero and unity, the metafrontier $f_t^M(X_{jit})$ does not necessary envelop all firms' observed outputs y_{jit} due to the possible random noise. The unrestricted ratio in (3) distinguishes the metafrontier modeling using the SFA from using the data envelopment analysis (DEA). To account for the random noise component, (5) can be re-expressed as:

$$MTE_{jit} \equiv \frac{Y_{jit}}{f_t^M(X_{jit})\, e^{V_{jit}}} = TGR_{it}^j \times TE_{it}^j \tag{6}$$

where MTE_{jit} denotes the ith firm's production efficiency with respect to the metafrontier production technology, $f_t^M(.)$, rather than the group-j production technology $f_t^j(.)$.

According to Battese et al. (2004) and O'Donnel et al. (2008), empirical measurement of the above metafrontier efficiency consists of two steps. The first step requires the use of the ML approach to estimate each group-specific frontier like (1). Let $\hat{f}_t^j(X_{jit})$ be the fitted value of the group-j's production function and $T\hat{E}_{it}^j$ the group-j's estimated technical efficiency score. In the second step, the metafrontier function $f_t^M(.)$ is obtained by minimizing the sum of absolute deviations or the sum of squared deviations between $f_t^M(.)$ and $\hat{f}_t^j(X_{jit})$. Standard errors for the parameter estimates of the metafrontier function can be obtained using either simulation or bootstrapping methods.

The so-derived deterministic metafrontier function $f_t^M(.)$ from the mathematical programming technique may have some inherent shortcomings worth mentioning. First of all, it is hard to give a meaningful statistical interpretation to the computed metafrontier function, since the statistical properties of the parameter estimates are unknown. Second, the programming approach is unable to distinguish the random shocks from the model such that the estimated metafrontier efficiency score is likely to be confounded with the shocks. We therefore utilize a new method to estimate the metafrontier production function in the second step, which is first proposed by Huang et al. (2012). The method suggests estimating the metafrontier function under the framework of the stochastic frontier approach, rather than the mathematical programming technique in the second step. In this manner, the above difficulties can be avoided.

Equation (3) can be re-formulated as

$$\ln f_t^j(X_{jit}) = \ln f_t^M(X_{jit}) - U_{jit}^M \tag{7}$$

The group-specific frontier $f_t^j(X_{jit})$ is unobservable, but its estimate can be obtained from the first step. Since the fitted value of $f_t^j(X_{jit})$, $\hat{f}_t^j(X_{jit})$, differs from the true frontier of $f_t^j(X_{jit})$ randomly, (7) can then be re-expressed as:

$$\ln \hat{f}_t^j(X_{jit}) = \ln f_t^M(X_{jit}) - U_{jit}^M + V_{jit}^M, \tag{8}$$

where the symmetric error V_{jit}^M denotes the noise representing the deviation between $\hat{f}_t^j(X_{jit})$ and $f_t^j(X_{jit})$, i.e.,

$$\ln \hat{f}_t^j(X_{jit}) = \ln f_t^j(X_{jit}) + V_{jit}^M \tag{9}$$

Equation (8) resembles the conventional stochastic frontier model and $\ln f_t^M(X_{jit}) + V_{jit}^M$ is referred to as the SMF. Since $\ln \hat{f}_t^j(X_{jit})$ is obtained by the ML, the parameter estimates are consistent and asymptotically normally distributed. It is legitimate to assume that the error V_{jit}^M is normally distributed as $N(0, \sigma_v^{M2})$. The non-negative technology gap component $U_{jit}^M(\geq 0)$ is assumed to be $U_{jit} \sim u_i e^{-\eta(t-T)}$,where $u_i \sim |N(0, \sigma_u^2)|$ is a half-normal random variable with a zero mean and a constant variance of σ_u^2. Technical efficiency increases, decreases, or constant over time depending upon whether $\eta > 0$, $\eta < 0$, or $\eta = 0$, respectively.

The new two-step stochastic frontier approach allows for the estimated group-specific frontier to be either less than or larger than the metafrontier, due to the presence of the error V_{jit}^M in (8). However, the metafrontier is always higher than the true group-specific frontier by construction, i.e., $f_t^j(X_{jit}) \leq f_t^M(X_{jit})$. The estimated TGR is computed according to the following formula:

$$T\hat{G}R_{it}^j = \hat{E}\left(e^{-U_{jit}^M} | \hat{\varepsilon}_{jit}^M \right) \leq 1 \tag{10}$$

where $\hat{\varepsilon}_{jit}^M = \ln \hat{f}_t^j(X_{jit}) - \ln \hat{f}_t^M(X_{jit})$ is the estimated composite residuals of (8).

In sum, the main difference between the new two-step approach proposed by Huang et al. (2012) and the one proposed by Battese et al. (2004) and O'Donnell et al. (2008) lies in the second step, where the original deterministic programming technique is replaced by the SMF approach. The new approach is preferable, because it allows for the presence of the random error V_{jit}^M, such that the estimated TGR in (10) immunes from the influence of random shocks, as opposed to the programming method. In addition, since (8) has to be estimated by the ML, the resulting parameter estimates have the usual statistical properties that allow for conducting statistical inferences.

3.2 Empirical model

As above mentioned, the metafrontier framework is specified to use output and input variables that are consistently defined across different groups. In another aspect, the data used in this study form different countries, the classification systems used for accounting firms' services differ among the three countries, which hinder the identification of three outputs as previous studies. This restriction forces this study to define only one output variable, three input variables, and limits the sample period to 2007–2009.

The production function is established as a flexible translog function and time trend is incorporated to capture variations in production techniques. The function is shown below:

$$\begin{aligned}\ln Y_{it} = \beta_0 + \sum_{j=1}^{3}\beta_j \ln X_{jit} + \frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3}\beta_{jk}\ln X_{jit}\ln X_{kit} \\ + \alpha_0 t + \frac{1}{2}\alpha_1 t^2 + \sum_{j=2}^{4}\alpha_j \ln X_j t \\ + \alpha_s SIZE + V_{it} - U_{it} \qquad (11)\end{aligned}$$

where α and β are the parameters to be estimated, and $V \sim N(0, \sigma_v^2)$ indicates random interference with a mean of 0. Variance is an unknown constant $\sigma_v^2, U_{it} \sim u_i e^{-\eta(t-T)}$, and $u_i \sim |N(0, \sigma_u^2)|$ is a non-negative variable of normal random inefficiency with a mean of 0 and an unknown constant σ_u^2 as variance. η represents the variance rate of technical efficiency; if it is a positive number this indicates that technical efficiency improves over time, but if it is a negative number this indicates that technical efficiency declines over time. U and V are assumed to be statistically independent.

The entire estimation procedure consists of two steps. The first step is the same as Battese et al. (2004) and O'Donnell et al. (2008), which requires the use of the conventional SFA approach to estimate each group-specific frontier like (1) by the ML. Let $\hat{f}_t^j(X_{jit})$ be the fitted value of the group-j's output for the ith firm at time t. This allows for calculating $T\hat{E}_{it}^j$ for each firm under study. In the second step, we estimate the metafrontier production function like (8), proposed by Huang et al. (2012). The estimated TGR is computed according to (10).

4 Variable definition and data sources

4.1 Data sources and sample selection

This study measures the technical efficiency of the accounting firms in the US, China, and Taiwan. Using the metafrontier production function model, we separately estimate the technical efficiency of the accounting firm in each nation and then estimate technology gap ratio (TGR) and metafrontier technical efficiency (MTE). We collect the input and output data of the top 100 accounting firms in each country (ranked on the basis of total revenues). In order to ensure that input and output variables for the accounting firm of each nation were consistently defined, this study limited the sample period to 2007–2009. This is because the same accounting firm may not always be ranked in the top 100 each year; therefore our research data is classified as unbalanced panel data.

The US samples are obtained from survey data published annually by Accounting Today. After eliminating incomplete data, we obtain information on 109 firms and 297 firm-year observations. For the accounting firm in Taiwan, we consult the database of the *Annual Survey of Accounting Firms in Taiwan*, which is published by the Financial Supervisory Commission ROC. After eliminating those firms with 0 professional staff, the final number of samples was 50 firms and 105 firm-year observations. Industry data from China comprised firm evaluation and ranking information published annually by the Chinese Institute of Certified Public Accountants (CICPA) since 2003, although the items published each year tended to lack consistency. We obtained data on 142 accounting firms and 300 firm-year observations.

4.2 The output

In accordance with previous research aimed at estimating the production function of accounting firms, e.g., Banker et al. (2003, 2005) and Chang et al. (2009a, 2009b), this study defines the output variable as total revenue received from the provision of services. Accounting firms offer three broad forms of service: (1) accounting and auditing services that include compilations, the auditing of financial statements, reviews, and other attestation engagements; (2) tax services that include tax planning and return preparation in the areas of income, property, and other taxation; and (3) consulting and advisory services including consulting, design or implementation of information systems, appraisal or valuation services, and any other form of management assistance. Unfortunately, the classification systems used for these services differ among the three countries,[3] which hinder the identification of three outputs and forces us to define the total revenues as a single output variable measured in millions of US dollars before tax.

To maintain mutual consistency in comparing the annual data of the three countries, we first use the 2005 base year consumer price index of each country to deflate the data

[3] However, the information provided by CICPA only provides data on two types of revenue: auditing and non-auditing service. The accounting and auditing services on US firms comprises compilations, special reports, and reviews in addition to engagement involving the attest function which could be categorized as revenue from auditing services and non-auditing services. The Taiwan's database on the other hand provided complete data on various revenue items.

and convert it into real variables. We then convert RMB and TWD into USD (in millions of dollars) based on annual average exchange rate.

4.3 Input variables

Following Banker et al. (2003, 2005) and Chang et al. (2009a, b), this study defines three inputs: the number of partners, the number of professionals, and the number of other employees. The first input includes all partners, owners, and shareholders who have the right to share the profits of an accounting firm. The input labeled "professionals" is measured by the number of professionally qualified staff providing accounting and other services to clients. Specifically, this input contains staff accountants, senior accountants, and managers, excluding partners. The third input includes all clerical and support personnel who are not included in either of the first two variables.

Furthermore, to avoid the accounting firm size could affect the estimate results, this study also include a firm size dummy variable for each country in the group frontier and the metafrontier. We first combine the samples in the three countries and use the percentiles of total revenue to divide the sample into three equally large sub-groups. Firms with a total revenue under USD 6.98 million are designated as small-size firms, those with a total revenue between USD 6.98 million and USD 38.87 million are regarded as medium-size firms, and those with a total revenue over USD 38.87 million are considered as large-size firms. However, we find that there are no sample firms from Taiwan in the medium-size group and no sample firms from the US in the small-size group, which prevents regression analysis.

We therefore use the median (USD 31.17 million) of total revenue to divide the samples into two sub-groups, i.e., large-size and small-size firms. Firms with a total revenue greater than or equal to USD 31.17 million are thus considered large-size firms (SIZE = 1), whereas those with a total revenue under USD 31.17 million are designated as small-size firms (SIZE = 0).

4.4 Descriptive statistics

Panel A of Table 1 presents sample statistics of all variables in the three countries. The average total revenue of accounting firms in the US is the USD 388.24 million, which is 15.8 times higher than China (USD 24.51 million) and 27.3 times higher than Taiwan (USD 14.22 million). With regard to input factors, the US scored the highest in X1 (153.87), approximately 9 times higher than China and 10.6 times higher than Taiwan. The average number of professionals in the US is 1,304.20, followed by 200.08 in China and 30.43 in Taiwan. It appears that the average number of professionals in the US exceeds that of Taiwan by more than 42.9 times. The three countries do not differ as significantly in relation to the number of administrators and other staff.

Panel B of Table 1 presents the average output of each input variable in each nation. The average output of partners is the highest in China (USD 6.944 million), followed by the US (USD 1.680 million) and then Taiwan (USD 0.445 million). The highest average output of professionals is in Taiwan (USD 1.004 million), followed by the US (USD 0.239 million) and China (USD 0.088 million). The highest average output of other employees is in the US (USD 0.971 million), followed by China (USD 0.045 million) and then Taiwan (USD 0.042 million). Because the average output of each input variable fluctuated from nation to nation, we are unable to use this type of single indicator to determine which nation has better operating performance. Production efficiency is an integrated indicator that can accurately represent the operating performance of the entities being assessed. This is the main reason why this study employed the stochastic metafrontier approach.

In order to understand whether accounting firms in each country differed in terms of production scale, we conduct difference tests on the mean of each variable. Table 2 presents the F statistics. It can be seen that all of the average values of output and input variables among the accounting firms of the three countries are significantly different at the 1 % level, except for the means of input X3, the F-statistic of which attained a 10 % level of significance.

5 Empirical results

5.1 Results of group frontier estimation

Using the two-step SMF proposed by Huang et al. (2012), this study estimates and compares the production efficiency of the accounting firms in US, China, and Taiwan. In the first step, we use SFA to estimate the production frontier function of each group (country).

Table 3 presents the parameter estimates for the group frontier. More than a half of the parameter estimates in each group attain significance at least at the 10 % level.[4] The coefficient estimates of the SIZE variable in the US and China are significant at the 1 % level, confirming the importance of firm size in the production process. As

[4] Our estimation results show that a little more than a half of the parameter estimates achieve statistical significance. This appears to be acceptable due to the fact that our data set is not large, including only 297, 105, and 300 observations in the US, Taiwan, and China, respectively.

Table 1 Descriptive statistics

Variables	US accounting firms (no. observations = 297)			Taiwan accounting firms (no. observations = 105)			China accounting firms (no. observations = 300)		
	Mean (SD)	Min	Max	Mean (SD)	Min	Max	Mean (SD)	Min	Max
Panel A: Summarized statistics of accounting industry data									
Output variable									
Total revenue (y)	388.24 (1,431.88)	25.22	10,309.86	14.22 (37.43)	0.52	190.05	24.51 (60.29)	2.33	357.26
Input variable									
Partners (X1)	153.87 (444.77)	8	2,949	14.50 (26.85)	2	136	17.14 (11.11)	2	46
Professionals (X2)	1,304.20 (4,378.96)	48	32,857	30.43 (93.65)	1	551	200.08 (191.61)	9	1,228
Other employees (X3)	384.48 (1,269.22)	11	9,123	229.99 (511.05)	11	2,281	479.41 (847.18)	20	5,490

	US accounting firms			Taiwan accounting firms			China accounting firms		
	X1	X2	X3	X1	X2	X3	X1	X2	X3
Panel B: Average output per unit of input									
Total revenue (y)	1.680	0.239	0.971	0.445	1.004	0.042	6.944	0.088	0.045

All dollar-valued variables were measured in millions of real US dollars with 2005 as the base year

Table 2 Joint tests for equality of mean inputs and outputs among sample countries

Variables	US	ROC	China	F stat. (p value)
Total revenue (y)	388.24	14.22	24.51	13.22 (<0.001)
Partners (X1)	153.87	14.50	17.14	19.28 (<0.001)
Professionals (X2)	1,304.20	30.43	200.08	14.02 (<0.001)
Other employees (X3)	384.48	229.99	479.41	2.43 (0.089)

Total revenue is measured in millions of real US dollars (USD) with 2005 as the base year

expected, the size of an accounting firm has a positive effect on output (total service revenues) of the firm. The estimated values of σ^2 and γ for the three nations are significant at the 1 % level, which confirms inefficiency of the accounting firms. The estimated value for η for China is significantly positive at the 1 % level, indicating that the technical efficiency of accounting firms in China grows over time, while the same estimates in the US and Taiwan is insignificant.

The translog production function contains the linear, quadratic, and interactive terms of the (log)input variables. Therefore, the marginal effect of an input on the output can be computed by taking the partial derivative of the output with respect to the input. The coefficient of the linear term of an input alone does not represent the marginal effect. We then evaluate $\partial \ln Y / \partial \ln x_i (i = 1, 2, 3)$ for each firm in each country and find that all of the mean values of those measures are positive, as expected.

Then, we use the parameter estimates in Table 3 to calculate the scale economies for each country. The measure of scale economies (SE) is defined as

$$\mathrm{SE} = \sum_{j=1}^{3} \frac{\partial \ln Y}{\partial \ln X_j} \tag{12}$$

where SE represents a primal measure of generalized returns to scale characterizing the production frontier. A value of SE > 1 shows increasing returns to scale, implying that firms should reduce their average long-term costs by expanding their production scale. A value of SE = 1 shows constant returns to scale, indicating that firms have attained optimal capacity, while SE < 1 shows decreasing returns to scale, indicating that firms should cut their production scale in order to reduce the average long-term costs. We calculate the measure of SE for each observation and then compute the average values of SE for the US, Taiwan, and China are equal to 0.909, 0.886, and 0.864, respectively. The result shows that decreasing returns to scale display in the accounting firms of these three countries, implying that mergers and acquisitions may not be advantageous for expanding and seizing a larger market share.

Again, the data in Table 2 confirms that the accounting firms in these three countries differ significantly with

Table 3 Parameter estimates of group-specific production frontiers

Variables	US		Taiwan		China	
	Parameter	SE	Parameter	SE	Parameter	SE
Constant	5.319***	0.420	3.133***	0.527	5.913***	0.824
$\ln x_1$	−0.230	0.261	−0.268	0.298	−0.218	0.239
$\ln x_2$	0.467	0.293	−0.098	0.159	−0.036	0.266
$\ln x_3$	0.322**	0.127	0.517	0.381	−0.243	0.292
t	−0.150***	0.040	0.156*	0.080	0.104	0.150
$\ln x_1 \times \ln x_1$	0.040	0.048	−0.032	0.069	0.146***	0.036
$\ln x_2 \times \ln x_2$	0.021	0.057	0.025	0.024	0.134*	0.072
$\ln x_3 \times \ln x_3$	0.043**	0.018	−0.032	0.067	0.103***	0.038
t^2	0.013**	0.006	−0.027**	0.014	−0.029	0.021
$\ln x_1 \times \ln x_2$	0.034	0.092	−0.164**	0.077	−0.077	0.064
$\ln x_1 \times \ln x_3$	0.021	0.042	0.184*	0.101	−0.036	0.043
$\ln x_1 \times t$	−0.052***	0.013	−0.047*	0.027	0.047**	0.022
$\ln x_2 \times \ln x_3$	−0.106*	0.054	0.091	0.065	−0.102	0.105
$\ln x_2 \times t$	0.066***	0.013	0.024	0.016	−0.011	0.048
$\ln x_3 \times t$	−0.015*	0.009	0.006	0.020	0.003	0.038
SIZE	0.060***	0.019	−0.032	0.313	0.177***	0.069
σ^2	0.143***	0.022	0.175***	0.042	0.322***	0.061
γ	0.984***	0.003	0.982***	0.006	0.947***	0.015
η	0.034	0.024	−0.010	0.042	0.119***	0.043
Log-likelihood	266.89		69.33		1.36	

***, **, * Significance at the 1, 5, and 10 % levels, respectively

regard to mean inputs and output. The estimated coefficients in Table 3 also show considerable variation among them. Determining whether the accounting firms in these three groups adopt the same production technique is an important hypothesis test, because if they do, there is no need to apply the two-step approach to estimate the metafrontier. Moreover, the technical efficiency scores of different countries can then be compared directly. Thus, this study uses the likelihood ratio statistic of $\lambda = -2\{\ln[L(H_0)] - \ln[L(H_1)]\}$ to test this hypothesis, where $\ln[L(H_0)]$ is the logarithmic likelihood value derived from (11),[5] using all of the data, and $\ln[L(H_1)]$ is the sum of the logarithmic likelihood values over each group frontier. λ is equal to 666.94 with 38 degrees of freedom, which is significant at the 1 % level. The null hypothesis, which states that the accounting firms in the three countries employ the same technologies, is decisively rejected. The accounting firms in these three countries adopt different technologies for their professional services, which justifies the use of the metafrontier model for a comparison of technical efficiency.

[5] Due to space limitations, we have not listed the coefficient estimation results; interested readers may obtain this data from the author.

5.2 Results of metafrontier estimation

Next, we use the parameter estimates in Table 3 to calculate the fitted output values for each group; i.e., $\ln \hat{f}_t^j(X_{jit})$ in (8). This allows us to estimate the stochastic metafrontier production function, in which the functional form of $\ln f_t^M(X_{jit})$ is the same as the translog production function in (11). The parameter estimates are presented in the first column of Table 4. Again, most of the estimates are significant at the 1 % level. The coefficient estimate of the size variable is also significant at the 1 % level. This implies that firm size plays a crucial role in determining the technology gap ratio.[6] The second column of Table 4 presents the estimates of the metafrontier obtained from the QP model, as proposed by Battese et al. (2004) and O'Donnell et al. (2008).[7] To calculate standard deviation, we employ a bootstrap method using 5,000 replications. Standard deviation can then be calculated using the bootstrapped results. It can be seen that the parameter estimates of the SMF and QP methods deviate substantially. Recall

[6] The estimation results are quite similar to the ones without the firm size dummy variable. But, including the firm size variable makes this empirical result more intuition about practices. We are grateful to anonymous referee for providing the suggestion.

[7] We have not listed the LP metafrontier estimates, as they are similar to those resulting from the QP model. Interested readers may obtain this data from the author.

Table 4 Parameter estimates of the metafrontier production function

Variables	SMF approach		QP approach	
	Parameter	SE	Parameter	SE
Constant	5.779***	0.206	7.266	0.729
$\ln x_1$	0.272***	0.069	0.897	0.353
$\ln x_2$	0.801***	0.053	−0.631	0.491
$\ln x_3$	−0.743***	0.076	−0.034	0.228
t	−0.226***	0.085	−0.137	0.313
$\ln x_1 \times \ln x_1$	0.158***	0.017	0.176	0.061
$\ln x_2 \times \ln x_2$	0.058***	0.009	0.179	0.111
$\ln x_3 \times \ln x_3$	0.158***	0.011	−0.002	0.030
t^2	−0.011	0.017	−0.010	0.072
$\ln x_1 \times \ln x_2$	−0.057***	0.021	−0.345	0.161
$\ln x_1 \times \ln x_3$	−0.098***	0.014	0.032	0.059
$\ln x_1 \times t$	0.012	0.013	−0.005	0.073
$\ln x_2 \times \ln x_3$	−0.146***	0.014	0.023	0.096
$\ln x_2 \times t$	−0.024***	0.009	0.091	0.092
$\ln x_3 \times t$	0.063***	0.010	−0.056	0.045
SIZE	0.491***	0.043	0.213	0.064
σ^2	0.140***	0.021	–	–
γ	0.840***	0.087	–	–
η	0.104*	0.054	–	–
Log-likelihood	44.06		–	

***, **, * Significance at the 1, 5, and 10 % levels, respectively

that mathematical programming techniques are deterministic in essence and apt to be influenced by shocks.

5.3 Various efficiency measures

Finally, we compute the average values of GTE, TGR, and MTE for each country, the outcomes of which are presented in Table 5. The left side of the table displays the results from the SMF model and the right side displays the results from the QP model. Note that both the SMF and QP models have the same mean GTE values, derived in the first step. According to the SMF approach, Taiwanese accounting firms have the highest mean MTE value (0.575), followed by American firms; however, the difference is quite small. Chinese firms present the lowest mean value of MTE. US firms have the highest TGR value (0.770), followed by Taiwan and then China, indicating that the production techniques employed by the American accounting firms are superior to those of the other two nations. Both the SMF and QP models verify that Chinese accounting firms have the lowest average values for TGR and MTE, implying that they employ technology inferior to that of American and Taiwanese firms. This could be attributed to the fact that China is an emerging market. It will take time for the auditing environment and professional training in China to catch up with the more advanced markets.

According to the QP model, accounting firms in the US achieve the highest mean MTE (0.529) and TGR (0.713), followed by Taiwan and China, which leads to a lower mean TGR and greater standard deviation, compared with the SMF results. This can be attributed to the fact that the QP approach is deterministic and suffers from random shocks.

Figures 1, 2, 3, 4, 5 and 6 illustrate the mean values of GTE, TGR, and MTE for each country over time. The SMF model reveals that the mean TGR of Chinese firms grows more rapidly than that of firms in the other countries, indicating that the gap between the metafrontier and Chinese frontier shrink more quickly than do the gaps in the US and Taiwan. This may be associated with Chinese governmental policies that encourage fast expansion in the scale of accounting firms. The mean TGR values in the US and Taiwan grow relatively slowly, perhaps due to their adoption of more advanced technologies. However, the QP model shows that the mean TGR of Taiwan increases substantially during the sample period, which does not appear to be feasible.

5.4 Hypothesis testing

Testing whether the foregoing measures in various countries attain statistical significance is crucial. This study uses paired t and joint F statistics to test for null hypotheses specifying that the respective mean values of TGR and MTE in different countries are the same for each year and the entire sample period. Table 6 summarizes the testing outcomes. The F statistics for TGR and MTE are significant at the 1 % level, implying that the sample firms in the three countries differ in the mean values of TGR and MTE. This arises from the fact that the US and Taiwan have significantly higher TGR and MTE than China, while the US and Taiwan present similar performance. This inference is confirmed using paired t statistics, where accounting firms in the US and Taiwan again present similar mean values for TGR and MTE throughout the sample period, while the mean values of TGR and MTE in China are significantly lower than those in the US and Taiwan.

6 Conclusion

As differences in economic environment, market scale, organization type, accounting standards, and industry regulations, accounting firms in different countries adopt different production techniques. To ensure accuracy in this transnational comparison, we first construct a metafrontier model and compare the MTE (comprising GTE and TGR) of the accounting firms of the US, China, and Taiwan. In

Table 5 Summary statistics of various measures of efficiency in accounting firms

	SMF estimates				QP estimates			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Period: 2007–2009								
US accounting firms								
TGR	0.770	0.148	0.134	1.000	0.713	0.140	0.252	1.000
GTE	0.745	0.131	0.231	0.986	0.745	0.131	0.231	0.986
MTE	0.571	0.137	0.031	0.923	0.529	0.130	0.058	0.913
Taiwan's accounting firms								
TGR	0.760	0.088	0.468	0.896	0.498	0.226	0.181	1.000
GTE	0.760	0.160	0.385	0.979	0.760	0.160	0.385	0.979
MTE	0.575	0.131	0.303	0.863	0.373	0.182	0.124	0.950
China's accounting firms								
TGR	0.619	0.111	0.363	0.926	0.330	0.161	0.130	1.000
GTE	0.627	0.181	0.156	0.985	0.627	0.181	0.156	0.985
MTE	0.393	0.149	0.070	0.828	0.216	0.143	0.024	0.769
Overall								
TGR	0.704	0.145	0.134	1.000	0.517	0.241	0.130	1.000
GTE	0.697	0.170	0.156	0.986	0.697	0.170	0.156	0.986
MTE	0.496	0.167	0.031	0.923	0.372	0.204	0.024	0.950

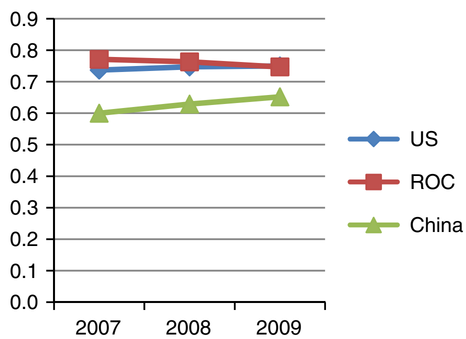

Fig. 1 SMF Approach-GTE

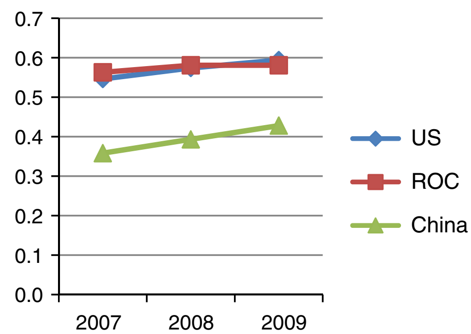

Fig. 3 SMF Approach-MTE

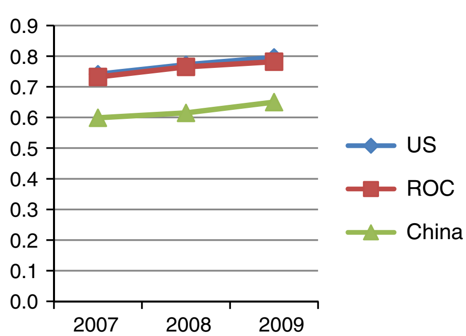

Fig. 2 SMF Approach-TGR

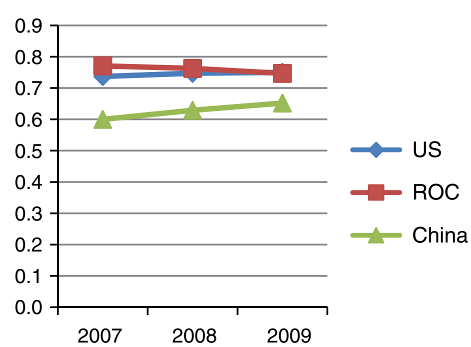

Fig. 4 QP Approach-GTE

building the stochastic metafrontier production function, we employ the two-step approach proposed by Huang et al. (2012) to prevent random factors from affecting the estimates. The estimated results demonstrate that the greater mean TGR and lower standard deviation, compared with the QP model results.

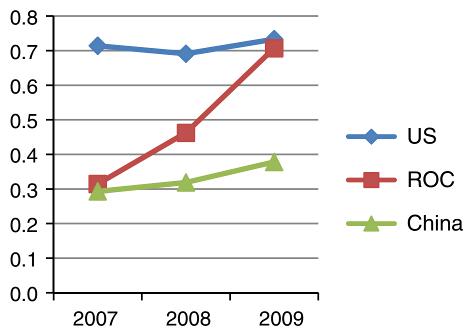

Fig. 5 QP Approach-TGR

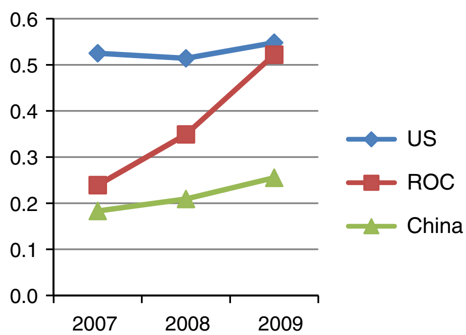

Fig. 6 QP Approach-MTE

The key findings are as follows: American firms have the highest TGR value, followed by Taiwan and then China, indicating that the production techniques employed by the US are superior to those of the other two countries. Moreover, Taiwanese accounting firms have the highest average MTE value, followed by American firms; however, the difference is quite small. Chinese firms present the lowest mean value of MTE. Taiwan is a small open economy and although its accounting firms are smaller in scale compared to the US and China, its overall production efficiency is superior. This may be attributed to the outstanding productivity of professional employee in Taiwan's accounting firms, indicating that the professionalism of employee plays a vital role in the production process of firms. Accounting firms should strive to cultivate and enhance the professionalism of its employee to enhance productivity, reduce costs, and increase profits.

Although Chinese accounting firms have the lowest average values for TGR and MTE, implying that they adopt technology inferior to that of American and Taiwanese firms. Nevertheless, the mean TGR of Chinese firms grows more rapidly than that of firms in the other countries, indicating that the gap between the metafrontier and Chinese frontier shrink more quickly than do the gaps in the US and Taiwan. This may be associated with Chinese governmental policies that encourage fast expansion in the scale of accounting firms.

This study is limited by discrepancies in the sources of sample data. To ensure that the variables of each country are consistently defined, we identify only one output and three input variables and limit the sample period to 3 years. Increasing the number of input and output variables, extending the sample period, and adding additional nations to the sample pool could provide results of greater value. The metafrontier framework is highly suitable for comparing variations in productivity and production characteristics in the accounting firms across countries.

Table 6 Significance tests for measures of TGR and MTE across countries

Variables	*t* test						*F* test	
	US versus Taiwan		US versus China		Taiwan versus China		Among	
	t stat.	*P* value	*t* stat.	*P* value	*t* stat.	*P* value	*F* stat.	*P* value
Period: 2007–2009								
TGR	0.783	0.434	14.084	<0.001	13.180	<0.001	120.75	<0.001
MTE	−0.254	0.799	15.219	<0.001	11.117	<0.001	138.04	<0.001
Period: 2007								
TGR	0.378	0.707	7.464	<0.001	6.734	<0.001	33.49	<0.001
MTE	−0.590	0.556	9.102	<0.001	7.167	<0.001	50.67	<0.001
Period: 2008								
TGR	0.353	0.725	8.758	<0.001	8.537	<0.001	47.24	<0.001
MTE	−0.262	0.794	8.988	<0.001	6.620	<0.001	48.60	<0.001
Period: 2009								
TGR	0.766	0.445	8.678	<0.001	8.227	<0.001	45.81	<0.001
MTE	0.499	0.618	8.566	<0.001	5.605	<0.001	41.38	<0.001

Average values of TGR and MTE are calculated on the basis of the SMF model

Acknowledgments The first author is indebted to the financial support of Ministry of Science and Technology, Taiwan, ROC, with grant number: NSC 100-2410-H-032-036. The three authors are also indebted to anonymous referees for their valuable comments and suggestions.

References

Banker RD, Chang H, Cunningham R (2003) The public accounting industry production function. J Acc Econ 35(2):255–281

Banker RD, Chang H, Natarajan R (2005) Productivity change, technical progress, and relative efficiency change in the public accounting industry. Manage Sci 51(2):291–304

Banker RD, Chang H, Natarajan R (2007) Estimating DEA technical and allocative inefficiency using aggregate cost or revenue data. J Prod Anal 27:115–121

Battese GE, Coelli TJ (1992) Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. J Prod Anal 3:153–169

Battese GE, Rao DSP (2002) Technology gap, efficiency and a stochastic metafrontier function. Int J Bus Econ 1:87–93

Battese GE, Rao DSP, O'Donnell CJ (2004) A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. J Prod Anal 21:91–103

Bos JWB, Schmiedel H (2007) Is there a single frontier in a single European banking market? J Bank Finance 31(7):2081–2102

Bröcheler V, Maijoor S, Witteloostuijn AV (2004) Auditor human capital and audit firm survival The Dutch audit industry in 1930–1992. Acc Organ Soc 29:627–646

Chang H, Choy HL, Cooper WW, Ruefli TW (2009a) Using Malmquist indexes to measure changes in the productivity and efficiency of US accounting firms before and after the Sarbanes–Oxley Act. Omega 37(5):951–960

Chang H, Choy HL, Cooper WW, Parker BR, Ruefli TW (2009b) Measuring productivity growth, technical progress, and efficiency changes of CPA firms prior to, and following the Sarbanes–Oxley Act. Socio-Econ Plan Sci 43(4):221–228

Chang H, Chen J, Duh R, Li S (2011) Productivity growth in the public accounting industry: the roles of information technology and human capital. Audit A J Pract Theory 30(1):21–48

Chen KH (2012) Incorporating risk input into the analysis of bank productivity: application to the Taiwanese banking industry. J Bank Finance 36(7):1911–1927

Cheng TW, Wang KL, Weng CC (2000a) A study of technical efficiencies of CPA firms in Taiwan. Rev Pac Basin Financ Mark Polic 3(1):27–44

Cheng TW, Wang KL, Weng CC (2000b) Economies of scale and scope in Taiwan's CPA service industry. Appl Econ Lett 7:409–414

Greenwood R, Li SX, Prakash R, Deephouse DL (2005) Reputation, diversification, and organizational explanations of performance in professional service firms. Organ Sci 16(6):661–673

Hayami Y (1969) Sources of agricultural productivity gap among selected countries. Am J Agric Econ 51:564–575

Hayami Y, Ruttan VW (1970) Agricultural productivity differences among countries. Am Econ Rev 60:895–911

Hayami Y, Ruttan VW (1971) Agricultural development: an international perspective. Johns Hopkins University Press, Baltimore

Huang CJ, Huang TH, Liu NH (2012) A new approach to estimating the metafrontier production function based on a stochastic frontier framework. Working paper, Vanderbilt University, National Cheng-chi University (Taiwan)

Knechel WR, Rouse P, Schelleman C (2009) A modified audit production framework: evaluating the relative efficiency of audit engagements. Acc Rev 84(5):1607–1638

Moreira VH, Bravo-Ureta BE (2010) Technical efficiency and metatechnology ratios for dairy farms in three southern cone countries: a stochastic meta-frontier model. J Prod Anal 33(1):33–45

Nordenflycht AV (2010) What is a professional service firm? Toward a theory and taxonomy of knowledge-intensive firms. Acad Manag Rev 35(1):155–174

O'Donnell CJ, Rao DSP, Battese GE (2008) Meta-frontier frameworks for the study of firm-level efficiencies and technology ratios. Empir Econ 34:231–255

O'Keefe TB, King RD, Gaver KM (1994) Audit fees, industry specialization, and compliance with GAAS reporting standards. Audit A J Pract Theory 13:41–55

Parker RH, Morris RD (2001) The influence of U.S. GAAP on the harmony of accounting measurement policies by large companies in the UK and Australia. Abacus 37(3):297–328

Simunic DA (1980) The pricing of audit services: theory and evidence. J Acc Res 18(1):161–190