Short- and Long-run Technical Efficiency Analysis: Application to Ethiopian Manufacturing Firms

Yismaw Ayelign and Lakhwinder Singh

This study attempts to investigate the level of transient and persistent technical efficiencies of large- and medium-scale manufacturing establishments in Ethiopia. A stochastic frontier approach was used for Cobb–Douglas production technology and a panel data set (1996–2015) was developed to obtain the coefficients of technical efficiency. The determinants of both components of efficiency were obtained while using the Tobit model. Results show that labor and real capital input coefficients are statistically significant, with positive input elasticities of 0.54% and 0.19%, respectively. The coefficient of the time trend variable, which captures the effect of exogenous technical progress on real value added by shifting the production frontier, is 0.019 (1.9%). Thus, as a year passes, the production frontier shifts outward due to technical change, which results in the increase of real value by 1.9%. The mean time-varying (short run), persistent (long run), and overall technical effciency effects are 64.2%, 57.2%, and 36.7%, respectively. Thus, firms can increase their output by 63.3% by removing transient and structural factors without increasing their input usage nor changing their technology. Particularly, trade variables have positive effects on transient efficiency but negative effects on persistent efficiency. Capital intensity has a negative coefficient in both cases, whereas average wage has a positive coefficient in both cases. Hence, policymakers, such as managers and public regulatory bodies, should give due attention to transient and structural problems. This study suggests that labor quality should be improved, which requires high average wage and participation in the global market. Such an improvement can be achieved by solving structural rigidities related to customs, promoting capital productivity updating and renovating the existing one, and importing capital goods that contain new technology.

Keywords: Transient efficiency, Persistent efficiency, Technical efficiency, Manufacturing

JEL Classification: O50, O47, O39, O14, L25, C23

Yismaw Ayelign, Debre Tabor University, PO box 272, Debre Tabor, Ethiopia. (Email) yismaway@gmail.com; yismayw@dtu.edu.et, (TEL) +251918815156; Lakhwinder Singh, Professor, Department of Economics and Centre for Development Economics and Innovation Studies (CDEIS), PO box 147002, Punjabi University, Patiala, India. (Email) lakhwindergill@pbi.ac.in, (TEL) +919888755642

The authors are grateful to two anonymous referees of the journal and Professor Keun Lee for their helpful suggestions on the previous version of the paper. We wish to thank the Central Statistical Agency of Ethiopia for providing us raw data free of charge. We have received the Stata code from Gudbrand Lien, with an initial request to Professor S.C. Kumbhakar for disentangling the short- and long-run technical efficiency components. We appreciate this precious gift.

[**Seoul Journal of Economics** 2019, Vol. 32, No. 4]

I. Introduction

The Ethiopian economy during the period of 2003–2004 and 2016–2017 has grown at a rate of 10.62% per annum. The gross domestic product (GDP) per capita has increased a rate of 7.79% per annum. Among the Sub-Saharan countries, Ethiopia has emerged as the fastest-growing country (World Bank 2018). However, it remained predominantly agricultural and service sector-oriented (Nyasha, Gwenhure, and Odhiambo 2017; Shiferaw 2017). Notably, sustainable development goals (SDGs), especially Goal 9's Target 9.2, entrust responsibility on the country's government to raise the share of industrial employment and valued added. Specifically, Target 9.2.1 focuses on raising the share of manufacturing value added relative to GDP, as well as increasing the per capita value added (UNDP 2018). According to UNIDO (2018), the average share of manufacturing out of the total Ethiopian GDP is approximately 4.3% during the last 17 years (1999/2000–2016/2017). A significant increase in the share and growth rate of manufacturing industries is required to sustain a high growth rate of the Ethiopian economy. This objective can be achieved either by increasing the efficient utilization of existing factors of production or by the increasing factor inputs.

Technical efficiency analysis at the firm level has remained a highly debated issue in academic discussions (Akinlo and Adejumo 2016; Belotti and Ilardi 2012, 2018; Gandhi, Navarro, and Rivers 2011;

Saliola and Seker 2011; Sena 2003; Syverson 2011) and policy analysis (Filippini, Greene, and Masiero 2018; Lai and Kumbhakar 2018). At present, firm-level technical efficiency analysis has attracted attention from academic point of view due to the development of new methods of estimation from increasing the availability of plant-level data (van Broeck 2007). Public policy analysis for increasing the emphasis on industrialization concern ignited once again due to the 9th SDG (Bigsten and Gebreeyesus 2007; Lemi and Wright 2018; UNDP 2018).

In Ethiopia, few studies have focused on the estimation of technical efficiency. Abegaz (2013) estimated the productivity and technical efficiency of large- and medium-scale manufacturing establishments by taking panel data from 1996 to 2009 from CSA annual surveys. However, although the time-varying technical efficiency of the model was specified using a two-error component approach developed by Battese and Coelli (1992, 1995), the author did not separate it from firm heterogeneity and did not include the determining factor of technical efficiency. Hailu and Tanaka (2015) used the same time period and type of data to estimate the *true* random effects model proposed by Greene (2005a, 2005b). By doing so, the time-varying technical efficiency from firm-specific time-invariant effect could be separated. The authors observed a significant degree of heterogeneity from Ethiopian manufacturing firms, as confirmed from the comparison of estimators that separate this heterogeneity from inefficiency and with those that do not. Significant variation in the estimated inefficiency was found between the two groups of estimators. However, all time-invariant effects are considered firm specific effects (heterogeneity). Lemi and Wright (2018) used the World Bank survey data on manufacturing enterprises in Ethiopia (2006, 2011) and Kenya (2007, 2013) and focused on analyzing the effect of export activities and share of ownership by foreign residents on technical efficiency level. The results showed that when firms engage in export activities, their respective efficiency increases, but an increase in the share of foreign ownership has a negligible effect on technical efficiency improvement in both economies. In addition, small-sized firms have a high degree of inefficiency compared with the larger ones.

Other studies have focused on productivity estimation and its determinants about certain factors, such as foreign ownership, employment expansion, and growth (Bigsten and Gebreeyesus 2007, 2009; Lemi and Wright 2018; Tekleselassie, Berhe, Getahun, Abebe and

Ageba 2018). Thus far, no research has been conducted on Ethiopia in terms of short- and long-run technical efficiencies using the stochastic frontier model with four random error components because it has only been recently developed. The current study used a panel data set obtained from Central Statistical Agency, which covers the period of 1996–2015. This study aims to investigate the level and determinants of transient and persistent technical efficiencies of medium- and large-scale manufacturing establishments in Ethiopia using a panel data set (1996–2015) on stochastic frontier approach while using the Cobb–Douglas production technology.

The remainder of this paper is organized as follows. Section II is devoted to the methodological evolution of technical (in)efficiency estimation and empirical aspects of the literature. It overviews the development in conceptual and methodological approaches and the incorporation of a heteroscedastic view of a one-sided component of the composed error that captures technical inefficiency. Section III represents the method used to estimate the model coefficients and describes the source and nature of data. Section IV shows the nature and distribution of the variables. The inferential part estimates transient and persistent technical efficiencies, calculates overall technical efficiency from the two methods, and illustrates using tables and graphs. It also examines the determinants of technical efficiency components. The conclusions and policy issues resulted from the empirical analysis are presented in the last section.

II. Review of Literature

A. Developments on Technical Efficiency Estimation using Stochastic Frontier Approach

The two main approaches compete for estimating the production frontier, namely, a mathematical programming that is deterministic in nature [*e.g.* data envelopment analysis (DEA)] and a stochastic (econometric) paradigm. The advantage of the deterministic approach is that it does not require prior functional form specification of the production technology and no distributional assumption regarding the inefficiency effect. However, this approach does not consider *statistical noise*, which affects the output but is beyond the control of a firm due to exogenous factors, such as *classical* measurement

error, chance, machine breakage, and draught (Kumbhakar and Lovell 2000). If production is significantly influenced by such factors, then the estimated frontier by DEA is highly liable that it lies far from the real frontier. Moreover, DEA is highly affected by outliers (extreme values) since the production frontier estimates are based on the best performer unit (Mattsson, Mansson, and Greene 2018). Then, inefficiency is calculated as the deviation from the *best frontier*. Thus, the technical inefficiency of each unit is measured relative to the best performer rather than direct estimation for each firm (Bauer 1990; Kumbhakar, Parmeter, and Zelenyuk 2018).

The econometric approach explicitly incorporates the stochastic error term into the production frontier estimation, that is, the error term is composed of two terms, namely, the inefficiency effect and the purely statistical noise where the functional form of the technological relationship between inputs and outputs is specified before estimation. In addition, this approach usually[1] considers the distributional assumption on the two error terms. Thus, the criticism toward the stochastic frontier paradigm arises from the restrictiveness due to these assumptions. In terms of estimating individual firm-level technical inefficiency effect, the econometric approach is superior compared with DEA (Bauer 1990).

The econometric approach of estimating the production function is more plausible because it is conceptually in line with the microeconomic foundation of firm objectives, such as maximization of output/profit or minimization of cost/loss. Second, firms can produce output either on or below the frontier. If a unit produces below the production frontier, then the distance from the frontier to the achieved score indicates productive inefficiency. Third, the shape of the estimated frontier provides information to policymakers (Bauer 1990).

The introduction of the stochastic frontier approach of estimating technical inefficiency independently was initiated by the advancement of literature on productive efficiency (Kumbhakar and Lovell 2000) but within same time period by Aigner, Lovell, and Schmidt (1977), Meeusen and van den Broeck (1977), and Battese and Corra (1977). This approach is continuously applied in the empirical world and extended methodologically (Belotti, Daidone, Ilardi, and Atella 2013; Kumbhakar

[1] Distribution free stochastic frontier estimators are present in case of panel data analysis (*e.g.*, Schmidt and Sickles (1984)).

and Lovell 2000; Paul and Shankar 2018). The original frontier approach is criticized on the ground that separatingthe inefficiency[2] effect from the composed error is impossible; thus, the estimation of technical inefficiency for each observation is also impossible and only the mean inefficiency is calculated (Forsund, Lovell, and Schmidt 1980). Jondrow, Lovell, Materov, and Schmidt (1982) developed a mechanism to solve this problem by using the mean or mode conditional on the composed error (*i.e.* $u_i|\varepsilon_{it}$; where $\varepsilon_{it} = \upsilon_{it} - u_i$) for each individual establishment.

The evolution of the methods of estimation of technical efficiency using the econometric approach, particularly for panel data, can be summarized into four phases (Colombi, Kumbhakar, Martini, and Vittadini 2014). The first phase (traditional) is considered the technical efficiency time-invariant (persistent), either fixed or random error (Battese and Coelli 1988; Kumbhakar 1987; Pitt and Lee 1981, Schmidt and Sickles 1984). The second phase is considered time-varying or transient (Battese and Coelli 1992, 1995; Cornwell, Schmidt, and Sickles 1990; Kumbhakar 1990; Lee and Schmidt 1993). In these phases, firm heterogeneity is not yet separated from inefficiency because the models consider inefficiency to follow the same pattern for all firms (Wang and Ho 2010), and the error term in this case is composed of technical inefficiency (time-varying) and statistical noise caused by exogenous factors (*i.e.* $\ln Y_{it} = \ln f\left(X_{it}, t; \beta_i\right) + \upsilon_i - u_i$; Colombi, Kumbhakar, Martini, and Vittadini 2014).

The third phase expands the random error to three components, and it has two groups. First, Kumbhakar and Heshmati (1993) and Kumbhakar and Hjalmarsson (1993, 1995) named the three error components as random noise (υ_i), long-run technical efficiency (η_i), and short-run technical efficiency (u_{it}), where the model becomes $\ln Y_{it} = \ln f\left(X_{it}, t; \beta_i\right) + \upsilon_i - \eta_i - u_{it}$. Here, heterogeneity is dumped into persistent (long run) technical inefficiency because it is time-invariant. The second group of three phases was first proposed by Greene (2005a, 2005b), followed by Kumbhakar and Wang (2005) and Wang and Ho (2010). This group overstates technical inefficiency by

[2] A firm is technically efficient if it can produce the maximum possible output given the set of inputs and current technology or produce a given output with minimum possible cost (Battese and Coelli 1995; Coelli, Rao, O'Donnell, and Battese 2005; Ismail and Abidin 2017; Kumbhakar and Lovell 2000; Kumbhakar, Wang, and Horncastle 2015)

accounting heterogeneity into persistent inefficiency. Although the second group continued with the three components of the composed error, they disregarded the time-invariant technical inefficiency and instead considered it as heterogeneity (γ_i). In this case, the model is $\ln Y_{it} = \ln f\left(X_{it}, t; \beta_i\right) + \upsilon_i - \gamma_i - u_{it}$. Here, technical efficiency is only a time-varying component; however, firm-specific factors cause deviation of firm output from the frontier. This group may underestimate the total technical inefficiency in the case when the persistent one is significant. The fourth phase is reconciled by the two debates in the third group by separating heterogeneity from persistent inefficiency and hence developed a model with four random error components. By doing so, it estimates the appropriate technical (in)efficiency (Colombi, Kumbhakar, Martini, and Vittadini 2014).

The need to separate the persistent and transient inefficiency effects arises from the policy intervention perspective because each of them requires different intertemporal views. Persistent inefficiency can be addressed by solving structural long-standing factors, whereas transient inefficiency can be reduced by solving time-varying factors related to units' day-to-day activities (Albalate and Rossel 2016; Lien, Kumbhakar, and Alem 2018).

Albalate and Rossel (2016) conducted a research on 32 Spanish motorway companies for 26 years (1988–2014) using production and cost stochastic frontier analysis. They found a significant effect of time-varying and time-invariant inefficiency effects. At least three reasons induced scholars to develop the four-component model. First, the models developed thus far cannot identify the determining factors of long-run inefficiency (Heshmati, Kumbhakar, and Kim 2016).Second, the previous models assume that inefficiency is independent (fixed) over time; however, units can reduce or even eliminate at least a part of it and fix the remaining ones (Mattsson, Mansson, and Greene 2018). Third, appropriate policy intervention will be designed and enforced for each type (*i.e.*, long and short runs) of inefficiency (Lien, Kumbhakar, and Alem 2018).

Thus far, the four-component model is applied to various economic sectors across various economies. For instance, it is applied to energy and electric networks efficiency (Filippini and Hunt 2016; Poudineh 2016), Switzerland's residential electricity consumption (Blasch, Boogen, Filippini, and Kumar 2016), Chinese banking sector (Fungáčová, Weill, and Klein 2018), and US commercial banks (Tsionas and Kumbhakar

2014), Germany's higher-education sector (Gralka 2018), on Italian and German universities (Agasisti and Gralka 2017) Italian hospital sector (Colombi, Martini, and Vittadini 2017), international airline sector (Heshmati, Kumbhakar, and Kim 2018), Swedish manufacturing sector (Mattsson, Mansson, and Greene 2018), Swiss railways (Filippini and Greene 2016); Spanish motor way sector (Albalate and Rosell 2016), Norwegian grain farming (Kumbhakar, Lien, and Hardaker 2014); and U.S. power-generating plant (Lai and Kumbhakar 2018). The recently developed model with four random error components is advantageous over the former ones in terms of explaining short- and long-run technical efficiencies. Some studies include determinants of each component of inefficiency (Lai and Kumbhakar 2018).

a) Determinants of Technical Efficiency

Some factors (producer-specific ones) are assumed to influence efficiency distribution, but they are neither factors of production and hence cannot be directly included in the production function nor outputs; thus, these factors are not dependent variables. The stochastic frontier approach includes the manner in which these variables affect the efficiency performance of an establishment in the estimation procedure. Such an approach can be in either or any combination of the following manners. First, the frontier can be exogenously moved outward (the structure of production process is changed), in which case the exogenous factors can directly be included in the production function together with production inputs. Such factors may include transportation network channels. Second, the efficiency utilization of the input set can be changed (Belotti, Daidone, Ilardi, and Atella 2013; Kumbhakar and Lovell 2000). Ignoring the existence of such determinants results in the biased prediction of inefficiency as it affects the variance of the parameters (Kumbhakar and Lovell 2000).

Various arguments exist regarding the direction and degree of influence of technical efficiency by different factors, particularly those of firm characteristics (Faruq and Yi 2010). For instance, researchers have approached the arguments regarding the effect of size on technical efficiency from two different angles. First, an increase in firm size is argued to improve technical efficiency because larger size enables firms to acquire and utilize higher market share and they can access resources along with utilizing economies of scale. Second, the arguments for small size state that

small firms operate in a competitive environment, forcing them to solve internal constraints for survival. Therefore, smaller firms can easily coordinate resources and thus improve their technical efficiency compared with the larger ones (Yang and Chen 2009).

No clear theoretical foundation is available regarding the determinants of technical efficiency because the classical view of the error term is homoscedastic (*i.e.*, constant variance; Kumbhakar and Lovell 2000). Several empirical studies have been conducted across economies and over various sectors. Helali and Kalai (2015) compared the traditional and Bayesian estimation on Tunisian manufacturing sector using a 50-year panel data (1961–2010). They found 77% average efficiency level with negligible growth over the target period. To address the question of what determines the 23% inefficiency level, the authors used Tobit maximum likelihood model on certain variables as determinants, including capital productivity (plants are grouped in three as low, medium, and high on the basis of capital productivity), trade openness[3], number of employees, and level of intermediate consumption. The continuous variables are transformed into a natural logarithm.

Gumbau-Albert and Maudos (2002) investigated the technical efficiency determinants in the Spanish *industrial sector*. The authors estimated it in two stages. The technical efficiency is predicted from the estimated frontier and then technical efficiency as a function of variables (*e.g.*, location, firm structure, ownership as public versus private, firm size, extent of competition, and investment on R&D) using first lag instrumental variable estimation (*i.e.*, generalized method of moments).The authors found that the average technical efficiency of Chinese firms fall close to 76%, with certain fluctuations around this value. Firm size has a positive effect on enhancing technical efficiency. Technical efficiency decreases with the increase in the share of public ownership. Chapelle and Plane (2005) used SFA-investigated technical efficiency and its determinants, as well

[3] Trade openness is an index that proxies the exposure to the international market and hence learning from international knowledge spillover, which is expected to enhance efficiency. It is related to trade liberalization. Trade openness is proxied by the ratio of the sum of export and import values to GDP

$$(i.e., \frac{(Export\ value + Import\ value)}{GDP}).$$

For further details, readers may refer to Hossain and Karunaratne (2004), Chu and Kalirajan (2011), and Sun, Hone, and Doucouliago (1999).

as cross-sectional data, on Ivorian manufacturing plants, focusing on wood and furniture, textile, food, and metallic manufacturing groups. The authors criticized the two-stage estimation on the ground that it assumes that the determinants of technical efficiency are purely exogenous. Hence, no co-variance exists between the input factors and the determinants, which in turn implies that the technical inefficiency effects in the two equations are independent to each other; that is, it shows contradiction. They adopted the single-stage maximum likelihood estimation developed by Battese and Coelli (1995), as specified as follows:

$$\ln Y_{it} = \ln f\left(X_{it}, t; \beta\right) + \upsilon_{it} - \left(\eta' Z_{it} + \varepsilon_{it}\right) \tag{1}$$

$\upsilon_{it} \sim iid\ N\left(0, \delta_{\upsilon}^{2}\right)$ and $-u_{it} \sim N^{+}\left(\mu, \delta_{u}^{2}\right)$ are the truncated normal distributions, where μ denotes mean of the inefficiency effect, which is a function of other factors as: $\mu = \eta' Z_{it}$. On this basis, technical efficiency is calculated as $TE = \exp\left(u_{it}\right) = \exp\left(\eta' Z_{it}\right)$, where Z_{it} is a set of determinants, and is a vector of coefficient for the determinants.

The authors found out that size (measured by the number of workers, that is, micro, small, medium, and large when the number of workers is ≤ 5, $5 - 49$, up to 99, and ≥ 100, respectively) has a significant positive effect on technical efficiency; that is, large firms are more efficient than smaller ones. Although location has a positive coefficient, it has insignificant effect on efficiency.

Cheruiyot (2017) utilized a two-stage DEA estimation approach using cross-sectional data collected from 396 plants by World Bank enterprises survey during 2007. Kenyan manufacturing enterprises are on average 68.3% efficient; that is, 31.7% output can be additionally produced only by removing the factors that hinder the firms from producing the maximum amount. The result showed that 63%, 2%, and 35% of the establishments operate under increasing, constant, and decreasing returns to scale, respectively. The second-stage estimation resulted in statistically significant and negative coefficients for firm age and firm size (measured by total firm value, including all fixed assets, such as land, vehicles, building, machinery, and equipment). Moreover, firms in the capital city (Nairobi) obtained a higher efficiency level than the business city (Mombasa); and foreign ownership, innovation, and managerial experience had a positive sign (as expected), although insignificant. Similar to Cheruiyot (2017), Faruq and David (2010) used a nonparametric method (*i.e.*, DEA) for panel data from 1991 to 2002 collected from six

categories of manufacturing plants in Ghana. The authors found that exogenous (environmental) variables, which were presumed to affect the efficiency performance, had positive and significant coefficients [*i.e.*, firm size (measured by the number of full-time equivalent employees), firm age, ownership structure (foreign), and capital-to-labor ratio (for measuring capital intensity)].

In the empirical literature, the sign and significance of firm size are mixed. Little (1987) investigated Indian and Colombian small manufacturing firms using World Bank-sponsored survey data. The results showed that small firms are less efficient and beyond expectations and are less labor-intensive. Unresolved arguments exist among scholars regarding this mixed result. Some scholars have raised points related to economies of scale that large firms can use to improve their level of efficiency. These economies of scale emerge from better access to resources and larger market share[4] (Faruq and David 2010; Lundvall and Battese 2000; Oczkowski and Sharma 2005). Other scholars, who stand in favor of small firms, have argued that small units are more efficient because they face a more competitive environment that requires them to address their respective weaknesses to survive. Moreover, some plants may fail to coordinate their resources (at least in the short run) as their size expands, which reduces their efficiency (Faruq and David 2010). The cause for the mixed result may come from the difference in measuring size. Some measures use the number of workers, whereas others use the amount of capital (Little 1987).

Firm age also has mixed empirical results on technical efficiency. The argument for positive result states that units learn from experience and tackle hindering factors (Malerba 1992), whereas the negative result argues that older enterprises are reluctant to changes in the production technology and market environment (Faruq and David 2010; Little, Mazumdar, and Page 1987). Lundvall and Battese (2000) researched on four groups of Kenyan manufacturing firms and concluded that the effect of age on technical efficiency varies over various industrial groups. They confirmed that age positively affects the efficiency of textile plants but not significantly affect the food processing, metallic manufacturing, and wood manufacturing sectors. Capital intensity

[4] From theoretical point of view, large market share implies the existence of monopolistic power, which, in turn, implies that firms with high monopolistic power are less efficient.

from less developed economies' viewpoint is expected to have an inverse relationship with efficiency. LDCs are labor-abundant and capital-scarce economies; thus, the efficiency will be higher when small capital supports more labor (Oczkowski and Sharma 2005).

Ownership structure: foreign ownership is argued as an efficiency-enhancing factor on the basis of better technology, managerial skill, better structure of the firm, and links in the distribution channel (Faruq and David 2010; Pitt and Lee 1981; Sinani, Jones, and Mygind 2007; Zhou 2014). However, this variable is not free from debatable results. Bernard and Sjoholm (2003) and Pitt and Lee (1981) argued that foreign-owned firms may be less efficient due to the challenge they may face to experience the new market environment and failure in coordination. On the other hand, firm ownership can be categorized as private and publicly owned. Privatization is considered one of the drivers of efficiency improvement due to the profit motive of private owners, which induce them to utilize resources in better coordination. The objectives set by the private sector and by publicly-owned ones differ significantly. The only way for a private unit to survive is to face the competition that requires the introduction of best utilization of the available inputs in a structurally dynamic system, along with the prevailing technology (Jerome 2008; Vining and Boardman 1992). Chirwa (2001) examined the technical efficiency performance differential on Malawian private and public manufacturing firms by deploying DEA for a panel data from 1970 to 1997. The author found that privatized enterprises score higher average technical efficiency compared with the public counterparts. Okten and Arin (2001) investigated a total of 23 privatized Turkish cement plants and showed that they have high technical efficiency due to the reduced average cost of production and a shift toward capital-intensive techniques of production. Lee (2016) investigated the effect of ownership on performance improvement in China and concluded that having *more propensity to invest*, privately owned firms perform better than the rest of the ownership categories.

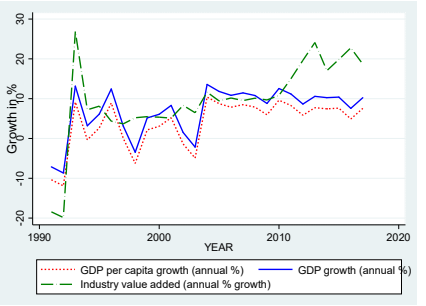
III. Trends of Macroeconomic Performance in Ethiopia

Over the last 27 years (1991–2017), the Ethiopian economy has shown tremendous fluctuation in terms of the economic growth rate (the blue solid line in Figure 1). In the first 14 years (1991–2004), the peak and the trough are registered, after which relatively stable high growth

rate was realized. In 1991, the economy was declining by approximately 7.14% GDP growth rate was approximately −7.14%), followed by further decline in 1992 by 8.67%. The reason for this declining facet during these years may be due to the fact that the economy was in transition from a long civil war. The following year experienced a remarkable positive growth rate (13.14%), which is closely comparable to the 2004 peak rate (13.57%). From 1994–1997, GDP remained positive but with a higher degree of fluctuations, ranging from 3.13% in 1997 to 12.43 % in 1996. In 1998, the GDP declined by approximately 3.46%, which might be caused by the war with Eritrea. From 1999 to 2002, GDP was positive yet significant, ranging from 1.51% in 2002 to 8.3 in 2001. In 2003, the GDP once again declined by 2.16%. The next 14 years showed a relatively stable positive growth revolving around 10%. The per capita GDP growth followed the same pattern, falling only beneath the GDP growth curve. The gap between the two is the population growth rate, which is relatively stable (red dotted line in Figure 1).

Industrial value added (green dashed line in Figure 1) declined during the first two years by 18.43% and 19.86%, respectively. This result may be due to regime change leading to policy confusion and loose coordination because it is a transition from a command system. The rate of decline was considerably higher even compared with the years before the change. From 1993 onwards, GDP remained positive yet with a high degree of frequent fluctuations. For instance, in 1993 it was approximately 26.9%, but it became 7.21% the following year. In 1995, it was 8.13%, whereas the growth rate in 1996 was nearly half of this rate (4.34%). What is peculiar in this case is that industrial value added continued to be considerably higher than the GDP growth rate for the last seven years (2011–2017). The GDP and industrial value-added growth curves followed a somewhat different pattern during all the higher GDP growth rate, whereas the industrial value-added growth was low, except in 1993. This finding implies that the industrial value-added growth does not significantly influence the growth structure of the GDP.

In summary, from 1991 to 2003 the average growth rates of GDP, per capita GDP, and industry value added were 2.9%, −0.31%, and 3.69%, whereas from 2004 to 2017, they were increasing by 10.62%, 7.74%, and 14.89%, respectively. The reason for the low and inconsistent performance of the first period is due to a lack of policies and strategies since the policies of the incumbent regime have been enacted since

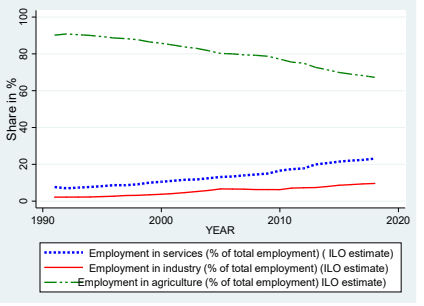


Source: Authors' sketch using World Bank WDI data (2019)

FIGURE 1
GROWTH TREND IN GDP, PER CAPITA GDP, AND INDUSTRY VALUE ADDED (1991–2017)

2002.

Employment shift share from agriculture to industry is an indicator of economic transformation from low to high productive sectors (Herrendorf, Rogerson, and Valentinyi 2014; Kabeta 2017). Thus, the status of the Ethiopian economy must be assessed in this regard. Figure 2 depicts the trend of employment share among agriculture, industry, and service sectors. The share of agriculture in employment has declined over the target period (green dashed line in Figure 2). Although it accounted for 90.16% of employment in 1991, which consistently declined to 67.27% in 2018, industry (red solid line) and service (blue dotted line) sectors showed modest growth in the share of employment. The service sector increased its share faster than the industry counterpart, as observed from the diagram where the gap between the two has been widening since 2006. During the entire period, the service sector employed more than the industry. Thus, majority of the shift of labor from agriculture was captured by the service sector than the industrial sector. Unless the service sector is more productive than the agricultural sector, the labor shift may not reflect structural transformation. Kabeta (2016) found that the high rate of service sector productivity growth has been the core contributor of the economic growth since 2004. From 1981 to 2011, the productivity of the industrial sector was declining, whereas the productivity of the service sector was growing. Thus, although the employment shift share from agricultural to service sector deviates from the traditional view of structural change, it is becoming prevalent in recently developing



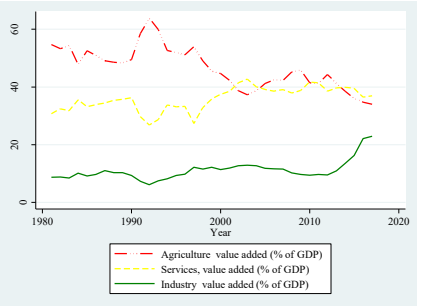
Source: Authors' sketch using World Bank WDI data (2019)

FIGURE 2
TRENDS IN SECTORAL EMPLOYMENT SHARE (1991–2018)

countries.

Figure 3 presents the trends of value-added share by sectors from 1981 to 2017. During the 37-year period, the value-added share in agriculture (red triple dotted line) of the total GDP declined from 54.74% in 1981 to approximately 34% in 2017. However, the trend did not follow a smooth pattern, as exhibited by the frequent fluctuations. After it reached its peak in 1992 (63.83%), it declined to 59.95% in 1993 and continued to decline to 51.16% in 1996, but it bounced back to 54.03% in 1997. Then, it declined until 2004, reaching 38.68%, which again recovered to 41.17% in 2005, followed by an increasing trend up to 2009 (45.88%). Thereafter, its pattern was fluctuating. The average share during the entire target period was 46.66%.

Although frequent fluctuations were observed in the case of the service sector (yellow dashed line), its share was growing, on average. It started with approximately 30.77% share in 1981, which successively grew to 36.31% in 1990. However, in the following year, it suddenly dropped to 29.67% and further decreased to 26.83% in 1992, after which it showed a recovery phase for the next four years (up to 1996). Once again, another trough was 27.37% in 1997, which revived for the next 6 years (1998–2003). In 2004, the share declined to 40.07% from 42.75% in 2003. It continued such an oscillating pattern up to 2017, in which the share was 36.92%. The average share during the 37-year period span was 35.92%, which is above the initial value. The trend of the industrial value-added share to total GDP (green solid line) is smoother relative to agricultural and service sectors, even if



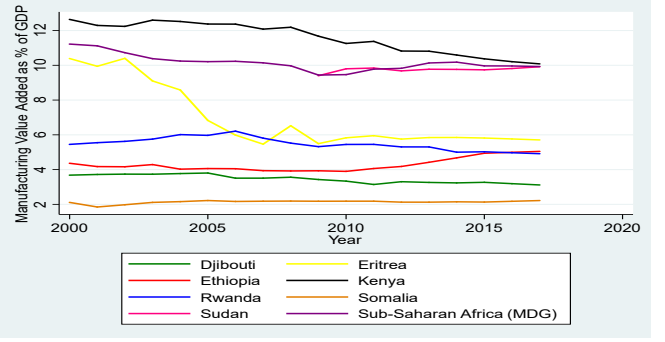
Source: Authors' sketch using World Bank WDI data (2019)

Figure 3
Trends of Value Added by Sector

fluctuations are prevalent. It showed an increasing pattern [*i.e.*, 8.74% in 1981, which increased for the following three years (*i.e.*, 8.83%, 8.48%, and 10.14%]. The share marginally declined from 10.14% (in 1985) to 9.17% in 1986, after which it moved around 10% up to 1990. However, in 1991, it dropped considerably below the previous year to 7.28% (even below the initial share), which further declined to 6.09% in 1992. From 1993 to 1997, the share increased to 12.2%. Between 1998 (11.57%) and 2008 (10.21%), it was oscillating around 11%, following the next five years revolving close to 9%. The last four years showed a dramatic surge in the share from 13.47% (2014) to 22.9% (2017).

According to UNIDO (2018), manufacturing value added, as percentage of GDP in Ethiopia, showed a fluctuating trend for the last 18 years (2000–2017), with an average of 4.29%. However, it remained below 5% up to 2015, after which it became 5%. This share is extremely small even relative to the Sub-Saharan standard which, on average, is 10.16%. The medium- and high-tech manufacturing industries account for a maximum of 16.08% (the minimum being 6.26%) share of the total manufacturing value added during the same period. On the other hand, the share of total industrial employment ranges from 3.7% in 2000 to 9.4% in 2017, showing successive increment.

As shown in Figure 4, compared with some selected African economies and the Sub-Saharan average, the Ethiopian manufacturing value-added share of GDP is low. It exceeded only in Djibouti and Somalia. Although it has been showing an increasing trend since 2010, it remained below the performance of the other countries, except for the



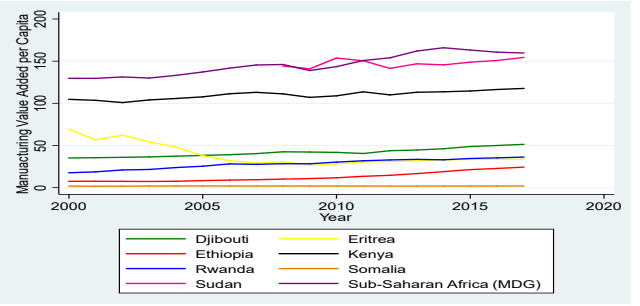
Source: Authors' sketch using UNIDO raw data

FIGURE 4
COMPARISON OF MANUFACTURING VALUED-ADDED SHARE OF GDP

two economies. Since 2015, it reached the level of Rwanda not solely due to its growth but also because Rwanda scored a declining trend since 2005.

When compared with real per capita manufacturing value added, Ethiopia achieved the lowest (except Somalia), although it showed an increasing trend. It is by far less than the Sub-Saharan average. The question to be addressed is why the performance of the Ethiopian manufacturing sector is poor compared with that of the other less developed countries. The answer may be obtained by examining the efficiency score of the manufacturing establishments, particularly distinguishing the short- and long-run efficiencies that will allow policymakers to take corrective measures to improve the manufacturing performance.

In sum, the Ethiopian macroeconomic performance is not stable because it shows some cyclical pattern. The issue to be addressed at this point of discussion is why the Ethiopian economy experience these fluctuations. Three periods are important to be considered. In 1991, a regime change occurred from a command economy to a relatively free economy. From then up to 2002, well-framed economic policies and strategies were lacking, and the economy was staggering due to natural phenomena. As Ethiopia was emerging from a command economic system, a well-functioning market mechanism was lacking. Moreover, agriculture was vulnerable to drought since it was dependent on rainfall, which re-occurred as a challenge. In 1998, war with



Source: Authors' sketch using UNIDO raw data

FIGURE 5
TRENDS OF REAL PER CAPITA MANUFACTURING VALUE ADDED

Eritrea caused a considerably devastating effect to the economy and human resources. After 2002, the economic policies started their implementation, and in 2003–2004, the growth momentum revived.

Although Ethiopia scored a good economic growth trajectory for 14 years since 2003–2004, with an average growth rate of 10.62%, the industrial base was still at its infancy stage in terms of employment generation, value addition, and growth contribution. Particularly, the manufacturing sector is lagging behind, let alone the Sub-Saharan standard, even relative to its neighboring economies. This finding initiates the need for undertaking research in the area, such that policymakers can design appropriate intervention mechanisms.

IV. Model Formulation and Data Base

This study used panel data (1996–2015) based on annual survey data of the large- and medium-scale manufacturing firms of Ethiopia. The source of data is the Ethiopian CSA. We included the time period before and during the GTP-I and the entire targeted time period is grouped into three as follows. First, the period from 1996 to 2003 (Period I) is considered separately, during which the economic growth rate was extremely slow, and even in some years, it was negative with an average of 3.87%. During this period, the ruling government had no clearly designed economic policies, except only stating as a transition from the command to a relatively liberalized market economy. Second, the period from 2004 to 2010 (Period II) is characterized by economic and related

policies of the incumbent governments that were placed possibly as a result of the economy scoring a high rate of growth in real GDP terms (average growth rate of 11.40%). Lastly, the period from 2011 to 2015 (Period III) is considered where the high GDP growth rate continued, and the government enacted its first growth and transformation ambitious plan (average growth rate of 10.21%). The present study compared the efficiency level across periods to evaluate the effects of policy orientations during the 20-year period.

A. Model Specification

The estimation of short- and long-run technical efficiencies requires a stochastic frontier model four random error components (recently developed by Colombi, Martini, and Vittadini (2014); Colombi, Kumbhakar, Martini, and Vittadini (2014); and Kumbhakar, Lien, and Hardaker (2014), which is specified as:

$$y_{it} = \beta_o + x_{it}\beta_i + \gamma_i - \eta_i + \upsilon_{it} - u_{it} \tag{2}$$

where y_{it} is the real gross value added in natural logarithm; is the row vector of input factors (full-time equivalent labor and real capital stock) in natural logarithm; β_i is the row vector input elasticities (technology coefficients); γ_i is time invariant, which varies across cross-sectional units caused by unit-specific effect (heterogeneity), and was first separated from the inefficiency component by Greene (2005a, 2005b); and denotes a positive value that captures time invariant technical inefficiency caused by structural factors related to the plant. These factors could be either internal or external. It measures the long-run component technical inefficiency, as recognized by various scholars since the traditional estimation period, and separated from heterogeneity by Colombi, Martini, and Vittadini (2011). υ_{it} represents the usual statistical noise. u_{it} is a positive random error component that captures the transient (short term) technical inefficiency part, which changes overtime and across units. It can be caused by variables changing occasionally (Lai and Kumbhakar 2018).

This model was estimated using a step-by-step procedure developed by Kumbhakar, Lien, and Hardaker (2014) that can estimate directly (Lai and Kumbhakar 2017).The overall efficiency is then obtained by multiplying the persistent technical efficiency by the transient one (*i.e.* $overallTE = \exp(-\eta_i) * \exp(-u_{it})$; Albalate and Rossel 2016; Mattsson,

Mansson, and Greene 2018). For the initial estimation, the model should be initially converted into the standard panel data model specification, as shown as follows.

$$y_{it} = \alpha_o^* + x_{it}\beta_i + \alpha_i + \varepsilon_{it} \tag{3}$$

Where; $\alpha_o^* = \beta_0 - E(\eta_i) - E(u_{it})$,

$$\alpha_i = \gamma_i - \eta_i + E(\eta_i)$$

and $\varepsilon_{it} = v_{it} - u_{it} + \mathrm{E}(u_{it})$

Here, α_I and ε_{it} are specified as having zero mean and constant variance, respectively. The first step helps obtain the predicted values of α_I and ε_{it}, applying fixed or random effects estimator, the choice being subject to a specification test (Hausman test). In the second step, the residual (time-varying) inefficiency u_{it} (form the relationship of $\varepsilon_{\mathrm{it}} = v_{it} - u_{it} + E(u_{it})$, where $v_{it} \sim \text{iid } N\left(0, \sigma_v^2\right)$ and $u_{it} \sim \text{iid } N^+\left(0, \sigma_u^2\right)$ (*i.e.* normal–half-normal distribution); hence,

$$E(u_{it}) = \sqrt{\frac{2}{\pi}}\sigma_u .$$

In order to obtain the technical efficiency estimates of the methods developed by Jondrow, Lovell, Materov and Schmidt (1982) and Battese and Coelli (1988) from estimated ε_{it}, it is important to employ the stochastic frontier approach. The third step is to acquire η_{it} (persistent inefficiency) by repeating Step 2 on $\alpha_i = \gamma_i - \eta_i + E(\eta_i)$. The assumption at this stage is that $\gamma_i \sim \text{iid } N\left(0, \sigma_\gamma^2\right)$ and $\eta_i \sim \text{iid } N^+\left(0, \sigma_\eta^2\right)$. Thus,

$$E(\eta_i) = \sqrt{\frac{2}{\pi}}\sigma_u .$$

This specification enables the use of normal–half-normal stochastic frontier technique.

B. Variable Description

The variables used in this study are real gross value added (dependent variable), real net capital stock (extracted from end-of-year capital stock of each establishment), full-time equivalent labor, and year.

Value added and capital stock variables are expressed in real terms by deflation using World Bank GDP deflator with 2011as the base year. The other variable is the full-time equivalent employed labor (*i.e.* temporary and seasonal workers are converted into full-time equivalent by CSA). Theoretically and empirically, the sign of the coefficients of the three factors of production is expected to be positive; thus, the real value added is positively affected by real capital and employed workers.

To account for various factors that influence short- and long-run technical efficiency levels, each of them are examined as a function of a set of determinants identified based on the reviewed literature. The value of technical efficiency is censored between zero and unity. Thus, the Tobit maximum likelihood estimation method is used to estimate the effect of each of the factors, as shown as follows:

$$R = X\beta + u_{it} \tag{5}$$

$$P = X\beta + \upsilon_{it} \tag{6}$$

where R and $P$are the residual (short-run) and persistent (long-run) technical efficiency levels, respectively; and X refers to a vector of determinant factors. A clear theoretical aspect of determining a persistent technical efficiency is unavailable (Kumbhakar and Lovell 2000); thus, the same regressors are used in both cases.

V. Results and Discussion

A. Descriptive Statistics

Table 1 summarizes the important variables in this study. After adjusting for missing values of the major variables, the total number of remaining observations for estimation is 8,715 during the five target years.

The average full-time equivalent labor employment is 97.53, ranging from 5 to 7,909. Its variability is given by the standard deviation (272.17). The average real labor productivity at value added is approximately 1,137.77 Birr per year, with significant variability (*i.e.*, 8,857.09 standard deviations). The remaining variables are presented in real terms (at 2011 price) in thousands of Ethiopian Birr. The average real sales value is 308, ranging between 15.78 to 37,000. Figure 6 shows a comparison among real value added, labor productivity, and mean real

Table 1
Summary of Major Variables

Variable	Obs	Mean	Std.Dev.	Min	Max
Value_Added	22,586	157,000	890,000	−8,790,000	3.64e+07
L_fulltime	22,586	97.53	272.17	5	7,909
Real LVA_productivity	22,586	1,137.77	8,857.09	−274,525	449,307.3
Real_Kstock	22,586	145	752	1.17	3.47e+04
Real_sales	22,586	308	1170	15.78	3.70e+04
Real_depreciation	22,586	20.36	141	0.04	1.40e+04
Real_investment	22,586	23.78	229	0	1.71e+04
Real_wages	22,586	18.7	785.49	5	555
Real_raw	22,586	151	484	1.03	1.61e+04

Source: Authors' computation using CSA raw data

wage.

Figure 6 shows that the average real value added reveals the fluctuating trend. From 2005 to 2011, it showed an average decreasing trend, after which it increased dramatically even though it failed to achieve the level in 2005. Mean real wage lies above the labor productivity at value-added curve and show a relatively stable trend. The gap between the mean value added and the other two variables is large and persisted to widen. This finding implies that in real terms, labor cost has not grown, but the gain from production in real values is high. The relatively narrow growth in labor productivity indicates that majority of the real value-added growth is realized due to factors other than labor.

B. Inferential Analysis

To obtain the short- and long-run technical efficiency scores, the production function was estimated while adopting a step-by-step procedure developed by Kumbhakar, Lien, and Hardaker (2014) and implemented by many researchers recently (Kumbhakar, Wang, and Horncastle 2015; Albalate and Rosell 2016). The values of the Hausman test (Table 2) show that the fixed effects model is consistent compared with the random effects counter model. The estimated coefficients from fixed effects estimates are presented in Table 3.a

Source: Authors' sketch using raw data from CSA

FIGURE 6
COMPARISON OF MEAN REAL WAGE, VALUE ADDED AND LABOR PRODUCTIVITY

TABLE 2
HAUSMAN SPECIFICATION TEST RESULT

	Coefficients			
	Fixed effects (b)	Random effects (B)	Difference (b – B)	S.E. $(\sqrt{diag\,(V_b - V_B)})$
ln(L_fulltime)	0.5441	0.7187	−0.1746	0.0118
ln(Real_Kstock)	0.1906	0.2948	−0.1042	0.0057
Year	0.0190	0.0313	−0.0123	0.0019

Note: b = consistent under H_o and H_a; B = inconsistent under H_a, efficient under Ho;
Test: H_o: difference in coefficients not systematic;
$\chi^2(4) = (b - B)'(V_b - V_B)^{-1}(b - B) = 569.792$ Prob > $\chi^2 = 0.0000$
Source: Authors' computation

The question to be addressed here is that whether fixed effects model agrees with the a priori expectation. The answer is that because heterogeneity is expected caused by usage of difference in technology, location of firms, and other unit features; hence, it agrees with the expectations. Fixed effects estimator is viable in the presence of high degree of heterogeneity (firm effect variation) *within* each group of individual units (Bartels 2008; Torres-Reyna 2007). Thus, a correlation exists between the unit effects component of the composed error with any or all the input variables.

The next question to be resolved is whether the data show serial correlation (because longer time period is considered) and heteroscedasticity problems and taking remedial measures accordingly. The results of the two tests are presented in the Appendix, which confirm the existence of both problems. Thus, cluster robust fixed effects estimation strategy is adopted because it solves both issues simultaneously (Torres-Reyna 2007).

Table 3 indicates that from a statistical standpoint, the two input factors (*i.e.*, full-time equivalent labor and real capital stock) in natural logs are significant at the 1% level. From a theoretical a priori perspective, they entail meaningful signs and magnitudes. The time trend variable is significant, indicating that a remarkable shift of the frontier exists (*i.e.*, the contribution of the technical progress). When a firm increases its use of labor input by 1% over time, other factors and technology remained unchanged; on average, its real value added increased by approximately 0.54%. As net real capital stock increased by 1%, the real value added increased by approximately 0.19%. These coefficient values agree with existing empirical literature on Ethiopia manufacturing sector. Abegaz (2013) used panel data from 1996 to 2009 and discovered that for all 10 industrial groups, the elasticity of real capital stock is less than the other inputs. Gebreyesus (2008) used data from 1996 to 2003and found similar pattern regarding elasticity of input. However, in five out of ten industrial groups, the elasticity of capital was negative but insignificant. Similarly, Tekleselassie *et al.* (2018) investigated the textile and garment industrial group using various models for comparison and found different values in terms of magnitude but similarities in pattern. The elasticity of capital in their finding is negative for ordinary least square (OLS), corrected OLS, and random effects but positive for fixed effects model and Levinsohn and Petrin method, and insignificant for all five models.

On the other hand, Lemi and Wright (2018) used World Bank enterprise surveys data and found that although the elasticity of output to changes in capital input was positive, the magnitude was statistically insignificant. In all the groups, the elasticity of real capital input is less than the labor and raw material elasticities. Hailu and Tanaka (2015) used panel data from 2000 to 2009 and found that the capital elasticity of output is insignificant (with negative sign for wearing apparel, paper and printing, chemicals, and fabricated metals) at the 5% significance level. Moreover, the interaction with other inputs is unsatisfactory. The reason advanced for the less responsiveness of output to capital input is that the firms

use old capital with relatively old technology embodied and may be due to capital maturity[5] being reached. In industrialized countries where *updated* and *renovated* capital is used (*e.g.*, Korea), capital elasticity is extremely high even when compared with Japan, which enhances its productivity (Lee, Miyagawa, Kim, and Edamura 2016).

Notably, the estimates of our study are statistically significant; however, the magnitude is relatively small compared with labor input. This result may be due to the recent efforts to improve the performance of the manufacturing sector. The coefficient of time trend variable (measured in years) captures the effect of technical progress on real sales value growth. After one year, the output increased by 1.9% caused solely by technical change. Thus, on an average, the frontier shifts after a year, which results in the output to increase by 1.9% for a given set of factors of production. According to Abegaz (2013), with the exception of the beverage industry, all the manufacturing groups were in technical retrogression because the sign of the time trend variable in translog production function was negative for them. Hailu and Tanaka (2015) found positive and significant coefficient for the time trend variable of industries, such as wearing apparel (3.08%), paper and printing (3.365%), chemicals (5%), fabricated metals (6.775%), and furniture (5.5%). For other groups, however, it was negative. This result is an indication of the large variations in terms of technical progress among the manufacturing groups in Ethiopia.

The proportion of the individual effect component (u_i) accounts for approximately 69.39% of the variation in the composed error. It is statistically significant proportion, which is confirmed by the F-test (in the last row of Table 3).

As shown in Table 4, the mean time-varying (short-run) technical efficiency is 64.2%, the persistent (long-run) technical efficiency is 57.2%, and the overall technical efficiency (the product of the two) is 36.7%. The firm efficiency is expected to be highly negatively affected by structural rigidities and other time-invariant factors. This finding signifies that large- and medium-scale manufacturing plants in Ethiopia can increase their value added by 63.3% (*i.e.* currently, they are producing 63.3% far below

[5] At first sight, it seems paradox of capital maturity in a capital scarce economy but firms may have large capacity of installed capital implying that because full capacity is not utilized (CSA, 2015) thus far, adding capital may cause *too many cooks spoil the broth* type of result.

Table 3
Fixedeffects (within) Clustered for Robustness Estimated Results

ln(Real_VA)	Coef.	RobustSt. Err.	t-value	p-value	[95% Conf.interval]	
ln(L_fulltime)	0.544	0.016	33.03	0.000	0.512	0.576
ln(Real_Kstock)	0.191	0.008	24.16	0.000	0.175	0.206
year	0.019	0.003	6.78	0.000	0.014	0.025
Constant	−32.315	5.647	−5.72	0.000	−43.383	−21.247
F-test		763.520	Prob > F			0.000
σ_u		1.4536025				
σ_e		0.96550153				
ρ	0.6939 (fraction of variance due to u_i)					
F test that all $u_i = 0$: F(8,312, 12,689) = 3.31				Prob > F = 0.0000		

Source: Authors' computation using CSA raw data

the frontier measuring the potential maximum solely due to inefficiency); hence, the overall inefficiency[6] level is 63.3%. Given the current technology and input set, whether they can remove the structural rigidities that cause the persistent technical inefficiency and whether they can address the factors that hinder production in their daily activities causing the short-run inefficiency, they will increase real value added by 63.3%. This finding is a potential for improving production without increasing input cost and cost related to the use of advanced technology, given that addressing the inefficiency-causing factors do not require incurring additional cost. In terms of measure of variability (measured by coefficient of variation[7]), the transient efficiency is higher (15.58%) than the short-run one (15.01%). The median transient technical efficiency is 65.22%, which is above its mean; hence, its distribution is more leftward skewed relative to the persistent efficiency whose median (55.69) is close to its mean.

[6] Inefficiency is calculated as 100%-efficiency level because the most performer firm is 100% efficient.

[7] Coefficient of variation (CV) is the ratio of standard deviation to mean expressed as percentage, *i.e.*

$$cv = \frac{sd}{mean} \times 100$$

TABLE 4
SUMMARY OF SHORT-RUN, LONG-RUN, AND OVERALL TECHNICAL EFFICIENCY

Variable	Obs.	Mean	Std. Dev.	Min.	Max.	CV	P(50)
Short-run technical efficiency	21,005	0.642	0.1	0	0.932	0.1558	0.6522
Long-run technical efficiency	21,005	0.572	0.086	0.015	0.837	0.1501	0.5769
Overall technical efficiency	21,005	0.367	0.08	0	0.651	0.2168	0.3724

Source: Authors' calculation using estimated production function

A comparison of the various industrial groups (Table 5) reveals that no significant difference exists in the transient efficiency performance among the industrial groups. It varies from 64% in three industries (*i.e.*, textile, chemicals, and other industries) to64.4% (*i.e.*, wood and wood products). The persistent technical efficiency ranges from 53.9% (wood) to 62.3% (others) and 62.2% (chemicals). Thus, in short-run efficiency terms, all manufacturing industries in Ethiopia are in somewhat similar status and should work toward improving their short-run efficiency score due to firms facing similar factors that affect transient technical efficiency in the country. However, observable variation exists in persistent efficiency among the groups. The maximum variation is 8.4% between 53.9% (wood) and 62.3% (others). However, six out of ten (*i.e.*, food, textile, leather, paper, metals, and nonmetals) industries have below 3% difference. The difference may arise from differences in factors that affect persistent efficiency. This result indicates that establishment-level decision makers and economic policy makers should strategically and in a coordinated manner intervene to the raise the performance of firms, such that each can utilize the potential rather than focusing merely toward some industries in the sense of priority, which is particularly important when striving to address structural rigidities to reduce persistent inefficiency.

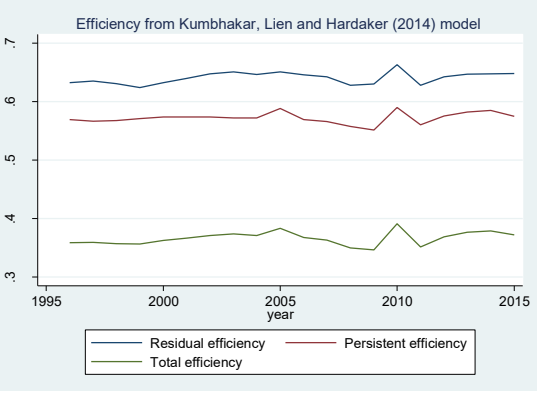
Figure 7 shows the trend of the technical efficiency components during the 20-year period of study. Observations indicate that all the short-run, persistent, and overall technical efficiency measures have marginally grown overtime, with minimal fluctuations. Although a leap could be observed in 2011, the onset of GTP-I has recovered immediately

Table 5
Comparison of Technical Efficiency Across Groups

		Transient	Persistent	Overall
Food and beverage	Mean	0.642	0.578	0.37
	Sd	0.109	0.086	0.084
Textile and wearing apparel	Mean	0.64	0.576	0.369
	Sd	0.109	0.076	0.08
Leather products	Mean	0.642	0.582	0.374
	Sd	0.102	0.073	0.076
Wood products, including furniture	Mean	0.644	0.539	0.347
	Sd	0.089	0.076	0.069
Paper, paper products, printing, and publishing	Mean	0.642	0.599	0.385
	Sd	0.091	0.059	0.067
Chemical and chemical products	Mean	0.64	0.622	0.398
	Sd	0.107	0.071	0.081
Rubber and plastic	Mean	0.642	0.612	0.393
	Sd	0.098	0.068	0.074
Nonmetal	Mean	0.643	0.541	0.348
	Sd	0.094	0.091	0.078
Basic and fabricated metals; machinery and equipment	Mean	0.643	0.582	0.374
	Sd	0.094	0.098	0.083
Others	Mean	0.64	0.623	0.4
	Sd	0.118	0.095	0.095

Source: Authors' computation using estimated technical efficiency

after it continued to show the marginal improvement. Contrarily, an uplift of persistent technical efficiency was observed in 2005 (Period II) and then immediately decreased in the following year and continued to decline until 2010. This circumstance influenced the overall technical efficiency to follow the same trend. The increase in persistent technical efficiency during 2005 may be caused by the relaxation restrictive regulation during the significant election campaign that year seeking vote from the sector. The reason for the declining trend may be due to the political crisis that occurred following the May 2005 general election



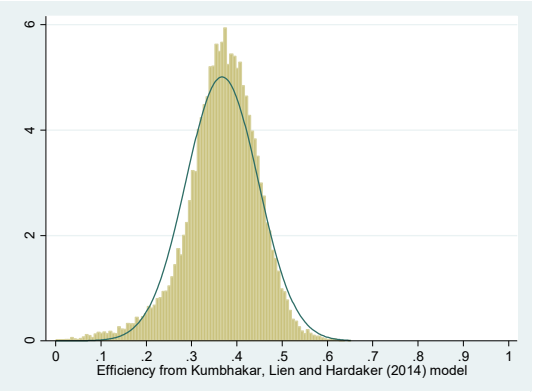
Source: Authors' sketch using CSA raw data

FIGURE 7
TRENDS OF MEAN TECHNICAL EFFICIENCY SCORES

in the country. A claim by the opposing (competing) parties indicates that they obtained majority of the votes; however, the electoral board announced as the ruling party acquired majority. This instance resulted in the public uprising and conflicted with the police wherein many lives were lost, business operations were often interrupted, and regulations and policy frameworks lacked direction.

The high inefficiency effects might arise from management quality in decision making, business coordination, production activities, and/or public regulatory rigidities, which cause structural rigidities in the market. In addition, factors might be related to each firm's daily activities. In both cases, the overall inefficiency is extremely high (63.3%). Thus, such potential problems should be addressed to obtain the maximum possible output from manufacturing. Accordingly, the problem of the Ethiopian manufacturing sector is more of a structural problem, which requires a coordinated and focused effort to escape from the inefficiency trap, and manufacturing production will then grow by utilizing the existing technical and input resources.

The overall technical efficiency is distributed more closely toward its mean (Figure 8), excluding few leftward-skewed firms, which is insignificant by statistical measure. Thus, on average, almost all firms are low in terms of efficiency performance. Hence, a focused intervention should be conducted to enhance the efficiency level, such



Source: Authors' sketch using estimated values

FIGURE 8
HISTOGRAM SHOWING DISTRIBUTION OF TOTAL TECHNICAL EFFICIENCY

that targeted industries should be selected and then promoted. An intervention performed simultaneously may fail due to coordination failure because no bench mark is available to learn lessons from.

Each of the technical efficiency components should be separated into the determining factors to assess the effect of firm size[8] and ownership structure on efficiency to assess the effect of firm size[9] and ownership structure on efficiency. Beforehand, the size and ownership distribution of the establishments should be observed. Table 8 shows that approximately 80.28% of the firms are medium size, and the remaining 19.72% are large. In terms of ownership, approximately 89.84% of the total privately owned, and 64.95% and 95.95% of the large- and medium-size firms, respectively, are privately[10] owned.

Table 6 summarizes the mean technical efficiency comparison across three ownership types and firm size. The short-run efficiency is the lowest (63.5%) in joint-owned medium firms and highest (65%) in public

[8, 9] The classification of large and medium is made by the number of full-time equivalent employees. Firms that employ more than 99 workers are considered as large firms as per the classification adopted by World Bank enterprise surveys.

[10] Private ownership includes cooperatives.

Table 6
Firm Size by Ownership Type

Ownership type	Firm size		
	Medium-size firm size	Large-size firm	Total
Private	16,872	2,806	19,678
Public	624	1,373	1,997
Joint	88	141	229
Total	17,584	4,320	21,904

Source: Authors' tabulation using CSA raw data.

ownership type of large firms. With regard to persistent efficiency, large firms are most efficient regardless of their ownership structure, where it is largest (67.7%) in the jointly owned large firms. The reason may be a relaxation from restrictive regulations and incentive packages that large firms enjoy in view of job creation and export orientation. One of the problems firms face in Ethiopia is scarcity of foreign currency to import raw materials and capital goods. Foreign currency rationing is as per priority sectors and priority to those that earn foreign currency from their exports. The survey data provide a clue in this regard because 73.33% of large firms participate in the international market by exporting their output, and 88.95% of them import raw materials. In addition, to learn from international trade, if their import and export is facilitated, then they could be efficient. Persistent efficiency of medium firms ranges from 55.7% in the private sector to 60.6% in public ownership. In terms of the overall technical efficiency, jointly owned large firms performed highest (43.3%), followed by public ones (42.4%), and the least is 40.2% for private ownership. Overall technical efficiency of medium firms across the three ownership types ranges from 35.7% (private) to 39% (public).

C. Determinants of Short and Long-run Technical Efficiencies

On the basis of the empirical literature reviewed in Section 2, several variables are identified. Some important works in the Ethiopian context are included in this study, and their respective effect is examined separately for time-varying (short-run) and time-invariant (long-run) technical efficiencies. In both cases, the method of estimation is the maximum likelihood Tobit model.

Table 7
Summary of Efficiency by Ownership

Technical Efficiency	Private		Public		Joint	
	Large	Medium	Large	Medium	Large	Medium
Transient efficiency	0.8377	0.8396	0.8253	0.8248	0.8029	0.8331
Persistent efficiency	1	0.6725	1	0.6872	1	0.6917
Overall technical efficiency	0.8377	0.5646	0.8253	0.5673	0.8029	0.5764

Source: Authors' tabulation using estimated efficiency

a) Determinants of Short-run Technical Efficiency

Table 8 indicates that among the 11 determining factors, including the categorical one, eight (*i.e.*, two trade variables; two time periods; Herfindahl–Hirschman index (ln(HHJi)), –a measure of market concentration; average wage; capital intensity; and size dummy) have statistically significant coefficients at the 5% level of significance. Ownership structure and firm age have no remarkable influence on the level of transient technical efficiency. Although literature reveals that privately owned firms have higher profit motive, which drives them to invest on more, manage resource utilization, and follow flexible management practice, which in turn helps them confront the problems during the production process. However, this case is not applicable to Ethiopia. The insignificant effect of firm age as a proxy for firm experience on transient efficiency implies that in their lifetime, learning from experiences during their existence in operation is limited. This instance may be caused by the firms following "business as usual" tradition rather than being innovative and adopting dynamic system.

Firm size dummy has a positive coefficient in line with some of the literature, although the literature revealed mixed results. Here, large firms have 0.8% higher transient technical efficiency level relative to the medium counter parts. This finding indicates that the economies of scale advantage outweigh the coordination failure argument of large size. Capital intensity holds a negative coefficient, which signifies that the prevailing capital deepening is not favorable toward improving short-run technical efficiency level. As the capital-to-labor ratio increases by 1%, the efficiency decreases by 0.1%.

Periods II and III (2004–2010 and 2011–2015, respectively) entail

TABLE 8
TOBIT MAXIMUM LIKELIHOOD ESTIMATION OF RESIDUAL EFFICIENCY DETERMINANTS

Transient efficiency	Coef.	St.Err.	t-value	p-value	[95% Conf.interval]	
Ownership (Private as base)						
Public	0.005	0.003	1.93	0.054	−0.0001	0.011
Joint	−0.010	0.007	−1.39	0.164	0.023	0.004
Size_large	0.008	0.002	3.73	0.000	0.004	0.013
Firm_Age	0.0001	0.0001	1.07	0.284	−0.0001	0.0002
ln(K_intensity)	−0.001	0.0004	−2.04	0.042	−0.002	−0.00003
Period (1996–2003 as base)						
Period II (2004–2010)	0.0089	0.002	4.92	0.000	0.005	0.012
Period III (2011–2015)	0.0093	0.002	5.04	0.000	0.006	0.013
ln(HHJi)	−0.003	0.0002	−13.68	0.000	−0.003	−0.003
ln(Wage_perworker)	0.019	0.001	21.38	0.000	0.018	0.021
Export_status	0.009	0.003	2.83	0.005	0.003	0.015
Import_status	0.003	0.002	2.00	0.045	0.0001	0.006
Constant	0.522	0.006	87.28	0.000	0.510	0.534
χ^2	555.37	Prob > χ^2				0.000

Source: Authors' computation using estimated short-run efficiency and determinants

higher short-run efficiency scores compared with the base period (1996–2003). Although Period II (with higher GDP growth rate) has higher efficiency score by 0.89%, that of Period III (GTP-I) is higher by 0.93%, which is only marginally higher compared with Period II. Thus, the policy effort in GTP-I failed to contribute significant percentage points toward the short-run efficiency score. Rather, only the strategies that enhanced GDP growth continued to increase the short-run efficiency level.

The Herfindahl–Hirschman index, which is a measure of market concentration, is introduced to capture the effect of monopoly power on technical efficiency level. Thus, increasing the degree of monopoly power (reducing competition) reduces short-run technical efficiency. As market concentration increases by 1%, the transient technical efficiency declines by 0.3%.

Average wage expenditure (as a proxy for labor quality) has positive

coefficient in line with a priori expectation that labor quality enhances the efficiency score. When average wage increases by 1%, short-run technical efficiency increases by 1.9%. This condition implies that when firms increase the number of their skilled laborers, which requires higher wage expenditure, their short-run efficiency increases by a significant percentage point. Hence, firms should focus on hiring skilled laborers and improving the skill of the existing employees by implementing on-and off-the-job training, continuous orientation, and follow up. The ministry of industry should design a strategy for industrial internship (attachment) programs for students of universities and technical schools, enabling them to gain skills.

The trade variables (export and import dummies) have the expected sign and the significance of coefficients. Firms that participate in the global market by exporting their output had higher efficiency performance than non-exporters by 0.9%. Firms that import raw material inputs have 0.3% higher short-run efficiency score than non-importers. This finding may be due to learning in the international competition, and the imported raw materials helped the firms to utilize their capacity, without which the potential capacity may remain underutilized. Hence, firms should engage in the international market to realize improvement in short-run efficiency by easing the business environment, simplifying the cumbersome custom procedure, and resolving the foreign exchange constraint.

b) Determinants of Persistent Efficiency

For the sake of consistency, all the factors, which are included in the transient efficiency discussion above are considered in Table 10. Out of the 11 variables, only two (*i.e.*, joint ownership and firm age) are insignificant. Therefore, joint ownership structure does not improve persistent and transient efficiency levels.

Public ownership, in contrast to the short-run case, significantly and positively affects the persistent efficiency level (*i.e.* publicly owned firms are 0.3% higher than their private counterparts in terms of long-run technical efficiency score). This finding may be due to the factors that are related to government regulation and rationing, such as credit and foreign exchange, in which case government prioritizes for firms under its ownership in view of public interest.

Although large firms have higher transient efficiency (lower transient

inefficiency) performance, they are less in the persistent one. Large firms have less persistent efficiency than medium firms by 1.6%. This observation may be due to persistent inefficiency being caused by structural rigidities and regulations, and large firms might adopt well-established long-standing system, which reduces flexibility to solve the problems faced by the firm.

Both trade variables have negative coefficients. Thus, output exporters have less long-run efficiency compared with the non-exporters by 0.8%. In addition, firms that use imported raw material input have less persistent efficiency by 0.5% than non-importers. Thus, large- and medium-scale Ethiopian manufacturing firms are significantly affected by the internal factors, which hinder improvement in the long-run efficiency to the extent that outweighs the positive effect from learning by participating in the international market.

The two time periods showed a better improvement in the run efficiency by 1.1% and 3.6% relative to the base period. Thus, the policy orientation toward the manufacturing sector has played a role toward reducing the factors that cause persistent inefficiency than those of transient inefficiency. Hence, the government should further focus on solving the problems that firms face to augment short- and long-run efficiency.

Capital intensity holds negative and significant effect. Thus, the performance of the capital input should be improved, such that its composition with the labor input provides efficiency improvement. This objective may be achieved by updating and renovating the capital stock. Moreover, although it may be initially costly, the capital input to be imported should contain new technology because its long-run effect would be higher with positive returns.

Market concentration entails positive significant influence toward long-run technical efficiency level, contradicting its effect on transient efficiency. As monopoly power increases by 1%, persistent efficiency increases by 1.4%.

VI. Conclusions

This study aims to analyze the transient and persistent technical efficiencies and its determinants of large- and medium-scale manufacturing establishments arising from the need to draw the attention of policy makers toward achieving the 9th SDG for industrialization of develop-

Table 9
Tobit Maximum Likelihood Estimation of Persistent Efficiency Determinants

Persistent Efficiency	Coef.	St.Err.	t-value	p-value	[95% Conf. Interval]	
Ownership (Private as base)						
Public	0.003	0.002	2.10	0.036	0.000	0.006
Joint	−0.002	0.004	−0.52	0.605	−0.010	0.006
Size_large	−0.016	0.001	−13.01	0.000	−0.019	−0.014
Firm_Age	0.0001	0.000	1.62	0.106	0.000	0.000
ln(K_intensity)	−0.001	0.000	−3.02	0.003	−0.001	0.000
Period (1996–2003 as base)						
Period II(2004–2010)	0.011	0.001	10.54	0.000	0.009	0.013
Period III (2011–2015)	0.036	0.001	35.03	0.000	0.034	0.038
ln(HHJi)	0.014	0.0001	113.62	0.000	0.014	0.014
ln(Wage_perworker)	0.012	0.001	23.59	0.000	0.011	0.013
Export_status	−0.008	0.002	−4.35	0.000	−0.011	−0.004
Import_status	−0.005	0.001	−5.81	0.000	−0.007	−0.003
Constant	0.631	0.003	187.41	0.000	0.624	0.638
χ^2		17,721.57	Prob > χ^2			0.000

Source: Authors' computation using estimated long run efficiency and determinants

ing countries.

Although Ethiopia has been scoring a good economic growth trajectory for 14 years since 2003/2004 with an average growth rate of 10.62%, the industrial base is at its stage of infancy in terms of its contribution to the employment generation, value addition, and growth. The Ethiopian manufacturing sector has been lagging behind not only compared with the Sub-Saharan African standards but even relative to its neighboring countries. Thus, research should be conducted in this area, such that policymakers can design appropriate interventions.

A panel data set of manufacturing firms covering the period 1996–2015 is obtained from annual survey of Ethiopian CSA to obtain empirical estimates. The method estimation adopted is the one that was recently developed to separate the error term into four random components. It uses the stochastic frontier framework, and the four random components are two time-varying and time-invariant technical ineffi-

ciency effects. Then, a Tobit model is used to investigate the determinants of each of the efficiency components. Hence, we adopt a two-stage estimation procedure. First, the production function is estimated, and the short- and long-run technical efficiency components are then predicted as sources for overall technical efficiency. Second, each of these components is examined against the determining factors.

In the first stage, the production function is estimated based on Hausman model specification test. In addition, serial correlation and heteroscedasticity tests are conducted, which show the presence of both problems. Thus, cluster robust standard error fixed effects estimation is adopted.

In line with a priori expectation, the size of the elasticities of full-time labor and net real capital are approximately 54.4% and 19.1%, respectively. The elasticity of the capital input is extremely small relative to the labor input elasticity. Therefore, the capital input used by firms is not up to date and is not renovated. This situation calls for improvement by importing and innovating new and technology-embodied capital machines. The coefficient of the time trend variable measures the effect of technical progress on real value added by shifting the production frontier. Its magnitude is 1.9%; thus, overtime output (real value added in this context) increases by 1.9% due to technical change.

The estimated technical efficiency is decomposed into short-run (transient) and long-run (persistent) efficiency effects. The average estimated time-varying, time-invariant, and overall technical efficiency effects are 64.2%, 57.2%, and 36.7% (63.3% inefficiency), respectively. Thus, establishments can increase their average real value added by 63.3% for given set of labor and capital input and using the prevailing technology if they can address the factors that hinder the efficient utilization of inputs and technical know-how.

Two trade variables (*i.e.*, export and import dummies), two time periods (2004–2010 and 2011–2015), Herfindahl–Hirschman Index (a measure of market concentration), average wage expenditure (a proxy of labor quality), capital deepening, and size dummy significant affect the transient technical efficiency level. Particularly, large firms are better in their short-run efficiency level by 0.8%; however, as capital deepening (intensity) increases by 1%, short-run technical efficiency decreases (inefficiency increases) by 0.1%. The two recent periods are higher by 0.89% and 0.93% when compared with the base period (1996–2003). However, the difference between the two is not sufficiently large to indicate that

GTP-I period is significant in reducing transient inefficiency effect.

As monopoly power (captured by Herfindahl–Hirschman index) increases by 1%, transient technical efficiency decreases by 0.3%. When per worker wage expenditure increases by 1%, short-run technical efficiency also increases by 1.9%. The export and import dummies have 0.9% and 0.3% higher short-run efficiency level, respectively, relative to those that do not export or import.

When it comes to the determinants of persistent technical efficiency, five variables acquire different effects than in the transient one. Public ownership is negative and insignificant in the transient; however, here, it is positive and significant, which implies that publicly owned firms have 0.3% higher long-run efficiency than privately owned ones. Larger firms have 1.6% less persistent efficiency that the medium counterparts. The two trade variable obtain negative coefficients; thus, those who participate in the international market have less persistent efficiency by 0.8% (exporters) and 0.5% (importers) when compared with the non-exporters and non-importers, respectively. As the market concentration increases by 1%, persistent technical efficiency increases by 1.4%.

Other variables, which are similar in sign with the transient determinants differ in magnitude of their coefficients. For instance, the two time periods have higher persistent technical efficiency relative to their effect on the transient one. Period II is higher by 1.1% and Period III is also higher by 3.6% compared with the base period.

Therefore, large- and medium-scale Ethiopian manufacturing establishments have low technical efficiency measures by short-and long-run factor perspectives. Some factors can enhance technical efficiency, whereas others hinder its improvement. Thus, strategically designed, coordinated with the firms themselves, and focused intervention are required to raise the real value added using the existing state-of-the-art technology and input combination along with advancing the technical know-how, higher labor quality, and advancement of capital equipment.

A. Policy Implications

The overall technical efficiency of 36.7% (63.3% inefficient) implies that firms can increase their output by 63.3% if they can remove all the factors that hinder their performance. The main cause of this low inefficiency level is the persistent inefficiency of 57.2%. By taking measures that address the factors that cause structural (long standing) in-

efficiency without using additional input factors, and technology firms can use their resources more efficiently. The factors can emerge either from firms' internal structure and/or from the business environment, such as public regulations. Thus, the responsible economic agents, that is, the government (*e.g.*, Ministry of Industry) and firms should concentrate their efforts to identify and eliminate such factors. Comparison of industrial groups of the manufacturing sector reveals that in terms of input elasticity, a wide difference exists; however, with the mean level of efficiency, the difference is small. Thus, attention should be paid toward all the sectors to augment the performance of the manufacturing sector and build the industrial base for advancing the structural transformation. Specifically, the government should focus on the following policy issues:

- Firms should focus on hiring skilled laborers and improving the skill of the existing employees using on-and off-the-job trainings, continuous orientation, and follow up. The ministry of industry should design a strategy for industrial internship (attachment) program for university students and technical schools, enabling them to gain skills in preparation for the employment industry.
- Firms should be encouraged to engage in the international market to improve short-run efficiency by easing the business environment, simplifying the cumbersome custom procedure, and resolving the foreign exchange constraint. Moreover, the reason why engaging into the international market causes persistent efficiency to decrease should be investigated. The problem is more of internal or may be at the import–export regulation rigidity and in the custom procedures.
- The capital elasticity is small, whereas the capital intensity has a negative but significant effect on persistent and transient efficiency levels. Hence, the performance of the capital input should be improved, such that its composition with the labor input boost efficiency. This objective can be achieved by updating the capital stock and renovating it and importing capital equipment that will bring embodied new technology, although at a high cost.

(Received 21 March 2019; Revised 24 September 2019; Accepted 25 September 2019)

Appendix

Modified Wald test for group-wise heteroscedasticity in fixed effect regression model

H_0: $\sigma_i^2 = \sigma_2$ for all i

$\chi^2(8313) = 2.8e + 08$

Prob > $\chi^2 = 0.0000$

Wooldridge test for autocorrelation in panel data

H_0: no first-order autocorrelation

F(1, 2074) = 53.062

Prob > F = fabstract 0.0000

References

Abegaz, M. T. "Total factor productivity and technical efficiency in the Ethiopian manufacturing sector" (No.010 2013).

Agasisti, T., & Gralka, S. "The transient and persistent efficiency of Italian and German universities: A stochastic frontier analysis." *Applied Economics* (2019): 1-19.

Albalate, D. & Rosell,J. "Persistent and transient efficiency on the stochastic production and cost frontiers–an application to the motorway sector." *XREAP2016-04* (2016).

Badunenko, O., & Kumbhakar, S. C. "When, where and how to estimate persistent and transient efficiency in stochastic frontier panel data models." *European Journal of Operational Research* 255 (No.1 2016): 272-287.

Badunenko, O., & Kumbhakar, S. C. "Economies of scale, technical change and persistent and time-varying cost efficiency in Indian banking: Do ownership, regulation and heterogeneity matter?" *European Journal of Operational Research* 260 (No.2 2017): 789-803.

Bartels, B. "Beyond" fixed versus random effects": a framework for improving substantive and statistical analysis of panel, time-series cross-sectional, and multilevel data." *The Society for Political Methodology* 9 (2008): 1-43.

Battese, G. E., & Coelli, T. J. "Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India." *Journal of productivity analysis* 3 (Nos.1-2 1992): 153-169.

_____. "A model for technical inefficiency effects in a stochastic frontier production function for panel data." *Empirical economics* 20 (No.2 1995): 325-332.

Bauer, P. W. "Recent developments in the econometric estimation of frontiers." *Journal of econometrics* 46 (Nos.1-2 1990): 39-56.

Becheikh, N., Landry, R., & Amara, N. "Lessons from innovation empirical studies in the manufacturing sector: A systematic review of the literature from 1993–2003." *Technovation* 26 (Nos.5-6 2006): 644-664.

Belotti, F., Daidone, S., Ilardi, G., & Atella, V. "Stochastic frontier analysis using Stata." *The Stata Journal* 13 (No.4 2013): 719-758.

Belotti, F., & Ilardi, G. "Consistent Estimation of the'True'Fixed-Effects Stochastic Frontier Model." 2012.

Bigsten, A., &Gebreeyesus, M. "The small, the young, and the productive: Determinants of manufacturing firm growth in Ethiopia." *Economic Development and Cultural Change* 55 (No.4 2007): 813-840.

Bigsten, A., & Gebreeyesus, M. "Firm productivity and exports: Evidence from Ethiopian manufacturing." *The Journal of Development Studies* 45 (No.10 2009): 1594-1614.

Blasch, J., Boogen, N., Filippini, M., & Kumar, N. "Transient and Persistent efficiency in residential electricity consumption in Switzerland and the role of energy literacy and energy saving behaviour." In 7th Atlantic Workshop on Energy and Environmental Economics (AWEEE). AWEEE (2016)

Blundell, R., & Bond, S. "GMM estimation with persistent panel data: an application to production functions." *Econometric reviews* 19 (No.3 2000): 321-340.

CSA. A. "Report on large and medium scale manufacturing and electricity industries survey." Statistical bulletin 580 (2015).

Chen, Y. Y., Schmidt, P., & Wang, H. J. "Consistent estimation of the fixed effects stochastic frontier model." *Journal of Econometrics* 181 (No.2 2014): 65-76.

Chu, S. N., & Kalirajan, K. "Impact of trade liberalisation on technical efficiency of Vietnamese manufacturing firms." *Science, Technology and Society* 16 (No.3 2011): 265-284.

Colombi, R., Martini, G., & Vittadini, G. "Determinants of transient and persistent hospital efficiency: The case of Italy." *Health economics* 26 (S-2 2017): 5-22.

_____. "A stochastic frontier model with short-run and long-run inefficiency random effects." (2011).

Constantin, P. D. *et al.* "Cobb-Douglas, translog stochastic production function and data envelopment analysis in total factor productivity in Brazilian agribusiness." *Journal of Operations and Supply Chain Management (JOSCM)* (No.2 2009): 20-33.

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

Diewert, W. E. "Decompositions of productivity growth into sectoral effects: some puzzles explained." *Productivity and Efficiency Analysis.* Springer, Cham (2016): 1-13.

Färe, R., Grosskopf, S., & Lee, W. F. "Productivity and technical change: the case of Taiwan." *Applied Economics* 33 (No.15 2001): 1911-1925.

Filippini, M., & Greene, W. "Persistent and transient productive inefficiency: a maximum simulated likelihood approach." *Journal of Productivity Analysis* 45 (No.2 2016): 187-196.

Filippini, M., Greene, W., & Masiero, G. "Persistent and transient productive inefficiency in a regulated industry: electricity distribution." *Energy Economics* 69 (2018): 325-334.

Filippini, M., & Hunt, L. C. "Measuring persistent and transient energy efficiency in the US." *Energy Efficiency* 9 (No.3 2016): 663-675.

Fungáčová, Z., Weill, L., & Klein, P. O. "Persistent and transient inefficiency: Explaining the low efficiency of Chinese big banks." (2018).

Førsund, F. R., Lovell, C. K., & Schmidt, P. "A survey of frontier production functions and of their relationship to efficiency measurement." *Journal of econometrics* 13 (No.1 1980): 5-25.

Gebreeyesus, M. "Firm turnover and productivity differentials in Ethiopian manufacturing." *Journal of Productivity Analysis* 29 (No.2 2008): 113-129.

Gralka, S. "Persistent inefficiency in the higher education sector: Evidence from Germany." *Education Economics* (2018): 1-20.

Greene, W. "Reconsidering heterogeneity in panel data estimators of the stochastic frontier model." *Journal of econometrics* 126 (No.2 2005): 269-303.

_____. "Fixed and random effects in stochastic frontier models." *Journal of productivity analysis* 23 (No.1 2005): 7-32.

_____. "The econometric approach to efficiency analysis. The measurement of productive efficiency and productivity growth." *The Measurement of Productive Efficiency: Techniques and Applications*. Oxford University Press, New York (2008): 68-119.

Gralka, S. "Persistent inefficiency in the higher education sector: evidence from Germany." *Education Economics* 26 (No.4 2018): 373-392.

Hailu, K. B., & Tanaka, M. A. ""true" random effects stochastic frontier analysis for technical efficiency and heterogeneity: Evidence from manufacturing firms in Ethiopia." *Economic Modelling* 50 (2015): 179-192.

Herrendorf, B., Rogerson, R., & Valentinyi, Á. "Growth and structural transformation, in Handbook of Economic Growth." Elsevier Vol.2 (2014): 855-941.

Heshmati, A., Kumbhakar, S. C., & Kim, J. "Persistent and transient efficiency of international airlines 444." Royal Institute of Technology, CESIS-Centre of Excellence for Science and Innovation Studies.

_____. "Persistent and transient efficiency of international airlines." *European Journal of Transport and Infrastructure Research* 18 (No.2 2018).

Hossain, M. A., & Karunaratne, N. D. "Trade liberalisation and technical efficiency: evidence from Bangladesh manufacturing industries." *Journal of Development Studies* 40 (No.3 2004): 87-114.

Ismail, R., & Abidin, S. Z. "Determinant of Technical Efficiency of Small and Medium Enterprises in Malaysian Manufacturing Firms." *International Business Management* 11 (No.2 2017): 299-307.

Kabeta, Z. E., & Sidhu, I. S. "Service sector: the source of output and employment growth in Ethiopia." *Academic Journal of Economic Studies* 2 (No.4 2016): 139-156.

Kabeta, Z. E. "Structure and Growth of Service Sector in Ethiopia." Doctoral dissertation, Punjabi University, Patiala. (2017).

Khalaf, L., & Saunders, C. J. "Dynamic Technical Efficiency." *Productivity and Efficiency Analysis*. Springer, Cham. (2016): 99-107.

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

Kumbhakar, S. C., Lien, G., & Hardaker, J. B. "Technical efficiency

in competing panel data models: a study of Norwegian grain farming." *Journal of Productivity Analysis* 41 (No.2 2014): 321-337.

Kumbhakar, S. C., & Lovell, C. K. "Stochastic production frontier." Cambridge University Press (2000).

Kumbhakar, S. C., & Zelenyuk, V. "Stochastic frontier analysis: Foundations and advances." Handbook of production economics. New York, NY: Springer (2017).

Kumbhakar, S. C., & Sarkar, S. "Deregulation, ownership, and productivity growth in the banking industry: evidence from India." *Journal of Money, Credit and Banking* (2003): 403-424.

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

Kutlu, L. "Battese-Coelli estimator with endogenous regressors." *Economics Letters* 109 (No.2 2010): 79-81.

Lai, H. P., & Kumbhakar, S. C. "Panel data stochastic frontier model with determinants of persistent and transient inefficiency." *European Journal of Operational Research* (2018).

Lee, H. T. "Causes of the changing performance of firms with diverse types of ownerships in China." *Seoul Journal of Economics* 29 (2016): 95-112.

Lee, K., Miyagawa, T., Kim, Y., & Edamura, K. "Comparing the Management Practices and Productive Efficiency of Korean and Japanese Firms: An Interview Survey Approach." *Seoul Journal of Economics* 29 (2016): 1-41.

Lien, G., Kumbhakar, S. C., & Alem, H. "Endogeneity, heterogeneity, and determinants of inefficiency in Norwegian crop-producing farms." *International Journal of Production Economics* 201 (2018): 53-61.

Lemi, A., & Wright, I. "Exports, Foreign Ownership and Firm-level Efficiency in Ethiopia and Kenya: An Application of Stochastic Frontier Model." *Springer-Verlag GmbH Germany* (2018).

Linna, M. "Measuring hospital cost efficiency with panel data models." *Health economics* 7 (No.5 1998): 415-427.

Mattsson, P., Månsson, J., & Greene, W. "TFP Change and its Components for Swedish Manufacturing Firms During the 2008-2009 Financial Crisis." (2018).

O'Donnell, C. J. "Productivity and Efficiency Analysis: An Economic

Approach to Measuring and Explaining Managerial Performance." Springer (2018).

Paul, S., & Shankar, S. "Estimating Efficiency Effects in a Panel Data Stochastic Frontier Model." (2018).

Ritter, C., & Simar, L. "Pitfalls of normal-gamma stochastic frontier models." *Journal of productivity analysis* 8 (No.2 1997): 167-182.

Schmidt, P., & Sickles, R. C. "Production frontiers and panel data." *Journal of Business & Economic Statistics* 2 (No. 4 1984): 367-374.

Sena, V. "The frontier approach to the measurement of productivity and technical efficiency." *Economic Issues-Stoke On Trent-* 8 (No.2 2003): 71-98.

Sinani, E., Jones, D. C., & Mygind, N. "Determinants of firm level technical efficiency: A stochastic frontier approach." Copenhagen Business School (2007).

Sun, H., Hone, P., & Doucouliago, H. "Economic openness and technical efficiency: a case study of Chinese manufacturing industries." *Economics of Transition* 7 (No.3 1999): 615-636.

Stevenson, R. E. "Likelihood functions for generalized stochastic frontier estimation." *Journal of econometrics* 13 (No.1 1980): 57-66.

Torres-Reyna, O. "Panel data analysis fixed and random effects using Stata (v. 4.2)." Data & Statistical Services, Priceton University (2007).

Tran, K. C., & Tsionas, E. G. "GMM estimation of stochastic frontier model with endogenous regressors." *Economics Letters* 118 (No.1 2013): 233-236.

Tsionas, E. G., & Kumbhakar, S. C. "Firm Heterogeneity, Persistent and Transient Technical Inefficiency: A Generalized True Random–Effects model." *Journal of Applied Econometrics* 29 (No.1 2014): 110-132.

Wang, H. J., & Ho, C. W. "Estimating fixed-effect panel stochastic frontier models by model transformation." *Journal of Econometrics* 157 (No.2 2010): 286-296.

Wikström, D. "Consistent method of moments estimation of the true fixed effects model." *Economics Letters* 137 (No.C 2015): 62-69.