Technical Efficiency and Total Factor Productivity Changes in Manufacturing Industries: Recent Advancements in Stochastic Frontier Model Approach

Huynh, Linh and Hoang, Hien

University of Economics, The University of Da Nang, Duy Tan University

2021

Technical efficiency and Total factor productivity changes in manufacturing industries: recent advancements in stochastic frontier model approach

Abstract

This paper aims to evaluate total factor productivity growth (TFPG) of Vietnamese manufacturing industries over the period 2000 – 2019. The stochastic frontier models were applied to decompose the sources of TFPG into technical efficiency changes, technological changes, allocative efficiency, and scale effects. We find that technological changes and the rate of scale component effect have been the major driving force of productivity growth in the 2-digit manufacturing industries as well as total manufacturing industry. In contrast, technical efficiency changes and allocative efficiency had negative effects on TFPG. Furthermore, TFP in the manufacturing sector has declined at an annual rate of -0.062 during the period of 2010 – 2015, then it grows continuously during the period of 2015 - 2019, with a rate of 5.4%. This study suggests that specific guidelines are required to promote productivity in each industrial sectors. For example, Industries with slow technological progress (textile and electrical products) require the introduction of new frontier technology. Government policy should encourage investments that can introduce newly developed production technology. In addition, considering allocative inefficiency, a policy to enhance TFP by improving resource allocation should be pursued, which be done by promoting free markets and lessening government intervention.

Keywords – Total factor productivity growth; Technical efficiency; Technological progress, Stochastic Frontier Production Function.

JEL Classification: C23, D24, O47, L60

Introduction

Total factor productivity growth (TFPG) has been recognized as one of main sources for economic growth, and particularly important for developing countries that depend on commodity exports (Krugman, 1997). The reason for this is that technological advancements and operational efficiency are core competences for competitiveness in the international market (Mattsson et al., 2020). Therefore, a great deal of effort has been expanded in measuring and identifying sources of productivity change (Solow, 1957; Kumbhakar, 1990; Kumbhakar et al., 2000; Murillo-Zamorano, 2004).

Since the economic reform in 1986, Vietnam's real gross domestic product (GDP) has experienced dynamic performance in response to the global economic fluctuations in the past decades, however, it is still considered as one of the fastest growing economies over the period. In addition, the country has been highly successful as attracting foreign direct investment (FDI), particularly into the fast-growing electronics and garments sectors. For example, in 2020, Vietnam was recognized among the world's top 20 host economies for FDI with an inflow of USD 16 billion (UNCTAD, 2021). The manufacturing sector is of specific importance for export and potential spillover effects on other sectors (Mattsson et al., 2020). Therefore, it is important to investigate TFPG within manufacturing sector in Vietnam in searching of an explanation for the successful economic transformation model.

Previous studies on TFP in Vietnam include either non-parametric approach using data envelopment analysis (DEA) (Coelli and Rao, 2005; Ho, 2014; Nguyen et al., 2019) or parametric using the production function such as Cobb-Douglas production in logarithm form or translog function (Ngo and Tran, 2020; Le et al., 2021). To overcome the problem of endogeneity problem may arise in Cobb-Douglas production function, some studies applied semiparametric methods proposed by Olley and Pakes (1996) and Levinsohn and Petrin (2003) or GMM estimator proposed by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998) (Nguyen, 2017; Hoang and

Huynh, 2020; Huynh et al., 2021; Thanh, 2021). [1] However, there is a lack of studies on TFP in Vietnam using stochastic frontier analysis (SFA) approach which decomposes the growth of TFP into technical efficiency change (TEC), technological change (TC), scale effects, and allocative efficiency (Kumbhakar and Tsionas, 2005; Tsionas and Kumbhakar, 2014; Mattsson et al., 2020).

The aim of this paper is: (i) using stochastic frontier model (SFM) to analyses the level of technical efficiency in manufacturing industry, and in particular for 2-digit industrial sectors in Vietnam for the period of 2010 – 2019; (ii) Based on results of SFM, examine TFPG and its decomposed factors. By using firm-level data from 2010 to 2019, this paper is significant different previous studies in several aspects. First, this study contributes to literature on TFP in Vietnam by using a large-unbalanced panel data set with over 330,000 observations. Second, by decomposing TFP into a four-component SFM, this study provides additional insights into TFP performance and help us better understand why some sectors improve efficiency levels at higher rates than do others. Consequently, results also help explain differences in TFPG over time.

1 Theoretical models

1.1 Technical efficiency

The SFM is motivated by the theoretical assumption that all firms operate as a maximize output given their quantities of inputs, however, no one can exceed the ideal "frontier" and deviations from this extreme represent firms' inefficiencies (Murillo-Zamorano, 2004; Belotti et al., 2013). To capture this, Aigner et al. (1977), Meeusen and van Den Broeck (1977), and Battese and Corra (1977) simultaneously developed a SFM that can capture not only efficiency term but also the effects of exogenous shocks beyond the control of the analyzed units. Here, we briefly describe the SFM for panel data since we are using firm-level data spanning for the period of 2010 – 2019.

Based on proposed models of Pitt and Lee (1981) and Schmidt and Sickles (1984), the standard model can be written as:

$$y_{it} = \beta_0 + \beta_i X_{it} + \varepsilon_{it}, i = 1, \dots., N, t = 1, \dots, T_i \qquad (1)$$

$$\varepsilon_{it} = v_{it} - u_i$$

$$v_{it} \sim \mathcal{N}(0, \sigma_v^2)$$

$$u_i \sim \mathcal{N}^+(0, \sigma_u^2)$$

Where y_{it} is the output of each firm *i* at time *t*, the vector X_{it} comprises factor inputs quantities, and β_i are corresponding coefficients to be estimated. Finally, ε_{it} is the composed stochastic error term contains technical inefficiency (u_i) and regular disturbance (v_{it}). Equation (1) can be rewritten as

$$y_{it} = \alpha_i + X_{it}\beta_i + v_{it} \text{ with } \alpha_i = \beta_0 - u_i \qquad (2)$$

Equation (2) can be estimated by fixed effects (FE) model (Schmidt and Sickles, 1984) or random effects (RE) model (Pitt and Lee, 1981) using the maximum likelihood (ML) method. It worth to note that the Equation (2) has considered technical inefficiency effects to be time-invariant. However, this assumption seems unrealistic as the time dimension becomes larger. Therefore, Cornwell et al. (1990) suggested to account for time-varying inefficiency effects by specifying a quadratic function form of time trend t so that

$$y_{it} = \beta_{it} + X_{it}\beta_i + \vartheta_{it} \text{ with } \beta_{it} = \beta_{0t} - u_{it} \qquad (3)$$

$$u_{it} = \theta_{1i} + \theta_{2i}t + \theta_{3i}t^2 \qquad (4)$$

Where β_{0t} indicates the common intercept, θ_s represent cross-section producer specific parameters. Similarly, researchers extend model of Pitt and Lee (1981) by allowing the mean of inefficiency to vary over time, however, the temporal patterns of inefficiency only depend on one or two parameters (see e.g., Kumbhakar, 1990; Battese and Coelli, 1992; Lee and Schmidt, 1993)

Recently, due to the methodological development, there has been modern SFM proposed simultaneously by Kumbhakar et al. (2014), Colombi et al. (2014) and Tsionas and Kumbhakar (2014). These models overcome some limitations of the previous models by splitting the error term into four

[1] The econometric issues within Cobb-Douglas function include possible simultaneity, measurement errors and the specification of the functional form.

components including firms' latent heterogeneity (Greene, 2005a, 2005b), short-run (time-varying) inefficiency, persistent (time-invariant) inefficiency, and the random shocks (Kumbhakar et al., 2015). The model is specified as

$$y_{it} = \alpha_0 + X_{it}\beta_i + \mu_i + \vartheta_{it} - \eta_i - u_{it} \quad (5)$$
$$v_{it} \sim_{iid} \mathcal{N}(0, \sigma_v^2)$$
$$u_{it} \sim_{iid} \mathcal{N}^+(0, \sigma_u^2)$$
$$\mu_i \sim_{iid} \mathcal{N}(0, \sigma_\mu^2)$$
$$\eta_i \sim_{iid} \mathcal{N}^+(0, \sigma_\eta^2)$$

The model (5) has four components two of which, η_i and u_{it} are inefficiency and the other two are firm effects and noise, μ_i and v_{it}, respectively. In this study, we apply the model (5) to estimate the technical efficiency of manufacturing firms in Vietnam from 2010 to 2019. [2]

1.2 Total factor productivity decomposition

The measurement of TFP is based on a production function which is identical to the SFM without an inefficiency component, written as

$$Y_{it} = \gamma_0 + X_{it}\beta_i + t_t + u_{it} \quad (6)$$

where Y_{it} denotes total output of the *i*th firm, X_{it} is vector of *j* inputs. The γ_0 measures the mean efficiency level across firms and over time, T_t the time-specific effects and u_{it} the stochastic error term.

The TFPG is defined as output growth unexplained by input growth, such that

$$T\dot{F}P = \dot{Y} - \sum_j S_j X_j \quad (7)$$

Where S_j is input *J*'s share in production costs. [3] Following Kumbhakar et al. (2015), we differentiate (6) and substitute (7), thus

$$T\dot{F}P = TC + TEC + (RTS - 1)\sum_j \lambda_j \dot{X}_J + \sum_j (\lambda_j - S_j)\dot{X}_J \quad (8)$$

Where $RTS = \sum_j \frac{\partial lnY}{\partial lnX_j} \equiv \sum_j e_j$ is measure of return to scale, and e_j are input elasticities defined at the production frontier, $\lambda_j = {}^{e_j}/_{RTS}$ is marginal product of input X_j.

The equation (8) decomposes TFP change into:

Scale components (SC), $(RTS - 1)\sum_j \lambda_j \dot{X}_J$,

Technological change (TC),

Technical efficiency change (TEC),

And allocative component (AC), $\sum_j (\lambda_j - S_j)\dot{X}_J$

2 Methodology and data

2.1 The model

Since the four-component SFM is perform better than previous model, we adopt it in this paper to analyze TFP change for manufacturing firms in Vietnam (Mattsson et al., 2020). We apply the multistep procedure proposed by Kumbhakar et al. (2014) because it is straightforward to implement and possible verification for each step. Although some may argue that Kumbhakar et al. (2014)'s procedure is not efficient as other single-stage procedures, however, this argument is not crucial as the number of observations is large in this paper (Mattsson et al., 2020). To apply the multistep procedure, equation (5) is rewritten as

$$y_{it} = \alpha_0^* + X_{it}\beta_i + \alpha_i + \varepsilon_{it} \quad (9)$$
$$where\, \alpha_0^* = \alpha_0 - E(\eta_i) - E(u_{it})$$
$$\alpha_i = \mu_i - \eta_i + E(\eta_i)$$
$$and\, \varepsilon_{it} = v_{it} - u_{it} + E(u_{it})$$

[2] For more details of estimating model (5), please see Kumbhakar et al. (2015).

[3] Subscripts *i* and *t* are omitted to avoid notational clutter.

The most common functional forms of the model in equation (9) are Cobb-Douglas production function and translog function (Murillo-Zamorano, 2004). While the former is preferred because of its simple linear regression, the latter provides for some generality and encompasses all commonly used specifications (Sharma et al., 2007). In addition, the translog model also allows for non-constant return to scales as well as varying of elasticities among inputs. Therefore, following Sharma et al. (2007), this study applies the translog specification of model (9), so that

$$lnY_{it} = \beta_0 + \beta_1 lnK_{it} + \beta_2 lnL_{it} + \beta_3 lnK_{it}^2 + \beta_4 lnL_{it}^2 + \beta_5(lnK_{it} * lnL_{it}) + \beta_6 t + \beta_7 t^2 + \beta_8(t * lnK_{it}) + \beta_9(t * lnL_{it}) + \varepsilon_{it} \quad (10)$$

Where *K*, *L* are capital and labor inputs, respectively. Technological change is captured by the time trend, t, and the production function in equation (10) is allowed to vary over time. The model in equation (10) turns out to be a standard panel data model and can be estimated by panel data estimation methods. [4] The estimated results of model (10) will be used to estimate TFP change basing on equation (8).

2.2 Data

An unbalanced firm-level panel data set that covers all firms within manufacturing industry in Vietnam during the period 2010 – 2019 is obtained from the General Statistics Office (GSO) of Vietnam. The manufacturing sector consists of the two-digit VSIC2018 from 10 to 35. The data set includes capital assets (*K*), number of full-time employees (*L*), and value-added (*Y*). All nominal variables were converted into 2010 constant price using annual GDP deflator.

Table 1 reports the descriptive statistics after elimination of outliers. Although there are no universally accepted method for outlier detection, we follow the method proposed by recent literature on TFP and exclude observations that have the value added in present year changes more than 80% in comparison with previous year (Mattsson et al., 2020). In addition, variables in SFM are in logarithm form, hence, we also exclude missing and zero observations after performing log transformation. After these exclusions, the data consists of 363,807 observations. We also report the summary statistics of variables in three-groups of firm ownerships including state-owned enterprises (SOEs), foreign invested enterprises (FIEs), and private enterprises (PRIVs).

Table 1: Descriptive statistics of the used variables

	Total	SOEs	FIEs	PRIVs
Observations	363,807	7,400	45,393	311,014
Value added (*Y*)	886.61	4,812.00	3,823.35	326.64
	(19,474.87)	(29,703.28)	(51,525.82)	(2,205.98)
Capital (*K*)	6,924.62	2,488.91	55,075.63	139.39
	(3,993,629.00)	(12,369.48)	(11,400,000.00)	(20,529.59)
Labour (*L*)	114.79	459.56	508.41	50.91
	(726.72)	(738.45)	(1,892.73)	(250.55)
Time variable	2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019			
Industrial dummies	5-digit from 10101 to 33200			

Notes: the value without parentheses is mean of variables, standard deviations are in parentheses.

3 Results

First, we present results of technical efficiency and its relative specifications. Second, TC, SC and AC are presented before we use them to calculate TFPG.

3.1 Technological efficiency

Column (1) of Table 2 presents baseline estimates of the equation (10). All coefficients in the production function are individually statistically significant at conventional level of confidence. In order to check for the robustness of our results, we include the industry dummy variables which

[4] The multistep procedure is implemented in Stata using the commands which is written by Kumbhakar et al. (2015).

are constructed on 5-digit industry level (VSIC 5-digit classes) to control for industry specific effects. [5] The results are presented in column (2) of Table 2. It can be seen from Table 2 that the inclusion of industry dummy variables does not alter the baseline results of this study.

Table 2: coefficient estimates of translog production function, 2010 -2019

	(1)	(2)
	Y	Y
β_1	0.193***	0.153***
	(0.003)	(0.003)
β_2	0.894***	0.878***
	(0.004)	(0.004)
β_3	0.101***	0.088***
	(0.001)	(0.001)
β_4	0.108***	0.124***
	(0.001)	(0.001)
β_5	-0.095***	-0.089***
	(0.001)	(0.001)
β_6	-0.125***	-0.111***
	(0.004)	(0.004)
β_7	0.027***	0.025***
	(0.001)	(0.001)
β_8	0.012***	0.013***
	(0.001)	(0.000)
β_9	-0.031***	-0.031***
	(0.001)	(0.001)
β_0	2.711***	2.972***
	(0.012)	(0.076)
Industry dummy	No	Yes
usigmas		
t	-0.044***	-0.035***
	(0.002)	(0.002)
_cons	1.119***	1.100***
	(0.011)	(0.010)
vsigmas		
_cons	0.089***	-0.104***
	(0.005)	(0.005)
Observations	336201	336201
chi2	835471.302	951400.356
p	0.000	0.000

Notes: Standard errors are in parentheses; *, ** and *** denote 10%, 5% and 1% levels of significance, respectively; for brevity, the coefficients of industrial dummies are not reported here. The estimation is based on ML method.

Source: Authors' estimation.

The TE measures are presented in Table 3. The results indicate that the TE on average is to be around 42 percent. Comparing the level of efficiency by sector, the Table 3 showed that for the whole period 2010 – 2019, the TE differs from 0.394 for FBT to 0.411 within ONMP. The other industries have estimates that range from 0.387 to 0.410. The average TE for all industries fluctuates throughout the sample period, 2010 – 2019, and reaches peaks in 2011 and 2016.

[5] In order to save space, we have not listed the estimation results of industry dummies in column (2) of Table 2. However, it is worth noting that the inclusion of these dummies increased the fit of the estimated model, since dummies are significant at conventional levels.

Table 3: technical efficiency (TE) by year and by sub-sector

Year	Mean	Std. Dev.	Max
2010	0.370	0.169	0.887
2011	0.434	0.150	0.843
2012	0.406	0.170	0.894
2013	0.400	0.167	0.890
2014	0.426	0.175	0.884
2015	0.398	0.173	0.857
2016	0.432	0.145	0.865
2017	0.424	0.157	0.860
2018	0.427	0.161	0.879
2019	0.415	0.150	0.862
By Industry sector for 2010 - 2019			
All manufacturing	0.418	0.155	0.894
Food products, beverages, and tobacco (FBT)	0.394	0.182	0.881
Textile and leather products	0.403	0.157	0.880
Wood and products of wood	0.397	0.174	0.858
Pulp, paper, paper products, publishing, and printing	0.406	0.159	0.890
Coke, refined petroleum products, chemicals, rubber and plastic products	0.406	0.164	0.870
Other non-metallic mineral products (*n.e.c*) (ONMP)	0.411	0.146	0.850
Basic metals products	0.400	0.174	0.862
Machinery and equipment	0.403	0.165	0.894
Electrical and optical products	0.406	0.163	0.884
Other manufacturing products (OMP)	0.410	0.152	0.842
Transport equipment	0.407	0.155	0.843
Repair of manufacturing equipment, personal and household goods	0.403	0.165	0.882

Notes: *n.e.c* is not else where classified.
Source: Authors' estimation.

3.2 Technological changes, scale change and TFP

Table 4 presents the averages of the rates of technological change (TC), the scale components (SC), the changes in allocative efficiency (AC), technical efficiency change (TEC) and the total factor productivity growth (TFP) for selected time periods. [6] Performances of manufacturing firms could be separated into two sub-periods, 2010 – 2015 and 2015 – 2019. The average rate of TC was declined continuously at -0.037 for the first sub-period, then increased significantly at an average rate of 0.067 in the total sample during the second sub-period. The rate of the scale components increased continuously over two sub-periods ranging from 0.3% to 0.6%. The results of SC, which measure the effects of input changes on output growth, indicate that RTS is increasing over the period (Kim and Han, 2001). However, technical efficiency change (TEC) and the allocation efficiency effects in most of the manufacturing firms in Vietnam are found to be negative during the entire period of our study as well as during both the two sub-periods. In fact, allocative inefficiency results when factor prices are not equal to their marginal product. Almost every estimate of AC has a negative value, implying the existence of allocative inefficiency. For the total sample, the average rate of AC was -0.051, implying the existence of inefficient allocation of inputs in production with a resulting decline of TFP.

Table 4 also shows that technological change exceeds efficiency change and has played a greater role in contributing to TFPG during the period, 2010 – 2019. Therefore, TFPG (TFPG) of

[6] The decomposition results by year are omitted here to save space, but are available from the authors on request.

manufacturing firms in Vietnam is due more to outward shifts of the production frontier than by movement towards it. The TFPG rates and all its components, except the economic scale effect component (SC), of almost all the manufacturing firms in Vietnam have declined during the first sub-period. However, the decline in TFPG rates of most of the manufacturing industries in the first sub-period is mostly responsible for the decline in TC of the same during that period as it has become the major contributor to TFPG during the entire period of our study. In contrast, while the rate of growth of TC of the manufacturing industries became higher during the second sub-period, the rate of growth of TFPG became higher too. Our findings correspond most closely to those in Sharma et al. (2007) and Roy et al. (2017), who showed that the technological progress was the most important factor of the TFPG of manufacturing industries in United States and India.

Table 4: technological change (TC), scale component (SC), technical efficiency change (TEC), allocative component (AC), and TFPG period 2010 – 2019

	TC	TEC	SC	AC	TFPG
2010-2015	-0.037	-0.028	0.006	-0.060	-0.062
2015-2019	0.067	-0.026	0.003	-0.041	0.054
2010-2015					
Food products, beverages, and tobacco (FBT)	-0.020	-0.028	0.005	-0.058	-0.045
Textile and leather products	-0.054	-0.028	0.007	-0.053	-0.072
Wood and products of wood	-0.017	-0.028	0.005	-0.074	-0.058
Pulp, paper, paper products, publishing, and printing	-0.017	-0.028	0.006	-0.058	-0.041
Coke, refined petroleum products, chemicals, rubber and plastic products	-0.029	-0.028	0.007	-0.058	-0.052
Other non-metallic mineral products (*n.e.c*) (ONMP)	-0.033	-0.028	0.004	-0.076	-0.076
Basic metals products	-0.032	-0.028	0.006	-0.070	-0.067
Machinery and equipment	-0.020	-0.028	0.006	-0.070	-0.056
Electrical and optical products	-0.046	-0.028	0.010	-0.044	-0.052
Other manufacturing products (OMP)	-0.033	-0.028	0.005	-0.061	-0.060
Transport equipment	-0.049	-0.028	0.007	-0.052	-0.066
Repair of manufacturing equipment, personal and household goods	-0.033	-0.028	0.006	-0.066	-0.065
2015-2019					
Food products, beverages, and tobacco (FBT)	0.073	-0.026	0.002	-0.036	0.065
Textile and leather products	0.034	-0.026	0.003	-0.047	0.016
Wood and products of wood	0.076	-0.026	0.003	-0.055	0.050
Pulp, paper, paper products, publishing, and printing	0.072	-0.026	0.002	-0.031	0.069
Coke, refined petroleum products, chemicals, rubber and plastic products	0.060	-0.026	0.002	-0.029	0.058
Other non-metallic mineral products (*n.e.c*) (ONMP)	0.067	-0.026	0.003	-0.055	0.042
Basic metals products	0.064	-0.026	0.004	-0.048	0.046

Machinery and equipment	0.069	-0.026	0.002	-0.049	0.049
Electrical and optical products	0.037	-0.026	0.004	-0.024	0.043
Other manufacturing products (OMP)	0.059	-0.026	0.002	-0.040	0.048
Transport equipment	0.044	-0.026	0.004	-0.030	0.044
Repair of manufacturing equipment, personal and household goods	0.057	-0.026	0.003	-0.048	0.038

Source: Authors' estimation.

For industry-level estimation, TC was highest in the wood and products of wood industries with estimates greater than 7.6% for the second sub-period, and it was lowest in the textile and leather industries with estimates of about 0.034 in the same sub-period. The rate of TC increased continuously over time across all manufacturing industries. This increase was most apparent in the non-metal industries, where initially the TC in this sector was declined at -3.3% in the first sub-period, then increased significantly at average rate of 6.7% from 2015 to 2019.

The Vietnamese government pursued an industrial policy to promote manufacturing sectors from begin of 1990s to now. This policy tried to direct limited national resources into strategically chosen industries (mostly in car manufacturing, machinery and equipment, chemical and plastic products). One of the policy objectives was to enable firms to grow large enough to utilize scale economies and to compete in foreign markets, especially in state-owned enterprises (SOEs). However, estimated scale component in TFPG for the heavy industries (chemical, machinery and equipment, and other manufacturing products) are very small, implying that firms in these industries had already reached a certain size where scale economies no longer existed. Therefore, this study suggests that the prior industrial policy of exploiting economies of scale is no longer effective in promoting productivity in such industrial sectors.

TFPG is calculated as the sum of technological changes, technical efficiency changes, changes in allocative efficiency, and changes in scale components. In Vietnamese manufacturing industries, TC has been a key contributor to TFPG, and improvements in scale components made a considerable contribution to TFPG, especially in the food, paper products, and chemical industries. AC exerted a negative effect on TFPG, although its magnitude was smaller than that of TC. Total TFP in the manufacturing sector has declined at an annual rate of -0.062 during the period of 2010 – 2015, then the TFPG grows continuously during the second sub-period, with a rate of 5.4%. For industry estimates during the sample period, TFP grew fastest in the paper industry, with an annual average growth rate of 6.9%, followed by the food products, beverages, and tobacco industry with a rate of 6.5%, and the chemical industry with a rate of 5.8%. The remaining industries have grown by about 2-5% per annum. During the early 2010s (from 2010 to 2015), a large downturn in TFP was observed in every industry. This downturn coincided with an economic slowdown in the Vietnamese economy during the same period, supporting the presumption that lagging productivity was a major reason for the depression of the Vietnamese economy during the early 2010s.

Compared to previous studies on TFP in Vietnam, this study suggests the following. First, previous studies aggregate data and measured TFP as a residual of the growth accounting method proposed by Solow (1957). they cannot examine changes in technological efficiency, which this study estimates to had considerable effects on TFPG. Second, this study implies that part of the increase is due to an improvement in TC. Thus, attributing all changes in TFP to technological progress, as in previous growth accounting studies, is misleading, and overestimates actual technological progress.

conclusion

Using recent advancements in stochastic production frontier approach, this study examines the sources of TFPG of the 2-digit manufacturing industries as well as total manufacturing industry in Vietnam during the period of 2010 – 2019. The methodology involves decomposition of the sources of TFPG into four components, including technological change, technical efficiency change, economic scale effect and allocation efficiency effect.

The main findings of the study is that, from 2010 to 2019, technological changes and the rate of scale component effect have been the major driving force of productivity growth in the 2-digit manufacturing industries as well as total manufacturing industry in Vietnam. Further, the growth rates of TFP of almost all the 2-digit manufacturing industries in Vietnam have declined during the first sub-period, 2010 – 2015. The rate of technical efficiency effect has also declined in the period of study and in almost all the afore-mentioned industries. With respect to scale effect, its contribution to TFPG in Vietnamese manufacturing industries has been decreased over the period. Overall, it can be said that the manufacturing industries of different 2-digit manufacturing industries in Vietnam have benefitted from economies of scale. Although its estimates are still far below the estimates of technological changes in our study. However, from the results of our study it can be inferred that factor accumulation has led to the TFPG through increasing returns to scale, but the technological progress happens to be the most important factor of the TFPG of organized manufacturing industries in Vietnam. The change in allocation efficiency component shows that resource allocation in almost all the industries in our study has decreased during the period.

Policy implications derivable from this study suggest that specific guidelines are required to promote productivity in each industry. Industries with slow TC (textile and electrical products) require the introduction of new frontier technology. Government policy should encourage investments that can introduce newly developed production technology. In addition, considering allocative inefficiency, a policy to enhance TFP by improving resource allocation should be pursued, which be done by promoting free markets and lessening government intervention. Meanwhile, industries where TE is small (food, wood, and basic metal), a policy to enhance the efficient use of existing technology is recommended to catch up to frontier technology. Finally, this study shows that the recent advancements in stochastic frontier production function model could be a complementary and alternative model to growth accounting methods for measuring and explaining productivity growth.

Acknowledgement

This research is funded by Vietnam National Foundation for Science and Technology Development (NAFOSTED) under grant number **502.01-2019.318**

References

Aigner, D., Lovell, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics, 6*(1), 21-37.

Arellano, M., & Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *The Review of Economic Studies, 58*(2), 277-297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error component models. *Journal of Econometrics, 68*(1), 29-51.

Battese, G. E., & Coelli, T. J. (1992). Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. *Journal of Productivity Analysis, 3*(1), 153-169.

Battese, G. E., & Corra, G. S. (1977). Estimation of a production frontier model: with application to the pastoral zone of Eastern Australia. *Australian journal of agricultural economics, 21*(3), 169-179.

Belotti, F., Daidone, S., Ilardi, G., & Atella, V. (2013). Stochastic frontier analysis using Stata. *The Stata Journal, 13*(4), 719-758.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics, 87*(1), 115-143.

Coelli, T. J., & Rao, D. P. (2005). Total factor productivity growth in agriculture: a Malmquist index analysis of 93 countries, 1980–2000. *Agricultural Economics, 32*, 115-134.

Colombi, R., Kumbhakar, S. C., Martini, G., & Vittadini, G. (2014). Closed-skew normality in stochastic frontiers with individual effects and long/short-run efficiency. *Journal of Productivity Analysis, 42*(2), 123-136.

Cornwell, C., Schmidt, P., & Sickles, R. C. (1990). Production frontiers with cross-sectional and time-series variation in efficiency levels. *Journal of Econometrics, 46*(1-2), 185-200.

Greene, W. (2005a). Fixed and random effects in stochastic frontier models. *Journal of Productivity Analysis, 23*(1), 7-32.

Greene, W. (2005b). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics, 126*(2), 269-303.

Ho, D. B. (2014). Provincial Total Factor Productivity in Vietnamese Agriculture and Its Determinant. *Journal of Economics and Development, 6*, 5-20.

Hoang, H. T., & Huynh, L. T. (2020). Impact of Firm's Characteristics on Gender Discrimination: Evidence from Vietnamese Firm-level Data. *Montenegrin Journal of Economics, 16*(1), 21-35.

Huynh, L. T. D., Hoang, H. T., & Tran, H. N. (2021). Does FDI enhance provincial productivity? A panel data analysis in Vietnam. *Journal of the Asia Pacific Economy*, 1-22.

Kim, S., & Han, G. (2001). A decomposition of total factor productivity growth in Korean manufacturing industries: A stochastic frontier approach. *Journal of Productivity Analysis, 16*(3), 269-281.

Krugman, P. R. (1997). *The age of diminished expectations: US economic policy in the 1990s*: MIT press.

Kumbhakar, S. C. (1990). Production frontiers, panel data, and time-varying technical inefficiency. *Journal of Econometrics, 46*(1-2), 201-211.

Kumbhakar, S. C., Denny, M., & Fuss, M. (2000). Estimation and decomposition of productivity change when production is not efficient: a paneldata approach. *Econometric Reviews, 19*(4), 312-320.

Kumbhakar, S. C., Lien, G., & Hardaker, J. B. (2014). Technical efficiency in competing panel data models: a study of Norwegian grain farming. *Journal of Productivity Analysis, 41*(2), 321-337.

Kumbhakar, S. C., & Tsionas, E. G. (2005). Measuring technical and allocative inefficiency in the translog cost system: a Bayesian approach. *Journal of Econometrics, 126*(2), 355-384.

Kumbhakar, S. C., Wang, H., & Horncastle, A. P. (2015). *A practitioner's guide to stochastic frontier analysis using Stata*: Cambridge University Press.

Le, Q. C., Nguyen, T. P. T., & Do, T. N. (2021). State ownership, quality of sub-national governance, and total factor productivity of firms in Vietnam. *Post-Communist Economies, 33*(1), 133-146.

Lee, Y. H., & Schmidt, P. (1993). A production frontier model with flexible temporal variation in technical efficiency. *The measurement of productive efficiency: Techniques and applications*, 237-255.

Levinsohn, J., & Petrin, A. (2003). Estimating Production Functions Using Inputs To Control For Unobservables. *The Review of Economic Studies, 70*(2), 317-341.

Mattsson, P., Månsson, J., & Greene, W. H. (2020). TFP change and its components for Swedish manufacturing firms during the 2008–2009 financial crisis. *Journal of Productivity Analysis, 53*(1), 79-93.

Meeusen, W., & van Den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review*, 435-444.

Murillo-Zamorano, L. R. (2004). Economic efficiency and frontier techniques. *Journal of Economic Surveys, 18*(1), 33-77.

Ngo, Q., & Tran, Q. (2020). Firm heterogeneity and total factor productivity: New panel-data evidence from Vietnamese manufacturing firms. *Management Science Letters, 10*(7), 1505-1512.

Nguyen, H. Q. (2017). Business reforms and total factor productivity in Vietnamese manufacturing. *Journal of Asian Economics, 51*, 33-42.

Nguyen, T. V., Simioni, M., & Le Van, D. (2019). Assessment of TFP change at provincial level in Vietnam: New evidence using Färe–Primont productivity index. *Economic Analysis and Policy, 64*, 329-345.

Olley, G. S., & Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica, 64*(6), 1263-1297. doi:10.2307/2171831

Pitt, M. M., & Lee, L.-F. (1981). The measurement and sources of technical inefficiency in the Indonesian weaving industry. *Journal of Development Economics, 9*(1), 43-64.

Roy, P. K., Das, P. S., & Pal, M. K. (2017). Decomposition of Total Factor Productivity Growth of the 2-Digit Manufacturing Industries in West Bengal: A Stochastic Frontier Approach. *Arthaniti-Journal of Economic Theory and Practice, 16*(1-2), 101-124.

Schmidt, P., & Sickles, R. C. (1984). Production frontiers and panel data. *Journal of Business & Economic Statistics, 2*(4), 367-374.

Sharma, S. C., Sylwester, K., & Margono, H. (2007). Decomposition of total factor productivity growth in US states. *The quarterly review of economics and finance, 47*(2), 215-241.

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, 312-320.

Thanh, H. H. (2021). Tác động của hoạt động xuất khẩu đến năng suất các nhân tố tổng hợp (TFP): bằng chứng từ doanh nghiệp tại Việt Nam doanh nghiệp tại Việt Nam. *Tạp chí Kinh tế và Phát triển*(289), 74-82.

Tsionas, E. G., & Kumbhakar, S. C. (2014). Firm heterogeneity, persistent and transient technical inefficiency: A generalized true random-effects model. *Journal of Applied Econometrics, 29*(1), 110-132.

UNCTAD. (2021). *World investment report*. New York, United States of America: United Nations Publications.