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Technical efficiency, technological progress and productivity growth of large and medium manufacturing industries in Ethiopia: A data envelopment analysis

Obsa Teferi Erena[1]*, Mesfin Mala Kalko[2] and Sara Adugna Debele[1]

Abstract: The purpose of this study is to assess empirically how the technical efficiency scores for 43 sub-sectors and their determinants over the period 2010 to 2017 show significant variation across the sub-sectors. The study applied a two-step approach for measuring technical efficiency and its determinants. A data envelopment analysis output-orientation (i.e. both CCR & BCC models) is used to estimate technical efficiency scores for 43 sub-sectors over the period 2010 to 2017. Malmquist productivity index (MPI) output orientation is also applied to compute technical efficiency change, technological progress, and productivity change. The estimated technical efficiency score shows significant variation across the sub-sectors. Thus, we used a Tobit regression model to scrutinize what defines the variation in technical efficiency scores using three years of panel data which covers 2015 to 2017. Moreover, the 43 sub-sectors were further grouped into 14 major sub-

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PUBLIC INTEREST STATEMENT

This paper uses data envelopment analysis to measure technical efficiency, technological change, and productivity growth in 43 manufacturing industries over the period 2010 to 2017. Malmquist productivity index (MPI) output orientation is also applied to compute technical efficiency change, technological change, and productivity change. The results show that the sector had experienced a 37 percent technical efficiency in overall average when the CCR model was used. The findings of the study would have implications for policymakers, government, and firm owners in that it provides an insight into the source of productivity growth in the sector.

sectors and classified as public and private to examine whether there is a technical efficiency score discrepancy between the same sub-sectors operating under different ownership. For measuring overall technical efficiency, we used two output variables (i.e., value-added and operating surplus) and two input variables (i.e., total fixed assets and a total number of employees). When reducing the sub-sectors to fourteen major groups, the operating surplus was not included, thus we used value-added and total sales as output variables and total fixed assets, the total number of employees, and cost of raw materials used in the production process as input variables. To shed light on the source of inefficiency, technical efficiency is decomposed into pure technical efficiency and scale efficiency. This study found that the sector had experienced a 37 percent technical efficiency in overall average when the CCR model was used. The study also claims that public owned subsectors are less likely to be efficient than private subsectors. The regression results show the capital expenditure ratio has a significant positive influence on technical efficiency. The Malmquist index result also shows, on average, the sector had registered a 10.5% technological progress and a 13% productivity growth over the period 2010–2017. The findings of the study would have implications for policymakers, government, and firm owners in that it offers an insight into the source of productivity growth in the sector.

Subjects: Economics; Finance; Business, Management and Accounting

Keywords: Technical efficiency; Technological progress; Productivity; DEA; Tobit Model; Ethiopian manufacturing sector

1. Introduction

The manufacturing sector plays a crucial role in production, growth, and job creation (Naudé & Szirmai, 2012). It is the most important engine of long-term growth and development, both in developed and developing countries (McKinsey, 2012). In the former, for instance, in 2015 the manufacturing sector shares 12% and 19% of the gross domestic product (GDP) of the United States and Japan, respectively (UNCTAD, 2015) and it remains a vital source of innovation & competitiveness, making enormous contributions to research & development, exports, and productivity growth (McKinsey, 2012). While, in the latter, the manufacturing sector shares 27% and 16% of the GDP of China and India in 2015, respectively (UNCTAD, 2015) and it continues to provide a pathway from subsistence farming to rising incomes and living standards. For the least developed countries, such as Ethiopia, agriculture makes up the highest proportion of the economy. According to the Ethiopian CSA (2018), the net contribution of the manufacturing sector to the GDP growth rate increased from 0.4% in 2011 to 1.1% in 2017. The agriculture and services sectors accounted for 36.3% and 39.3% in 2017, respectively. This low contribution of the manufacturing sector to the GDP is a common feature of Sub-Saharan African countries. oFr instance, it takes 8.4% of Kenya`s GDP (Kenya Association of Manufacturers, 2018) and 2.4% of Djibouti`s GDP (United Nations, 2016). In this regard, Ethiopia has shifted its economic strategy from agricultural to industrial lead in 2011. The strategic plan was divided into two five-year plans, with Growth and Transformation Plan I, which covers from 2011 to 2015, and Growth and Transformation Plan II, which covers from 2016 to 2020. Nevertheless, the agriculture sector has continued to dominate the GDP of the country, which was followed by the service sector. Indeed, the manufacturing sector`s contribution to GDP demonstrates Ethiopia`s infant stage of manufacturing activities or industrialization. Empirical evidence (Ayelign & Singh, 2019; Oqubay, 2015; Hailu & Tanaka, 2015; UNDP, 2017) has also confirmed that the sector had faced several problems, such as limited access to and interrupted electricity power, a low level of export performance and competition, a shortage and irregular supply of domestic raw materials, limited access to and poor quality of internet services, and weak logistic support.

Technical efficiency is the ability of a firm to produce as much output as possible with a specified level of inputs, given the existing technology. It can also be a situation wherein it is impossible, with current technical knowledge, to increase output from given inputs or produce a given output using less than one input without using more of another input (Farrell, 1957). Efficiency is a major problem in Ethiopia. Because Ethiopia`smanufacturing industries were not operating at full capacity (Hailu & Tanaka, 2015), there was a need to improve the sector`s efficiency (Bekele & Belay, 2007). Ethiopia has very limited capital but an abundant workforce, and hence its industries are predominantly labor-intensive instead of capital-intensive. Productivity growth might come from the enhancement of productivity based on catching up capability and innovation by effective use of human capital in the labor market and adoption of new technology. Conversely, switching from labor-intensive to capital-intensive would increase productivity if an optimal benefit is achieved from technology change. The Ethiopian manufacturing sector tends to be labor-intensive. This is common in the least developed countries because of the presence of a massive pool of unemployed labor force (Wu, 1993). Being labor-intensive or capital-intensive might not result in efficiency or inefficiency, but being able to produce additional units of production (output) while keeping input constant or reducing input while keeping output constant could lead to the efficient frontier. There have been contradicting results in the literature that suggest capital-intensive firms are more efficient than labor-intensive one. For example, Arrow et al. (1961) suggested that differences in the efficiency of firms arise due to variations in the efficiency of the labor force. Wu (1993), using econometric and group-wise analyses, finds that labor-intensive firms are relatively more efficient than capital-intensive firms. In contrast, Alvarez and Crespi (2003) and Sun et al. (1999) suggest firms that are capital-oriented tend to be more efficient. Similarly, Li and Zhao (2017) indicated that capital-intensive firms were found to perform better and have higher stock value than labor-intensive firms.

There have been few studies on measuring the productivity of manufacturing firms in Ethiopia. For example, Goshu et al. (2017) proposed a framework for measuring productivity in manufacturing companies. Tsegay et al. (2018) applied conventional OLS and panel data to test determinants of performance in manufacturing with regard to the textile and garment industry. Rao and Tesfahunegn (2015) used the Cobb-Douglas production function to examine the performance of manufacturing industries. Abegaz (2013), Hailu and Tanaka (2015), and Ayelign and Singh (2019) estimate the technical efficiency and total productivity changes of medium and large manufacturing firms using a comprehensive panel data set annually collected by the central statistical agency. Bekele and Belay (2007) analyzed technical efficiency and its determinants in the grain mill products manufacturing industry, using the stochastic frontier model. Moreover, the recent study by Oqubay (2018) analyzed the structure and performance of manufacturing industries. Most of the studies stated here have employed a linear function, stochastic frontier approach to computing technical efficiency score which is subject to model diagnostic tests such as the normal distribution of residual terms (which is a part of technical inefficiency score), model identification, and specification. In addition, no attempt has been made in these prior studies to examine what defines the variation in technical efficiency scores of the firms under study. Thus, this study attempts to fill this gap by using two-fold analyses: (1) measuring technical efficiency and total productivity growth using a non-linear programming approach, data envelopment analysis approach, and (2) a Tobit regression model has been employed to analyze determinants of technical efficiency. Furthermore, a comparative analysis has been performed to understand whether the technical efficiency score differs between public-owned industrial groups and privately owned industrial groups.

We assume that this study contributes to the body of knowledge in two ways. First, it has used a more comprehensive analysis to answer the question that addresses why some firms are more efficient than other firms? This question has been partially answered by identifying the potential firm-specific factors that largely define a firm technical efficiency score. Second, the study asserts that public-owned firms are less likely to be efficient than privately-owned firms. The important question to be raised here is: do resource providers worry about their firm's technical efficiency and productivity growth? This question may not be relevant and sound where there are strong shareholders/resource providers' laws and regulatory provisions that impose duties and responsibilities on the management of the company. However, in developing countries such as Ethiopia, shareholders` law and other provisions are scarce and limited in their application, so public-owned firms are assumed to be less efficient than those firms that operate under private investors. The best resolution to this problem would be privatizing public-owned firms. Ethiopia is currently working on a privatization strategy.

The remainder of the paper is organized as follows: Section 2 presents a review of literature relevant to this study. Section 3 presents the methodology employed in the study. Section 4 reports results and discussion and Section 5 presents the conclusion. Sections 6 & 7 present practical implications and limitations and suggestions for further studies, respectively.

2. Literature review

2.1. The link between the relative technical efficiency and technological change to productivity growth

Productivity growth permits a company to increase profit and market share at the micro-level, and it assists a country to create jobs, counteract inflation, and force the necessary industrial restructuring at the macro-level (J.D. Lee & Heshmati, 2009, p.1). There is widespread agreement among academic researchers in the field of growth theory, policymakers, and businessmen that productivity raise is essential for continued economic growth (J.D. Lee & Heshmati, 2009, p.1). In one of the original contributions to economic growth theory, the investigations of economic growth by Abramovitz (1956), Denison (1962), and Kendrick (1956), productivity/efficiency was considered transcendent for clarifying a noteworthy portion of growth, as Griliches (1998) indicated. In these studies, the authors wanted to review the behavior of growth rates of physical and labor capital as well as the growth rates of per capita production within the USA. From their conclusions, they asserted that much of the growth was because of productivity or, agreeing to Abramovitz (1956), the measure of our ignorance. Having confirmed the significance of productivity for economic growth, Denison (1962) contended that one of the explanations for its acceleration rested in economies of scale, but this might not be directly influenced.

Among the contributions of Solow (1956) and Swan (1956), who introduced productivity into an economic growth model, where it had been called technical progress. The growth model was supported by the analysis of a neoclassical production function, which assumed constant returns to scale and decreasing returns on inputs. Solow (1956) stated technical progress was an increasing factor of scale by which production was multiplied. Meanwhile, Swan (1956) said technical progress was initially neutral but increased its responsibility for rises in output that were not caused by rises in capital or labor and indirectly increased production by increasing the contribution of capital. In contrast to those models, endogenous models appeared within which technical progress would be internal to the model of economic growth. Among these studies are Lucas (1988), Romer (1986, 1990), who were also known for their attention to increasing incomes at scale and the consideration of models in flawed equilibrium, assuming equilibrium in monopolistic competition and the inclusion of human capital stock in the production function. Though, considering TFP, technical progress, or technological change, there is also the model of Mankiw et al. (1992) which wanted to defend Solow's contributions to economic growth by finding solutions to some of the critiques indicated in the original model. Thus, it was treated as an augmented Solow model with human capital, and to the authors, that alternation better fit the explanation of the growth of nations.

In a similar vein, the mainstream approaches to economies of innovation by Acemoglu and Zilibotti (2001) pointed out that many technologies used by the least developed countries (LDCs) are developed in the advanced economies and are designed to make optimum use of the skills of these richer countries' workforces. Differences in the supply of skills create a mismatch between the requirements of these technologies and the skills of LDC workers and lead to low productivity in the LDCs. Even when all countries have equal access to new technologies, this skill-technology disparity can lead to sizable differences in TFP and production per worker. For example, the evolutionary approach of Nelson and Winter (1973) to the economics of innovation indicated diffusion processes for new technologies and the existence of significant differences among firms in terms of profitability, the technology used, lead to differences in productivity and growth. Similarly, Geroski et al. (1993) in their studies on the profitability of 721 innovating manufacturing firms in the UK, found the number of innovations achieved by manufacturing firms had a positive impact on operating profit. They also indicated innovative firms were more profitable than non-innovative firms in general, although the effect of specific innovation types on firm profit margin was only modest in size.

The term economic efficiency refers to the use of resources to maximize the production of goods and services. In absolute terms, the situation can be called economically efficient if: (1) no one can be made better-off without making someone else worse-off, (2) no additional output can be obtained without increasing the amount of input, and (3) production proceeds at the lowest possible per-unit cost (Sullivan & Sheffrin, 2007 p. 15). Efficiency can be categorized into technical, allocative, or the combination of the two (i.e. total economic efficiency) based on the scope of efficiency targeted (Bhat et al., 2001). Technical efficiency means producing maximum output with given inputs, or equivalently, using minimum inputs to produce a given output (Farrell, 1957). Farrell (1957) considered a production function for a fully efficient firm and analyzed technical efficiency for a production firm as the ratio of the output of any given firm to that of a fully efficient firm. Allocative efficiency deals with the minimizing of the cost of production with a proper combination of inputs for a given level of output and a set of input prices, assuming that the entity examined is working at full technical efficiency. These technical and allocative efficiencies can be combined as a measure of economic efficiency.

TFP can effectively contribute to output growth by improvements in technology and efficiency, as these are two determinants of TFP, under constant returns to scale. If returns to scale are variable, TFP growth can be generated by technical change, efficiency improvement, and scale effects. This also reinforces the potential role played by technical efficiency in determining productivity and therefore the need for the relation of assumptions to accommodate inefficiency and efficiency variations. Technical efficiency reflects firm-specific technical knowledge and effort (Page, 1980), the will, skills, and determination of employees and management (Aigner et al., 1977; L.-F Lee & Tyler, 1978), and the effects of work stoppages, managerial skills, material bottlenecks, worker efforts and other disruptions to production (L.-F Lee & Tyler, 1978).

To explore sources of productivity growth in the presence of inefficiencies, it is essential to appropriately model production technology and inefficiencies among economic agents. Data envelopment analysis (DEA) has been extensively used to analyze productivity growth and inefficiencies. Data envelopment analysis represents a method of analysis that can serve as an aid in identifying best practice performance in the utilization of resources amongst firms of a similar category. Such identification can highlight where the most significant benefits can be made from efficiency improvements and assist organizations to realize their maximum potential. Measurement tools such as DEA are useful in situations where government bodies operate in markets, which are distorted by prices closely controlled by the government, subsidies, and a lack of contestability. In these cases, the same old market indicators of performance such as profitability and rates of return cannot be used to measure an organization's economic performance accurately. Despite this, governments and the public at large are still worried that these organizations operate efficiently. In these situations, DEA provides comparative monitoring that identifies variations and hence provides encouragement and direction for the improvement of the performance (Abbott & Doucouliagos, 2003).

Most of the prior literature on productivity focused on input productivity like labor or capital as a measure of input efficiency. A rise in the level of productivity reflects a rise in the efficiency of inputs. Hence, the same level of inputs can produce higher output levels, which suggests a reduction in the cost of production. In other words, it reflects betterment in the input qualities. A study conducted by Bhatia (1990) on misleading growth rates in the manufacturing sector argued that unstable socio-demographic changes and lower levels of technology are causing low productivity in India as compared to the United Kingdom and the United States. In his study of the manufacturing sector in India using data for 21 years (from 1965 to 1985), it was pointed out that factor efficiency was influenced by the factor of production, socio-demographic, socio-politics, development and management of the human resource, workplace, and working condition where a higher capital-labor intensity ratio is associated with a higher level of technology.

2.2. Manufacturing sector of Ethiopia

Ethiopia began its first series of economic reform programs in 1992. The reform programs are aimed at reorienting the economy from a command to a market economy, rationalizing the role of the state, and creating legal, institutional, and policy environments to enhance private-sector investment. Different sectoral policies, strategies, and plans were developed and implemented in an effort to make the manufacturing industry play a great role in the economy. As a result of the economic reforms and priorities given to the sector, its contribution to the economy has increased from 11.4% in 2003/2004 to 13.4% in 2010/11 and within the industry, the construction and manufacturing sub-sectors have registered a high growth rate of 12.8% and 12.1% respectively (MoFED, 2011). The fact that the contribution of the manufacturing sector to GDP is minimal exhibits the infant stage of manufacturing activities or industrialization in Ethiopia. This low contribution of the manufacturing sector to the GDP is the common feature of most developing countries that are especially found in Sub-Saharan African countries. The share of the manufacturing value added (MVA) is one of the indicators which pave the way to assess the sector's performance against other economies.

The Ethiopian manufacturing sector is dominated by food products and beverages and non-metallic mineral manufacturing sub-sectors. In 2017, the former made up about 26% of the establishments in the manufacturing sector (CSA, 2018). The relatively high number of food products and beverage manufacturing industries is mainly explained by the high local input content and the availability of large local markets for food products and beverages (Befekadu & Berhanu, 2000). In 2017, grain mill products manufacturing firms (GMPMF) contributed about 35% of the manufacturing of food products and beverages industrial group (CSA, 2018). Industries such as metal processing, electrical and electronics, chemical, and other engineering industries, which help build technical capabilities and dynamism, have not yet been developed. Most manufacturing exports are focused on agriculture, including drinks, clothes, shoes, and semi-processed hides. On the other hand, most capital goods and manufactured consumer goods are imported into Ethiopia, which is also heavily reliant on the importation of fuel. On the policy facet, the government is committed to creating a favorable environment for attracting direct foreign investment and promoting domestic investment. A variety of foreign companies from China, India, Turkey, and Japan are presently competing in the country to leverage this opportunity. The preferential duty-free trade access provided by Ethiopia to the United States of America and European Union markets also provides strategic opportunities (Hailu & Tanaka, 2015).

Ethiopia has abundant resources that can provide valuable inputs for light manufacturing, namely, cattle, which can be used as an input for making leather and leather products; forests, which can be used as an input for the furniture industry; cotton, which can be used as an input for the garment industry; and agricultural land and lakes are used to provide inputs for agro-processing industries (Dinh et al., 2012). Moreover, Ethiopia has plentiful low-cost labor, which gives it a comparative advantage in less-skilled, labor-intensive sectors (Dinh et al., 2012; Sonobe et al., 2009). In such light manufacturing areas as leather products and apparel, textile, wood products industries, it has a good opportunity for low-cost manufacturing exports.

2.3. Determinants of technical efficiency of manufacturing firms in Ethiopia

The aim of this section is to identify the factors that affect each firm's efficiency levels. These determinants of technical efficiency can be summarized as follows:

2.3.1. Capital expenditure

Prior studies on capital investment in fixed assets indicated a significant and positive relationship between capital expenditures in fixed assets and productivity growth (Abdi, 2008; Delong & Summers, 1991; Gort et al., 1999; Gumbau-Albert & Maudos, 2002; Sala-i-Martin, 1997). For instance, Delong and Summers (1991) found a rising 1% investment share in machinery and equipment could lead to a 0.2 to 0.3% rise in long-run productivity growth. In support of their findings, Sala-i-Martin (1997) pointed out that a 1% increase in equipment investment could cause a 0.2% rise in output growth, while a 1% rise in non-equipment investment could lead to a 0.06% rise in productivity growth of output. Similarly, Gumbau-Albert and Maudos (2002) indicated that differences in efficiency are typically due to a higher ratio of investment to physical capital if it is believed that new production technologies are integrated into new capital purchases, and that technological improvement accelerates the growth of efficiency/productivity in the sector.

Thus, we propose new capital investment in fixed assets is positively associated with firm efficiency in manufacturing firms in Ethiopia.

2.3.2. Capital intensity

The relationship between capital intensity and technical efficiency has been studied by many scholars with inconsistent results (Latruffe et al., 2004; Mathijs & Vranken, 2000; Sun et al., 1999; Wu, 1993). An important finding of previous studies indicates that capital intensity, measured as capital divided by labor, has a significant and positive impact on technical efficiency in the food, machinery, and electronics sectors of Chinese manufacturing industries (Sun et al., 1999). They pointed out that a rise in the utilization of capital inputs such as machinery and equipment in relation to labor, or capital deepening, is expected to improve productivity and lead to a growth in technical efficiency in these industries. Similarly, Mathijs and Vranken (2000) indicated more capital-intensive farms are efficient in Bulgarian crop farms. In contrast, Latruffe et al. (2004) pointed out more capital-intensive farms are less efficient in crop and livestock farms in Poland. Hence, we propose capital intensity is positively associated with manufacturing firm efficiency in Ethiopia. In prior literature, capital intensity is measured as the ratio of total assets (book value) to the total number of employees (Blomström & Persson, 1983). Abenoja and Lapid (1991) measured capital intensity as the ratio of the gross book value of fixed assets to the total number of production workers. Following Abenoja and Lapid (1991), for this study, we used the ratio of the book value of machinery and equipment of the establishment to the total number of production workers.

2.3.3. Account-book ratio

To our knowledge, extant research has not addressed the impact of internal control on manufacturing firm efficiency. When sound internal controls are maintained and effectively monitored, they are an important aid to enhancing productivity and effectiveness. Firms that maintain proper record-keeping are assumed to be efficient. Firms that keep a complete book of account are in a better position to prudently plan and track the day-to-day operations of their production unit (Bekele & Belay, 2007). This will aid them to improve their technical efficiency level by preventing waste of resources. In this study, the account-book ratio, as a proxy for internal control, is measured as the ratio of firms that maintain books of account to the total number of firms in the industry. Thus, we hypothesize that the account-book ratio is positively related to the technical efficiency of manufacturing firms in Ethiopia.

2.3.4. Skill intensity
Prior literature on the relationship between skill intensity and technical efficiency indicates that skill-intensive firms are more capital-intensive, larger in size, tend to be exporters, and more productive (Bernard & Jensen, 1999). Firms with better managerial skills tend to have higher earnings, production, and technical efficiency (Kirkley et al., 1998). Similarly, Ray (1997) indicates an increase in the proportion of non-production white-collar and managerial staff might impose certain rigidities in the production process, causing slow adjustments to variations in demand. In this study, skill intensity is measured as the ratio of production workers to total employees. Thus, we expect a positive correlation between skill intensity and technical efficiency. This expectation is also consistent with conventional trade theory, which claims that firms with higher skill intensity specialize in higher quality products and tend to be more profitable and efficient (Whang, 2016).

2.3.5. Industry size
Theoretical research on the relationship between firm size and efficiency indicates that larger firms benefit from economies of scale and operate at lower average costs of production, implying that firm size has a positive impact on efficiency. Similarly, a theory developed as a model of firm growth by Jovanovic (1982) indicates larger firms are more efficient than smaller ones. This result is an outcome of a selection process, in which efficient firms grow/prosper and survive, while inefficient firms stagnate or leave the industry. Furthermore, empirical studies on the firm size and efficiency relationship indicate various results. For instance, Lundvall and Battese (2000) indicated technical efficiency increases with firm size. Sun et al. (1999) also pointed out a rise in the size of firms is likely to promote a firm's market share and competitiveness, which in turn is expected to improve a firm's access to new technology, scale efficiency, innovative capability, and productivity. These improvements tend to improve the firm's technical efficiency. Similarly, Sur et al. (2018) indicated a positive association between size and technical efficiency. They found that as the capacity of a firm increases, its efficiency also increases. In contrast, Betancourt and Clague (1975) assumed a negative association between efficiency and firm size. They argue small firms adopt more appropriate technology and foster competitive factors and product markets with their flexibility to respond to changes in technology, product markets, and markets. Hence, we hypothesized that firm size is positively correlated to technical efficiency.

2.3.6. Advertising expense
According to the Resource-Based Theory of the firm, firms that invest in R&D and advertising are more likely to create firm-specific assets that cannot be imitated by their rivals/competitors and serve as the foundation for their long-term competitive advantage. Firms' advertisement and R&D choices, according to Geroski (1995), may help to better capture relative efficiency and its evolution over time. Firms that obtain innovations and conduct advertising improve their efficiency, making them more likely to succeed.

Extant literature on the relationship between advertising expenses and technical efficiency is scarce. OCED (2014) indicated that advertising is an example of firms` responses to competition and is associated with improved productivity. Firms that spend money on advertising tend to be more productive than their competitors. Similarly, advertising expenditures may also be thought of as endogenous sunk costs, as Sutton (1991) suggests, strengthening the firms' perceived brand reputation and increasing customers' willingness to pay for their goods. As a result, advertising is supposed to boost survival chances. Comanor and Wilson (1967) suggest that advertising has an anticompetitive impact because it increases entry barriers, softening the resilience of competition. Following Özçelik and Taymaz (2004), in this study, the advertising ratio is measured as the ratio of advertising expense to total sales. Thus, we hypothesize that advertising expense is positively associated with technical efficiency.

3. Methodology
The manufacturing sector is one of the rapidly growing sectors in Ethiopia. According to the CSA (2018) report, about 3,529 large and medium manufacturing companies are operating in Ethiopia.

About 40% of them are found in Addis Ababa (the capital city of the country), whereas 23% found in the Oromia region, 11% in the Amhara region, and 9% in the Tigray region. Food products and beverages share the highest percentage, at 26%, followed by non-metallics at 18%. The textile industry shares only 1.7%.

3.1. Data and variables

We obtained data from the Ethiopian central statistical agency on large and medium manufacturing industries for the year 2010 to 2017. We focus on this period because it is a period in which the Ethiopian government adopted the Growth and Transformation Plan I (GTP-I) to lay the foundation for a structural transformation in the economy and hoped to transform the country into a lower-middle-income. As such, the manufacturing sector was expected to play a catalyst role in driving the growth momentum, employing factor inputs, and changing the structure of the exports, which were dominated by agricultural primary commodities.

Forty-three (43) sub-sectors were considered in the analysis, which further classified into 15 major industry groups. To measure the Malmquist productivity index, eight years of panel data from 2010 to 2017 was used. Technical efficiency is computed for each year. Consistent with Rezitis and Kalantzi (2016) and Lakner et al. (2017), we compute at an aggregate industry level efficiency rather than firm individual level as it is not permitted for data confidentiality. Following prior studies of efficiency (Taymaz & Saatci, 1997; Diewert, 2000; Fu, 2005; Hossain & Karunaratne, 2004; Kim, 2003; Larossi et al., 2009, p.110; Murat & Federica, 2018; Salim & Kalirajan, 1999) this study used two output variables (i.e., value-added at market price and operating profit or surplus) and two input variables, namely, capital and labor. For instance, Hossain and Karunaratne (2004), Kim (2003), Larossi et al. (2009), Murat and Federica (2018), and Salim and Kalirajan (1999), employed value-added output variable. While Tzeng and Huang (2013) utilized operating surplus as an output measure. In this study, value-added is measured as the gross value of production less industrial and non-industrial costs. Similarly, operating surplus or profit is measured by deducting the total cost from total revenues (Tzeng & Huang, 2013). Since using a large number of input variables can cause most or all of the firms to be ranked as efficient (Leibenstein & Maital, 1992), we included capital and labor as inputs to minimize potential measurement errors. Various capital input measurements have been used in several empirical studies. For instance, Kim (2003) measured capital by the number of tangible fixed assets for Korean manufacturing firms. Hossain and Karunaratne (2004) also measured capital as the gross fixed assets. In this study, following the existing literature, capital is measured by gross fixed assets. There have been various ways to measure labor in literature. Taymaz and Saatci (1997) measured labor as the total number of hours worked in production. Diewert (2000) measured labor as total wages and salaries paid. Fu (2005) measured labor by the number of employees. In this study, labor is measured by the number of employees (both permanent and seasonal employees). Furthermore, the original 43 sub-sectors were classified into fourteen (14) major sub-sectors and each sub-sector is separated as public-owned and private-owned to examine whether the technical efficiency score varies between the public and private-owned industries. As we could not get data on operating surplus at the major industry level, value-added and total sales were assumed as output variables. The input variables used for this particular analysis include fixed assets, the number of employees, and the costs of raw materials.

3.2. Model specification

To measure technical efficiency, various approaches have been addressed in the literature over the last four decades. The most extensively applied methods are DEA and Stochastic Frontier. The first DEA model was proposed by Charnes et al. (1978) and was later named the CCR model. DEA is an approach to measuring the relative efficiency of a set of decision-making units (DMUs) with multiple inputs and multiple outputs using mathematical programming. DEA has relied on certain simple assumptions like positive numerical data should be available for all output and input items of DMUs. The input and output items are easily disposed of by management. Unlike a production function, DEA does not assume the functional relationship between variables (input and output) and insensitive to model specification (Alvarez & Crespi, 2003). However, the DEA approach has been criticized in literature for two reasons (Green & Mayes, 1991). First, all firms may not have access to the same technology. If this is the case, there is no basis for measuring technical efficiency relative to a single frontier, since each firm may be efficient with regard to its own set of production possibilities. Second, the measure neglects differences in the physical environment and product differentiation of firms. If the environment varies between firms, apparent differences in efficiency may arise from the degree to which the environment of a particular firm is favorable or unfavorable. These two problems were minimized in this paper by considering industry-level analysis rather than individual firms.

CCR model assumes an input-oriented approach with constant return to scale (CRS). The input-oriented approach reflects minimizing input quantity while keeping the current output constant (Farrell, 1957). In contrast to the CRS assumption, an alternative model called a variable return to scale (VRS) has been developed by Banker et al. (1984). The ideal way to introduce DEA is via the ratio form. For each firm, we would like to obtain a measure of the ratio of all outputs over all inputs (Coelli, 1996).

Say we have a population of n productive units, DMU1, DMU2, …, DMUn.

Each unit produces s outputs while consuming m inputs. Let us write an input matrix as follows:

X = [xij, i = 1, 2, …, m, j = 1, 2, …, n] and an output matrix

Y = [yij, i = 1, 2, …, s, j = 1, 2, …, n]. The q-th line—i.e.

Xq and Yq—of these matrixes show quantified inputs/outputs of unit DMUq. The efficiency rate of such a unit can then be generally expressed as:

$$\frac{Weighetedsumofoutputs}{Weightedsumofinputs} = \frac{\sum_{j=1}^{s} u_i y_i q}{\sum_{i=1}^{m} v_j x_j q} \tag{1}$$

Where:

vj, j = 1, 2, …, m, are weights assigned to j-th input,

ui, i = 1, 2, …, s, are weights assigned to i-th output

DEA models derive input and output weights by means of an optimizing calculation. Based on that, DMU can be classified as efficient and inefficient. Inefficient units tell us target values of inputs and outputs which would lead to efficiency. In other words, the actual output obtained is less than the maximum capacity that the firm can produce, so the inefficiency score is the difference between the actual outputs produced and the firm's production capacity.

3.3. CCR and BCC Models

Following empirical studies, we adopted CCR and BCC models to estimate the relative technical efficiency and the Malmquist productivity index in order to measure total productivity change (TFP). Sarkis (2000) argued that the use of the CCR and BCC models together help to determine the overall technical and scale efficiencies of the firm and whether the data exhibit variable returns to scale.

To estimate efficiency scores and identify sources of inefficiency, this study applied output-oriented DEA because we assume that manufacturing industries are more likely to influence their output level than the input. The sector is suffering from a lack of adequate raw materials, skilled labor, less access to machinery and equipment due to foreign currency problems. The sector, therefore, given the resources available to it, can take maximum effort to obtain the optimal output. This seems the sound strategic approach in the current real Ethiopian environment.

First, we have adopted the CCR model which assumes Constant Return to Scale (CRS) according to the following equation (Charnes et al., 1978):

$$min\theta - \varepsilon\left(\sum_{i=1}^{m} S_i^- - \sum_{r=1}^{s} S_r^+\right) \tag{2}$$

Subject to:

$$\sum_{j=1}^{n} \mu_j x_i + S_i^- = \theta_k x i_k i = 1, \ldots, m \tag{3}$$

The scalar variable is the proportional reduction which should be applied to all inputs of DMU, in order to make them efficient, and ε is non-Archimedean defined to be smaller than any positive real number, whereas S^- and S^+ are "slack variables" and a standard linear programming terminology for additional variables added to the model in order to convert inequality constraints to equality constraints. This terminology in DEA is also used when additional improvement is possible in specific inputs or outputs.

Coelli (1996) indicated that the use of the CRS specification when some of the DMUs are not running at optimal scale will result in measures of technical efficiency which are mixed up with scale efficiency. The assumption of CRS that all DMU are operating at optimal scale is quite unrealistic. It might hold true where there are no market inconsistencies or fluctuations, like no competition, no technological constraint, and changes in customer behavior which are seldom in the real environment. To overcome this problem, Banker et al. (1984) suggested their model known as the BCC model. It improves the CCR model by introducing a variable that represents the returns to scale. The BCC model allows a calculation of technical efficiency that is free from the scale efficiency effects. In the BCC model, the formulation is written as below (Banker et al., 1984)

$$min\theta - \varepsilon\left(\sum_{i=1}^{m} S_i^- - \sum_{r=1}^{s} S_r^+\right) \tag{4}$$

Subject to

$$\sum_{j=1}^{n} \mu_j x_i + S_i^- = \theta_k x_{ik} i = 1, \ldots, m$$

$$\sum_{j=1}^{n} \mu_j y_{rj} - S_r^+ = y_{rk} r = 1, \ldots, s$$

$$\sum_{j=1}^{n} \mu_{j=1} j = 1, \ldots, n$$

$$\mu_j, S^+, S^- \geq 0, j = 1, \ldots, n \tag{5}$$

A DMU is BCC-efficient if and only if $\theta^* = 1$ and all slacks are zero. The envelopment surface in BCC mode1 is variable returns to scale and this is the result of the presence of the convexity constraint ($\sum_{j=1}^{n} \mu j = 1$).

3.4. Determinants of efficiency

In the overall technical efficiency analysis, both under CRS and VRS, there is a high variation of efficiency scores among the sub-sectors. The variation in efficiency scores is not surprising because the sub-sectors under study comprise all medium and large-scale manufacturing firms operating in different regions of the country. Accordingly, there is heterogeneity between sub-sectors, for instance, in terms of age, geographical location, capital, skilled manpower, and access to markets. Given these factors, we believe that firm-level data is required to conduct a more detailed analysis to understand the variation in efficiency. In this study, based on the data obtained, we have tried to regress efficiency against industry characteristics, in part to answer the question: why are some sub-sectors more efficient than others? The total technical efficiency estimated by CRS is taken as a dependent variable. Since the dependent variable, technical efficiency takes a value between 0 and 1, which are bounded or censored, using ordinary least squares would provide biased estimates as noted in Martin and Page (1983). Thus, the Censored Tobit maximum likelihood method is applied to estimate parameters. Based on the data obtained, the following determinant factors were taken to define the variation in efficiency, namely, advertising ratio, skill intensity, industry size, capital expenditure ratio, account book ratio, and capital intensity. There are several factors recommended in the empirical literature (Alvarez & Crespi, 2003) like export performance, firm owner education level, import performance, research and development, but we could not include these variables in the model due to data unavailability. The Tobit model is expressed as follows:

$$Efficiency_{i,t} = \alpha_{i,t} + \beta_1 AR_{i,t} + \beta_2 ABR_{i,t} + \beta_3 SI_{i,t} + \beta_4 IS_{i,t} + \beta_5 CER_{i,t} + \beta_6 CI_{i,t} + \varepsilon_{i,t} \quad (6)$$

Where: $Efficiency_{i,t}$ denotes technical efficiency of the i^{th} sub-sector at time t, AR represents advertising ratio and is measured as the ratio of advertising expense to total expenses, ABR is account book ratio measured as firms which have a book of account to a total number of firms in the sub-sector. SI represents skill intensity measured as production workers divided by total employees, IS denotes industry size measured as firms with 50 and over employees divided by the number of firms in the sub-sector. CER is the capital expenditure ratio as measured by annual capital expenditure divided by total fixed assets. CI represents capital intensity as measured by the book value of machinery and equipment to production workers and $\varepsilon_{i,t}$ is the error term.

3.5. Malmquist productivity index

The most popular approach for productivity change (growth) measurement in DEA is the Malmquist productivity index (MPI), which was named after Professor Sten Malmquist, on whose ideas the MPI is based and was designed by Caves et al. (1982). It is an index representing the TFP growth of a DMU which is considered as an entity transforming inputs into outputs. It reflects progress or regress, along with progress or regress in frontier technology between two periods of time. In a non-parametric approach, productivity growth is the product of *catch-up* and *frontier-shift* terms. The catch-up (or recovery) term relates to the degree to which a DMU improves or worsens its efficiency. The frontier-shift (or innovation) term reflects the change in the efficient frontiers between the two time periods. (Catch-up) > 1 indicates progress in relative efficiency from period 1 to 2. While (Catch-up) = 1 and (Catch-up) < 1 indicate no change and regress in the efficiency, respectively (W.W. Cooper et al., 2004). The frontier shift is defined by geometric mean. Frontier-shift > 1 indicates progress in the frontier technology around DMU from period 1 to 2, while (Frontier-shift) = 1 and (Frontier-shift) < 1 indicate the status quo and regress in the frontier technology, respectively. Therefore, the Malmquist index is the result of (Catch-up) X (Frontier-shift), in that MI > 1 indicates progress in the TFP of the DMUo from period 1 to 2, while MI = 1 and MI < 1 respectively indicate the status quo and deterioration in the TFP (Färe et al., 1994).

The Malmquist index measure of productivity change decomposed into technological progress (technical change) and technical efficiency change (pure technical efficiency change and scale efficiency change). Technological change means that the set of feasible combinations of input and output quantities expands or the curve shifts in the productivity limit, while technical efficiency change means that the firm moves closer to or further away from the frontier or changes in efficiency reaching the production limit (Balk, 2001). These two components are independent of each other. There can be technological change without efficiency change, and efficiency changes without technological change. Consider a single firm, going from a base period input-output quantity combination (x°, y°) to a comparison period combination (x^1, y^1). The single-input single-output case`s productivity change is then measured by the ratio:

$$\frac{y^1/y^0}{x^1/x^0} = \frac{y^1/x^1}{y^0/x^0} \tag{7}$$

It indicates that the ratio of output over the input quantity index number or as the ratio of output quantity per unit of input. In the multiple-input multiple-output case productivity function measured F(x^1, y^1, x°, y^0)

$$\mathrm{F}\left(\lambda x^0,\ \mu y^0,\ x^0,\ y^0\right) = \frac{\mu}{\lambda}(\lambda, \mu > 0) \tag{8}$$

MPI comprises pure technical efficiency change, scale efficiency change, and technological change.

Technological change

$$\mathrm{TC}_0^{1,0}(\mathrm{x}, \mathrm{y}) = \frac{\mathrm{D}_0^1(\mathrm{x}, \mathrm{y})}{\mathrm{D}_0^1(\mathrm{x}, \mathrm{y})^2} \tag{9}$$

Efficiency change

$$EC_0\left(x^1, y^1, x^0, y^0\right) = \frac{D_0^1\left(x^1, y^1\right)}{D_0^0\left(x^0, y^0\right)^2} \tag{10}$$

4. Results and discussion

This section presents technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE) values of 43 large and medium manufacturing subsectors in the period 2010–2017. The same data were used to compute technological change and total factor productivity (TFP) change during the study period.

4.1. Descriptive statistics

Descriptive statistics provide a guarantee of whether or no variation in the data is large. Table 1 reports the descriptive statistics (mean, standard deviation, minimum and maximum) for output and input variables used in the study. The mean value of the value-added, output variable is Birr 1,103,119, the minimum value is Birr 557, 272 and the maximum value is Birr 13,512,495. Whereas the mean value of operating surplus/profit, the output variable is Birr 696,044.9. The minimum and maximum values are Birr 1,024,703 and Birr 8,263,285, respectively. The sampled sub-sectors, on average, had 6,038 employees (input1) over the observation years. The minimum and the maximum number of employees were 4 and 80,016, respectively. Fixed assets, input variable had Birr 1,230,444 mean value with Birr 41 minimum & Birr 52,373,626 maximum values.

On the other hand, the value of the standard deviation of all variables exceeds its corresponding mean, showing there has been big variation among sub-sectors in the period 2010 to 2017. One of the reasons for the variation could be the size and technological differences. Since the model used in this study is non-parametric so that data variation does not have an impact on computing technical efficiency score.

4.2. Results of data envelopment analysis models

This section discusses the results obtained from the DEA models: the CCR model with the assumption of CRS and the BCC model under the assumption of VRS. The study employed the output-oriented approach, assuming that maximizing output while keeping input constant is more feasible than minimizing the use of the input quantity without reducing the current level of output in Ethiopian manufacturing firms. It is also the Ethiopian government's strategy to maximize the production of manufacturing industries in order to build industry lead economies. The technical efficiency obtained from a CRS is decomposed into two components: pure technical inefficiency and scale inefficiency. Technical efficiency is computed by a CCR model, whereas a BCC model estimates pure technical efficiency. If there is a difference between the two efficiency values, there is scale inefficiency which is computed from the ratio of technical efficiency to pure technical efficiency (TE/PTE).

This study measured relative efficiency by comparing the best practice sub-sector in the sample. The source of inefficiency can be computed by comparing the relative sizes of various efficiency measures. If pure technical efficiency is greater than scale efficiency, then inefficiency is caused by scale inefficiency (Banker et al., 1984).

4.3. CCR model results

The CCR model measures the overall or technical efficiency under the assumption of CRS. CRS assumes that a change in the input changes the output proportionately. Table 2 presents the overall efficiency of the sampled sub-sectors.

As it can be observed in Table 2, in 2010, four sub-sectors were relatively technically efficient, namely sugar and sugar confectionery; tobacco; other chemical products; and cement, lime and plaster. These sub-sectors had relatively efficiently utilized their inputs in the year. It indicates the management's success in allocating and converting inputs to outputs. On average, the sector achieved 34.3 percent technical efficiency, implying that if best practices had been implemented, the sector could have increased output from the same input quantity by 65.7 percent. The number of relatively technical efficient sub-sectors declined to three in 2011. Malt liquors and malt; paints, varnishes and mastics; and basic iron and steel were efficient. Out of the inefficient subsectors (40 subsectors), knitting mills from the textile major sector scored the least efficiency value in the year. This indicates poor use of resources and inappropriate selection of inputs to produce output. The sample sub-sector efficiency value rose by 0.1 percent on average (from 0.343 in 2010 to 0.344 in 2011).

A larger number of technically efficient sub-sectors were found in 2012. Namely, macaroni and spaghetti; tobacco; wood and product of wood; paints, varnishes and mastics; cement, lime and plaster; other fabricated metal; and parts & accessories for the vehicle were efficient. The tobacco product sub-sector has registered better efficiency scores over three consecutive years (2010, 2011 & 2012). The inefficient sub-sectors can further be decomposed into two: sub-sectors that have efficiency scores more than the average (0.507 for 2012) and less than the average. Nine sub-

Table 1. Descriptive statistics

Variable	Obs.	Mean	SD	Min	Max
Value added	344	1,103,119	1,722,435	557,272	13,512,495
Operating profit	344	696,044.9	1,194,240	1,024,703	8,263,285
Number of employees	344	6,038	9,564	4	80,016
Fixed assets	344	1,230,444	3,575,366	41	52,373,626

*Note: the data value is in ('000) and in Ethiopian Birr; obs. 344 (43*8).*

sectors have efficiency scores more than the average, while twenty-seven (27) sub-sectors are found with an efficiency score less than the average. The overall average efficiency scores of the sector have increased from 0.344 in 2011 to 0.507 in 2012 as some sub-sectors have shown improvement in resource utilization to produce products. Therefore, by adopting best practices, the sector could have on average produced more products by 49.3% than actually produced from the current level of inputs quantity.

The number of efficient sub-sectors slightly declined from 2012 to 2015. Three sub-sectors were efficient in 2013, whereas two sub-sectors were in 2014 and 2015. The average efficiency scores also declined from 2012 to 2016. Moreover, the average technical efficiency per sub-sector over the observation years (2010 to 2017) ranges from 0.122 for spinning, weaving & finishing of the textile to 0.916 for tobacco products. This implies there is a high-efficiency variance among the sampled sub-sectors over the observation years. This result is consistent with some prior studies such as Hailu and Tanaka (2015) who find there is technical efficiency score variation across Ethiopian manufacturing firms, suggesting shortage of raw materials supply was the main cause of the relative technical inefficiency of the sector.

On overall average, the sector understudy had a 37% technical efficiency value from 2010 through 2017. Our result is very consistent with the recent study by Ayelign and Singh (2019), who found that in the overall average Ethiopian medium and large-scale manufacturing industries registered 36.7% technical efficiency over the period 1996–2015. Low technical efficiency and productivity seem to be a common problem in manufacturing industries in Sub-Saharan African countries. For instance, the Kenyan manufacturing sector had low overall productivity and large productivity differences across industries (World Bank, 2014). Diaz and Sanchez (2007) indicated consistent findings that most industries in the manufacturing sector were inefficient and the inefficiency was greater among large firms than small firms. Abegaz (2013) addresses that Ethiopian manufacturing industries have the capability to use imported technology, but improvement and adoption of the technology are weak. This means that the sector has not utilized its maximum capacity. UNCTAD (2015) also provides evidence that the lack of access to and sharing of R&D facilities continues to hinder the ability of local firms to take advantage of opportunities both within Ethiopia and in other emerging markets. The World Economic Forum's Global Competitiveness Index (GCI) ranks Ethiopia 109th out of 140 countries with a score of 3.7 out of 7.0 in the 2015–16 report. It reflects that Ethiopian firms are not as competitive in the international market because innovative activity in the industry is very low. In conjunction with this data, the research and development (R&D) share of GDP was 0.5% in 2015 (UNCTAD, 2015). The aforementioned factors would collectively affect the efficiency of the sector.

4.4. BCC model results

The BCC model evaluates whether increasing, decreasing, or constant returns to scale would be taken to improve the efficiency value found. CRS arises when a percentage increase in (all) inputs produces the same percentage increase in outputs. However, VRS occurs when a proportionate increase in inputs produces a smaller (larger) proportionate increase in outputs (W. W Cooper et al., 2006, p.125). This assumption of the BCC model decomposed into decreasing returns to scale and increasing return to scale. In a decreasing return to scale, an increase in input produces a smaller increase in output. An increasing return to scale arises when an increase in inputs yields a larger increase in output. A VRS model allows the best practice level of outputs to inputs to vary with the size of industries and it also measures the efficiency of the management in utilizing inputs that are free of scale efficiency.

The CRS technical efficiency of the sample industries is divided into pure technical efficiency (PTE) and scale efficiency (SE) in the BCC model. PTE measures the extent to which an industry can increase its output (in fixed proportion) while remaining within the VRS frontier. Thus, technical efficiency measures the industry's overall success in maximizing its output. SE reflects the extent to which an industry projected to the VRS efficiency frontier can further increase its output (again

Table 2. Technical efficiency of sub-sectors computed by CCR model under CRS assumption

Sub-sectors	2010	2011	2012	2013	2014	2015	2016	2017	Average
Processing & preserving of meat, fruit & vegetables	0.27	0.094	0.163	0.114	0.276	0.171	0.054	0.151	0.16
Vegetable & animal oils and fats	0.168	0.16	0.272	0.311	0.348	0.399	0.692	0.803	0.39
Dairy	0.259	0.31	0.285	0.499	0.39	0.355	0.326	0.486	0.36
Grain mill	0.118	0.122	0.194	0.185	0.172	0.341	0.141	0.232	0.188
Animal feeds	0.237	0.137	0.36	1	0.12	0.29	0.358	0.788	0.41
Bakery	0.113	0.276	0.839	0.154	0.145	0.159	0.145	0.135	0.24
Sugar and sugar confectionery	1	0.68	0.35	0.415	0.444	1	0.538	0.517	0.618
Macaroni & spaghetti	0.259	0.237	1	0.161	0.19	0.071	0.095	0.198	0.27
Food products n. e.c.	0.179	0.163	0.262	0.377	0.464	0.279	0.319	0.162	0.27
Distilling, rectifying & spirits	0.794	0.682	0.682	0.255	0.288	0.293	0.147	0.31	0.431
Wines	0.745	0.884	1	0.854	0.797	0.45	0.562	0.771	0.757
Malt liquors & malt	0.391	1	0.88	0.843	0.464	0.197	0.781	0.677	0.65
Soft drinks & mineral water	0.455	0.6	0.226	0.198	0.315	0.59	0.135	0.119	0.32
Tobacco products	1	0.685	1	1	1	0.648	1	1	0.916
Spinning, weaving & textiles	0.133	0.079	0.287	0.182	0.03	0.09	0.071	0.11	0.122

(*Continued*)

Table2. (*Continued*)

Sub-sectors	2010	2011	2012	2013	2014	2015	2016	2017	Average
Cordage, rope, twine & netting	0.155	0.358	0.218	0.08	0.123	0.242	0.171	0.086	0.179
Knitting mills	0.02	0.018	0.032	0.317	0.27	0.03	0.161	0.333	0.147
Wearing apparel except fur apparel	0.084	0.214	0.424	0.122	0.195	0.162	0.517	1	0.339
Tanning & dressing of leather, luggage & handbags	0.11	0.258	0.32	0.484	0.299	0.142	0.195	0.898	0.33
Footwear	0.12	0.194	0.809	0.148	0.265	0.316	0.127	0.161	0.26
Wood & wood products	0.035	0.083	1	0.785	0.041	0.153	0.192	0.181	0.308
Paper	0.251	0.281	0.19	0.078	0.143	0.243	0.33	0.442	0.244
Publishing & printing services	0.261	0.226	0.245	0.383	0.227	0.342	0.482	0.225	0.298
Basic chemicals	0.264	0.182	0.376	0.419	0.308	0.289	0.491	0.111	0.3
Paints, varnishes & mastics	0.889	1	1	0.771	0.897	0.907	0.309	0.607	0.79
Pharmaceuticals & medicinal chemicals	0.305	0.682	0.435	0.536	0.595	0.172	0.425	0.175	0.415
Soap and detergents cleaning	0.332	0.228	0.771	0.469	0.263	0.371	0.239	0.218	0.361
Chemical products n.e.c.	1	0.077	0.374	0.38	1	0.258	0.307	0.642	0.504
Rubber	0.14	0.182	0.577	0.169	0.353	0.366	1	0.894	0.46
Plastic	0.282	0.224	0.258	0.321	0.281	0.185	0.261	0.216	0.25

(*Continued*)

Table2. (*Continued*)

Sub-sectors	2010	2011	2012	2013	2014	2015	2016	2017	Average
Glass	0.21	0.23	0.547	0.364	0.374	0.623	0.226	0.309	0.36
Structural clay	0.104	0.213	0.183	0.101	0.191	0.132	0.084	0.182	0.14
Cement, lime & plaster	1	0.862	1	0.324	0.946	0.496	0.23	0.242	0.63
Articles of concrete & plaster	0.096	0.129	0.251	0.185	0.315	0.479	0.213	0.277	0.24
Non-metallic mineral	0.089	0.132	0.34	0.314	0.098	0.151	0.083	0.143	0.168
Basic iron & steel	0.278	0.294	0.509	0.377	0.344	0.417	0.291	0.321	0.35
Structural metal	0.327	0.142	0.409	0.208	0.141	0.414	0.174	0.284	0.262
Cutlery, hand tools & general hardware	0.358	0.288	0.69	0.057	0.381	0.35	0.153	0.218	0.31
Other fabricated metal	0.395	1	1	0.554	0.394	0.622	0.225	0.028	0.52
Other general-purpose machinery	0.281	0.255	0.158	0.165	0.405	0.518	0.269	0.289	0.29
Parts & accessories for motor vehicles	0.658	0.361	1	0.692	0.457	1	0.273	0.344	0.59
Passenger cars, commercial vehicles & busses	0.26	0.375	0.491	1	0.558	0.042	1	0.437	0.52
Furniture	0.308	0.176	0.386	0.224	0.238	0.156	0.197	0.302	0.24
Mean	**0.343**	**0.344**	**0.507**	**0.385**	**0.361**	**0.347**	**0.325**	**0.373**	**0.37**

in fixed proportions) while remaining within the CRS frontier. Thus, SE measures the extent to which a firm can increase output by moving to a part of the frontier with more beneficial returns to scale characteristics.

The decomposition is needed to identify the sources of inefficiency by comparing the PTE and SE. When PTE exceeds SE, the source of inefficiency is due to scale inefficiency (inappropriate selection of scale size). In other words, if there is a difference between the technical efficiency score (CRS technical efficiency and VRS PTE), then it demonstrates scale inefficiency. Conversely, if SE is higher than PTE, then the source of inefficiency is due to poor utilization of inputs, i.e., pure technical inefficiency.

Table 3 reports results obtained from BCC model VRS. The results entail CRS technical efficiency, VRS technical efficiency, and scale efficiency. We present the results of the most recent three years observations in the data set, 2015–2017 for clarity.

In 2015, the number of technically efficient sub-sectors was two (2), about 5% of the sample when VRS TE was assumed, and five (5), 11.6% when CRS TE was assumed. Three sub-sectors found with scale efficiency, suggesting an appropriate selection of inputs and operating on the most productive scale size. Out of the inefficient sub-sectors, 38 sub-sectors experienced poor utilization of inputs as the source of inefficiency is pure technical inefficiency. However, two sub-sectors had higher PTE than SE which implies that the source of inefficiency is scale inefficiency. This indicates the industries are operating at an inappropriate scale. When looking at the type of scale, twenty-seven (27) sub-sectors (e.g., dairy products; bakery products; footwears; rubber products) appeared to have an increasing return to scale, showing that a proportionate increase in inputs yields a larger proportionate in the outputs. These industries would improve their efficiency by expanding the scale of operation. In contrast, eleven (11) industries (e.g., furniture; soap & detergent cleaning; plastic products; cement, lime & plaster) experienced a decreasing return to scale i.e., a proportionate increase in inputs produces a lower proportionate increase in outputs. This implies the industries have supra-optimal scale size (i.e. operates at the rising portion of long-run average cost curve) and thus, downscaling is needed for achieving efficiency frontier. Five sub-sectors, bakery products, sugar and sugar confectionery, macaroni and spaghetti, tanning and dressing of leather, and parties and accessories for a motor vehicle operate at a flatter portion of the long-run average cost curve that means a constant return to scale.

About 11.6% of the sub-sectors have experienced PTE as computed by VRS in 2016. Three sub-sectors (tobacco products, rubber products, and passenger cars, commercial vehicles & busses) appeared efficient both by CRS TE and VRS TE. All of the scale-inefficient sub-sectors experienced a decreasing return to scale, i.e., an increase in proportionate usage of input produces the less proportionate increase in outputs. On average, the sample sub-sectors recorded a 0.531 of PTE and a 0.629 of SE suggesting the source of inefficient are pure technical inefficient. Generally, the sector was at poor resource management and converting inputs to the output.

When looking in 2017, four sub-sectors, namely soft drink and mineral water, tobacco products, wearing apparel, and passenger cars, commercial vehicles and busses observed as pure technical efficiency as measured by VRS whereas, three sub-sectors (footwears, tobacco products, and soft drink and mineral water) were scale efficient. Out of the inefficient sub-sectors, 20 sub-sectors experienced a decreasing return to scale and 16 sub-sectors experienced an increasing return to scale.

On average, pure technical efficiency scores declined in 2017 indicating some sub-sectors had used excess inputs to produce output as compared to in 2016. However, a scale efficient score on average shows improvement in the year. The mean of scale efficiency was higher than the mean of pure technical efficiency. It reveals the source of technical inefficiencies of the sector is pure technical inefficient. The industries need to properly manage their input utilization in order to be efficient.

On average, the industries had faced a 49% of pure technical inefficiency over the observation periods. It shows a firm's inability to exploit inputs due to the poor skills of both operatives and management. The overall scale efficiency of 76% shows an appropriate section of production scale by the industries. It implies the organizational source of inefficiency. The Ethiopian manufacturing sector is characterized by a cheap labor force. This would benefit the sector in minimizing production cost as wage/salary is low. It could also be detrimental to the sector because of the inappropriate utilization of the resources by unskilled, low-cost labor forces. In essence, cheap labor implies less-skilled labor or labor incentive. It can be assumed that being labor or capital-intensive would not yield a guarantee for efficiency, but the quality of labor or capital utilized could determine the efficiency of a firm. In other words, a firm can be efficient, if it`s able to gain the optimum benefit from the resources utilized such as labor, capital, raw materials, or electric power.

When looking at the annual average efficiency score in each observation period, the lowest average TE score was reported in 2016. The highest average TE and PTE were observed in 2012. The SE with the highest efficiency score was observed in 2010. The sample sub-sectors had shown higher SE in all observation periods and in the overall average.

We further classify the sub-sectors considered in the previous analysis into fourteen major sub-sectors under both government and private ownership in order to measure technical efficiency and compare whether public sub-sectors are more efficient or not than private sub-sectors. To do the analysis, 2015 and 2017 observations were taken, assuming the sub-sectors are operating in the same environment and market. The results presented in Table 4 and 5 indicates, on average, private-owned sub-sectors had registered better total technical efficiency (0.821), PTE (0.939) and SE (0.876) than public-owned sub-sectors and they are relatively efficient. When comparing sub-sector to sub-sector, public-owned food products and beverages and machinery and equipment are efficient both under CRS and VRS models, whereas the same sub-sectors under private ownership are inefficient. On average, the technical inefficiency of public-owned sub-sectors highly driven by pure technical inefficiency suggesting they had poorly managed usage of resources. In contrast, scale inefficiency contributes more to the total inefficiency of private sub-sectors. It implies private-owned sub-sectors showed an inappropriate combination of resource use in 2015.

In 2017, the efficiency score has declined for both public and private sub-sectors in terms of total technical efficiency (CRS), PTE & SE (VRS). It is noted that the mean efficiency scores of private sub-sectors are much higher than public-owned sub-sectors, indicating private sub-sectors better manage resources and appropriately mix inputs to obtain the maximum benefit. Indeed, the number of private firms in each sub-sector is quite larger than the number of public firms in the same sub-sector. One of the reasons for the imbalance number of firms is privatization. The government sells state-owned firms to private investors that cause a decline in public firms and increase private firms at the same time. Given this practical issue, we assume the variation between the efficiency of the private and public firms might partially be defined by size (in terms of total asset proxy or number of employees proxy). The result is consistent with Alvarez and Crespi (2003) and Gumbau-Albert and Maudos (2002) findings that public firms on average tend to be less efficient as compared to private firms.

4.5. Determinants of technical efficiency: Tobit regression results

The important finding observed in this study is the capital expenditure ratio has a positive effect on technical efficiency, suggesting a significant investment in new capital would lead the firm to an efficiency level. A firm with advanced machinery and equipment more likely to engage in innovative products which in turn increases production and sales performance when minimizing the length of production time, inventory and accounts receivable turn over and other irrelevant costs. On the other hand, a higher depreciation and maintenance cost would offset the advantage of

Table 3. Technical efficiency (TE), pure technical efficiency (PTE), scale efficiency (SE), and type of scale (TFS)

Sub-sectors	2015				2016				2017			
	TE	PTE	SE	TFS	TE	PTE	SE	TFS	TE	PTE	SE	TFS
Processing & preserving of meat, fruit & vegetables	0.171	0.174	0.983	irs	0.054	0.059	0.913	drs	0.151	0.198	0.762	drs
Vegetable & animal oils and fats	0.399	0.419	0.95	irs	0.692	0.757	0.915	drs	0.803	0.808	0.993	irs
Dairy	0.355	0.363	0.977	irs	0.326	0.357	0.914	drs	0.486	0.491	0.989	irs
Grain mill	0.341	0.465	0.733	drs	0.141	0.477	0.295	drs	0.232	0.375	0.617	drs
Animal feeds	0.29	0.335	0.866	irs	0.358	0.468	0.764	drs	0.788	0.869	0.907	drs
Bakery	0.159	0.159	1	-	0.145	0.326	0.446	drs	0.135	0.184	0.734	drs
Sugar and sugar confec tionery	1	1	1	-	0.538	1	0.538	drs	0.517	0.518	0.999	-
Macaroni & spaghetti	0.071	0.071	0.994	-	0.095	0.22	0.431	drs	0.198	0.277	0.713	drs
Food products n. e.c.	0.279	0.281	0.994	irs	0.319	0.386	0.827	drs	0.162	0.303	0.535	drs
Distilling, rectifying & spirits	0.293	0.294	0.994	irs	0.147	0.352	0.417	drs	0.31	0.346	0.896	drs
Wines	0.45	0.495	0.909	irs	0.562	0.617	0.91	drs	0.771	0.789	0.977	irs
Malt liquors & malt	0.197	1	0.197	drs	0.781	1	0.781	drs	0.677	1	0.677	drs

(Continued)

Table3. (*Continued*)

Sub-sectors	2015				2016				2017			
	TE	PTE	SE	TFS	TE	PTE	SE	TFS	TE	PTE	SE	TFS
Soft drinks & mineral water	0.59	0.741	0.796	drs	0.135	0.673	0.2	drs	0.119	0.307	0.387	drs
Tobacco products	0.648	0.658	0.986	irs	1	1	1	-	1	1	1	-
Spinning, weaving & textiles	0.09	0.226	0.398	drs	0.071	0.274	0.259	drs	0.11	0.217	0.507	drs
Cordage, rope, twine & netting	0.242	0.247	0.981	irs	0.171	0.213	0.8	drs	0.086	0.086	0.995	-
Knitting mills	0.03	1	0.03	irs	0.161	0.185	0.87	drs	0.333	0.641	0.519	irs
Wearing apparel except fur apparel	0.162	0.164	0.992	irs	0.517	0.981	0.527	drs	1	1	1	-
Tanning & dressing of leather, luggage & handbags	0.142	0.142	0.999	-	0.195	0.311	0.627	drs	0.898	0.9	0.997	irs
Footwear	0.316	0.317	0.998	irs	0.127	0.239	0.529	drs	0.161	0.161	1	-
Wood & wood products	0.153	0.155	0.99	irs	0.192	0.587	0.327	drs	0.181	0.182	0.995	irs
Paper	0.243	0.245	0.991	irs	0.33	0.372	0.886	drs	0.442	0.443	0.999	irs
Publishing & printing services	0.342	0.343	0.998	irs	0.482	0.888	0.543	drs	0.225	0.652	0.346	drs

(*Continued*)

Table3. (*Continued*)

Sub-sectors	2015				2016				2017			
	TE	PTE	SE	TFS	TE	PTE	SE	TFS	TE	PTE	SE	TFS
Basic chemicals	0.289	0.3	0.961	irs	0.491	0.564	0.872	drs	0.111	0.117	0.942	irs
Paints, varnishes & mastics	0.907	0.93	0.973	irs	0.309	0.344	0.898	drs	0.61	0.608	0.998	irs
Pharmac euticals & medicinal chemicals	0.172	0.17	0.993	irs	0.425	0.627	0.678	drs	0.18	0.176	0.998	-
Soap and detergents cleaning	0.371	0.37	0.998	drs	0.239	0.564	0.424	drs	0.22	0.34	0.639	drs
Chemical products n. e.c.	0.258	0.27	0.97	irs	0.307	0.456	0.674	drs	0.64	0.666	0.964	irs
Rubber	0.366	0.42	0.883	irs	1	1	1	-	0.89	0.92	0.972	irs
Plastic	0.185	0.3	0.622	drs	0.261	0.971	0.269	drs	0.22	0.621	0.347	drs
Glass	0.623	0.73	0.854	irs	0.226	0.296	0.764	drs	0.31	0.313	0.987	drs
Structural clay	0.132	0.14	0.931	irs	0.084	0.118	0.708	drs	0.18	0.183	0.991	irs
Cement, lime & plaster	0.496	0.87	0.567	drs	0.23	0.594	0.388	drs	0.24	0.755	0.321	drs
Articles of concrete & plaster	0.479	0.67	0.716	drs	0.213	0.662	0.321	drs	0.28	0.466	0.594	drs
Non-metallic mineral	0.151	0.15	0.992	irs	0.083	0.163	0.511	drs	0.14	0.143	0.999	-

(*Continued*)

Table3. (*Continued*)

Sub-sectors	2015				2016				2017			
	TE	**PTE**	**SE**	**TFS**	**TE**	**PTE**	**SE**	**TFS**	**TE**	**PTE**	**SE**	**TFS**
Basic iron & steel	0.417	0.61	0.679	drs	0.291	0.99	0.294	drs	0.32	0.714	0.45	drs
Structural metal	0.414	0.65	0.635	drs	0.174	0.705	0.247	drs	0.28	0.407	0.697	drs
Cutlery, hand tools & general hardware	0.35	1	0.35	irs	0.153	0.158	0.97	drs	0.22	0.226	0.961	irs
Other fabricated metal	0.622	0.74	0.843	irs	0.225	0.239	0.943	drs	0.03	0.03	0.963	irs
Other general-purpose machinery	0.518	0.6	0.864	irs	0.269	0.499	0.54	drs	0.29	0.309	0.938	irs
Parts & accessories for motor vehicles	1	1	1	-	0.273	0.67	0.408	drs	0.34	0.533	0.645	drs
Passenger cars, comm ercial vehicles & busses	0.042	0.05	0.87	irs	1	1	1	-	0.44	1	0.437	Irs
Furniture	0.156	0.29	0.532	drs	0.197	0.471	0.419	drs	0.3	0.874	0.345	drs
Mean	**0.347**	**0.46**	**0.837**		**0.325**	**0.531**	**0.629**		**0.37**	**0.492**	**0.784**	

Note: TE- total technical efficiency computed by CRS model; PTE- pure technical efficiency computed by VRS model; SE- scale efficiency; TFS- type of scale; drs-decreasing return to scale; irs-increasing return to scale;—Dash- constant return to scale.

Table 4. Average annual technical efficiency

Type	2010	2011	2012	2013	2014	2015	2016	2017	AV
TE	0.343	0.34	0.51	0.385	0.361	0.347	0.325	0.37	0.37
PTE	0.409	0.44	0.70	0.523	0.524	0.455	0.531	0.49	0.51
SE	0.869	0.81	0.75	0.757	0.715	0.837	0.629	0.78	0.76

Where: AV – overall average; TE- technical efficiency; PTE- pure technical efficiency; SE –scale efficiency.

investing in capital expenditure. This result is consistent with prior findings (Abdi, 2008; Gort et al., 1999) that capital expenditures play a crucial role in long-term growth. For instance, Abdi (2008) pointed out investments in both machinery and equipment and non-machinery & equipment have a direct and significant impact on productivity and output levels.

"Insert Table 6 here please"

The account book ratio, which is used in this study as a proxy for internal control appeared positive and has a significant influence on technical efficiency. It indicates an effective internal control system helps firms reduce resource wastage and improves productivity. This finding seems new as it is ignored in prior studies so that one can further investigate more broadly on the role of internal control in enhancing firm technical efficiency. This result is consistent with the finding of Bekele and Belay (2007) that indicated firms that keep a complete book of account are in a better position to prudently plan and track the day-to-day operations of their production unit.

The sign of capital intensity is positive but statistically weak (significant at 10%) impact on efficiency. It slightly supports that capital-intensive industries are more likely to be efficient than labor-intensive industries. Similarly, Alvarez and Crespi (2003) suggest firms that are capital-oriented tend to be more efficient.

4.6. The Malmquist index summary of industries results

We compute Malmquist productivity index output-oriented using panel data (2010 to 2017) of 43 sub-sectors, in which the year 2010 is the base period. The Malmquist index for each year is computed. However, we present the Malmquist index industry mean of the observation periods and Malmquist index annual mean for clarity.

Table 7 presents the Malmquist index summary of sub-sectors geometric means, which contain technical efficiency change, technological change, PTE change, SE change, and total productivity growth. According to the technical efficiency change index, about 21 (48.8%) sub-sectors have experienced technical efficiency progress. Among the sub-sectors which made progress, knitting from the textile industrial group recorded the highest growth (49.9%) followed by wearing apparel (42.4%). In contrast, 22 sub-sectors experienced a decline in technical efficiency. Other fabricated metal products sub-sector faced the largest deterioration (31%) in technical efficiency. The technical efficiency of the tobacco product sub-sector remained unchanged. Moreover, the sector has shown TE progress by 2.2% from 2010 to 2017. The result is consistent with the findings by Abegaz (2013) that the share of technical efficiency change in TFP growth is small and negative in most of the industrial groups.

When looking at the technological index, 40 (93%) sub-sectors experienced technological progress whereas, the remaining 3 (7%) sub-sectors (bakery products; cordage, rope, twine & netting; and structural clay products) recorded regress over the study periods. This means 40 sub-sectors were able to cause shifts in their frontier due to innovation. The top-five in technological progress sub-sectors are cement, lime, and plaster (37%); other general-purpose machinery (34.5%); malt liquors & malt (32%); structural metal products, tanks & containers of metal (24.1%); and other

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Table 5. TE, PTE, SE, and TFS-public and private sub-sectors

Major sub-sectors	2015							
	Public				Private			
	TE	PTE	SE	TFS	TE	PTE	SE	TFS
Food products and beverages	1.000	1.000	1.000		0.950	1.000	0.950	drs
Textiles	0.309	0.311	0.991	irs	0.697	0.721	0.967	drs
Wearing apparel, except fur apparel	0.374	0.759	0.493	irs	1.000	1.000	1.000	-
Tanning of leather, footwear & luggage	0.481	1.000	0.481	irs	0.705	0.834	0.845	drs
Wood, wood products & cork	0.609	1.000	0.609	irs	0.645	1.000	0.645	irs
Paper, paper products and printing	0.493	0.509	0.968	irs	0.794	0.795	0.998	drs
Chemicals and chemical products	0.379	0.448	0.846	irs	0.728	1.000	0.728	drs
Rubber and plastic products	0.642	0.684	0.940	irs	0.566	0.789	0.717	drs
Other non-metallic mineral products	1.000	1.000	1.000	-	1.000	1.000	1.000	-
Basic iron and steel	0.765	0.779	0.982	irs	1.000	1.000	1.000	-
Fabricated metal products	0.409	0.424	0.963	irs	1.000	1.000	1.000	-
Machinery and equipment n.e.c.	1.000	1.000	1.000	-	0.779	1.000	0.779	irs

(*Continued*)

Table5. (*Continued*)

Motor vehicles, trailers & semi-trailers	1.000	1.000	1.000	-	1.000	1.000	1.000	-
Furniture; manufacturing n. e.c.	0.378	0.394	0.959	irs	0.631	1.000	0.631	drs
Mean	**0.631**	**0.736**	**0.874**		**0.821**	**0.939**	**0.876**	
Major sub-sectors	**2017**							
	Public				**Private**			
	TE	**PTE**	**SE**	**TFS**	**TE**	**PTE**	**SE**	**TFS**
Food products and beverages	0.140	0.794	0.177	drs	0.961	1.000	0.961	drs
Textiles	0.032	0.075	0.422	drs	0.551	0.564	0.976	irs
Wearing apparel, except fur apparel	1.000	1.000	1.000	-	0.627	0.717	0.875	irs
Tanning of leather, footwear & luggage	1.000	1.000	1.000	-	0.530	0.540	0.982	irs
Wood, wood products & cork	0.095	0.095	0.994	drs	0.519	1.000	0.519	irs
Paper, paper products and printing	0.088	0.129	0.678	drs	1.000	1.000	1.000	-
Chemicals and chemical products	0.010	1.000	0.010	irs	0.857	0.970	0.883	drs
Rubber and plastic products	0.369	0.411	0.896	drs	0.665	0.931	0.715	drs
Other non-metallic mineral products	0.337	0.442	0.761	drs	0.988	1.000	0.988	drs

(*Continued*)

Table5. (*Continued*)

Basic iron and steel	0.062	0.078	0.797	irs	1.000	1.000	1.000	-
Fabricated metal products	0.056	0.056	0.997	-	0.881	0.961	0.917	drs
Machinery and equipment n.e.c.	1.000	1.000	1.000	-	0.481	0.744	0.646	irs
Motor vehicles, trailers & semi-trailers	0.178	0.334	0.531	drs	1.000	1.000	1.000	-
Furniture; manufacturing n. e.c.	0.187	0.188	0.995	irs	1.000	1.000	1.000	-
Mean	**0.325**	**0.472**	**0.733**		**0.790**	**0.888**	**0.890**	

Note: TE- total technical efficiency computed by CRS model; PTE- pure technical efficiency computed by VRS model; SE- scale efficiency; TFS- type of scale; drs-decreasing return to scale; irs-increasing return to scale;—Dash- constant return to scale.

Table 6. Tobit analysis of the determinants of technical efficiency

Dependent variable: Technical efficiency score				
Variables	**Coefficient**	**Standard Error**	**Z-Value**	**P-Value**
Advertising ratio	−0.0033807	0.0041182	−0.82	0.412
Account book ratio	0.3028605	0.1305197	2.32	0.020**
Skill intensity	−0.0526141	0.1077387	−0.49	0.625
Industry size	−0.029757	0.1191436	−0.25	0.803
Capital expenditure ratio	0.2872345	0.0883343	3.25	0.001***
Capital intensity	0.0000537	0.0000321	1.67	0.094*
Constant	0.0813547	0.1075105	0.76	0.449

Observation: **114** Wald chi2(6) = **23.27** P-value = **0.0007**

*Note: ***, **, * represent significant level at 1%, 5% & 10% respectively. Advertising ratio—advertising expense/total expenses; Account book ratio—firms which have a book of account/total number of firms in the industry; Skill intensity—production workers/total employees; Industry size—firms with 50 and over employees/number of firms in the industry; Capital expenditure ratio—annual capital expenditure/total fixed assets; Capital intensity—machinery & equipment/production workers.*

fabricated metal products (17.2%). The largest deterioration in technical change has been witnessed in the cordage, rope, twine and netting sub-sector (5.5%). On average, the sector has shown 10.5% progress in the frontier shift (innovation).

The overall productivity growth, which is reflected by the Malmquist index, shows 33 sub-sectors had experienced growth in productivity. The first five sub-sectors that experienced growth in productivity are knitting mills (61.6%); wearing apparel (51.6%); rubber products (50.3%); tanning & dressing of leather, luggage & handbag (46.7%); and malt liquors & malt (42.8%). Among the sub-sectors with negative productivity growth, other fabricated metal products sub-sector (19.5%) faced the highest decline in TFP by 19.5%, which is contributed by a decline in technical efficiency change. The negative production growth suggests that the firm produced less output per unit of resources consumed in 2010 compared with 2017. The deterioration of technical efficiency was the major factor for the negative production growth of the industries. The change in TFP has been observed highly because of technological progress. This can be witnessed that several new and improved products are coming to market currently, suggesting an increase in product and process innovation in the sector. Gebreeyesus (2007) found consistent results that the Ethiopian manufacturing sector exhibited an annual average productivity growth of about 9.3 percent between 1996 and 2003. There was a large variation in productivity growth among the industries. On average, the TE, technological change, and productivity showed growth of 2.2%, 10.5%, and 13%, respectively over 2010 to 2017.

Table 8 shows the mean efficiency growth rates for the sub-sectors over various periods (2010–2017) to investigate the trend of the change in the efficiency measures. The progress in PTE, which is one of the important elements of the TE index, contributed to TE improvement. In terms of TE, 2012 is the year when the highest progress was made while 2013 is the year when the heaviest retrogression was observed. In terms of technological progress, 2016 witnessed the highest increase while 2015 showed the lowest. Accordingly, the highest rate in TFP was reached in 2016 whereas the lowest rate was recorded in 2015. In other words, 2016 was also characterized by the year in which the highest economic growth (GDP of 10.9%) has been recorded in Ethiopia.

The year 2011 is characterized by an increase both in technical efficiency and technological progress. The industry's improved utilization of resources and innovation caused an increase in productivity by 27.7% in the year. However, 2012, 2015, and 2017 are the years in which

Table 7. The Malmquist index summary of industries means (2010–2017)

Sun-sectors	EFFCH	TECHCH	PTECH	SECH	TFPCH
Processing & preserving of meat, fruit & vegetables	0.92	1.106	0.937	0.982	1.018
Vegetable & animal oils and fats	1.251	1.114	1.248	1.003	1.393
Dairy	1.094	1.118	1.095	0.999	1.223
Grain mill	1.1	1.143	1.133	0.972	1.258
Animal feeds	1.187	1.054	1.194	0.995	1.251
Bakery	1.026	0.965	0.978	1.049	0.99
Sugar and sugar confectionery	0.91	1.038	0.91	1	0.945
Macaroni and spaghetti	0.962	1.164	1.009	0.954	1.12
Food products n.e.c.	0.986	1.055	1.078	0.915	1.04
Distilling, rectifying & spirits	0.874	1.111	0.886	0.987	0.971
Wines	1.005	1.12	0.997	1.008	1.125
Malt liquors & malt	1.082	1.32	1.132	0.956	1.428
Soft drinks & mineral water	0.825	1.093	0.944	0.874	0.902
Tobacco products	1	1.165	1	1	1.165
Spinning, weaving & textiles	0.974	1.098	0.958	1.016	1.069
Cordage, rope, twine & netting	0.919	0.945	0.834	1.102	0.868
Knitting mills	1.499	1.078	0.938	1.597	1.616
Wearing apparel except fur apparel	1.424	1.065	1.41	1.01	1.516
Tanning & dressing of leather, luggage & handbags	1.349	1.087	1.349	1	1.467
Footwear	1.043	1.037	1.043	1	1.082
Wood & wood products	1.265	1.049	1.265	1	1.327

(*Continued*)

Table7. (Continued)

Sun-sectors	EFFCH	TECHCH	PTECH	SECH	TFPCH
Paper	1.084	1.107	1.084	1	1.2
Publishing & printing services	0.979	1.102	1.11	0.882	1.079
Basic chemicals	0.883	1.052	0.89	0.992	0.93
Paints, varnishes & mastics	0.947	1.055	0.943	1.004	0.999
Pharmaceuticals & medicinal chemicals	0.924	1.116	0.923	1.001	1.031
Soap and detergents cleaning	0.942	1.107	0.999	0.942	1.042
Chemical products n.e.c.	0.939	1.028	0.944	0.995	0.965
Rubber	1.304	1.153	1.304	1	1.503
Plastic	0.962	1.109	1.06	0.908	1.068
Glass	1.057	1.143	1.052	1.005	1.208
Structural clay	1.083	0.975	1.074	1.008	1.056
Cement, lime & plaster	0.817	1.37	0.961	0.85	1.119
Articles of concrete & plaster	1.163	1.119	1.181	0.984	1.302
Non-metallic mineral	1.07	1.062	1.04	1.029	1.137
Basic iron & steel	1.021	1.156	1.143	0.893	1.18
Structural metal	0.98	1.241	1.031	0.95	1.216
Cutlery, hand tools & general hardware	0.931	1.098	0.93	1.001	1.023
Other fabricated metal	0.687	1.172	0.69	0.996	0.805
Other general-purpose machinery	1.004	1.345	1.01	0.994	1.35
Parts & accessories for motor vehicles	0.911	1.126	0.968	0.942	1.027
Passenger cars, commercial vehicles & busses	1.077	1.097	1	1.077	1.181

(Continued)

Table7. (*Continued*)

Sun-sectors	EFFCH	TECHCH	PTECH	SECH	TFPCH
Furniture	0.997	1.001	1.095	0.911	0.999
Mean	**1.022**	**1.105**	**1.032**	**0.991**	**1.13**

Where: EFFCH-efficiency change; TECHCH- technology change; PTECH- pure technical efficiency change; SECH—scale efficiency change; TFPCH-total factor productivity change.

technological retrogression was shown which in turn caused negative productivity growth. The technical efficiency index shows worsening from 2013 to 2016. Generally, the industries are more focused on technological progress or innovation than technical efficiency during the study period.

5. Conclusions

This study estimates technical efficiency and total productivity growth of medium and large-scale manufacturing sub-sectors using census data annually collected by the Ethiopian Central Statistical Agency. A technical efficiency score is computed by a data envelopment analysis, whereas the Malmquist productivity index has been employed to estimate total productivity change. Furthermore, a censored Tobit regression model was used to identify potential factors which can define the variation in total technical efficiency scores.

The result shows that on average, medium- and large-scale manufacturing sub-sectors registered a 0.37 (37%) efficiency score over the study periods 2010 to 2017. It suggests that on average, the sector could minimize its input quantity by 63% without altering the level of production or could produce about 63% of production from the resources assumed in the observation periods. In practice, the sector has been suffering from a lack of adequate materials, electric power interruption, and skilled labor. It also could not appropriately utilize the available resources. Thus, it can be concluded that the manufacturing sector should look into its resource utilization methods to obtain the optimal benefit. The Malmquist productivity index shows on average, the sub-sectors made technological progress by 10.5%. The technological change index positive value indicates a decline in the quantity of output produced by a similar quantity of input. It indicates progress in innovation, which has greatly contributed to positive productivity growth in 31 sub-sectors. It suggests that most sub-sectors have paid more focus on technological change than technical efficiency change. Moreover, productivity grew by 13% over the study periods, 2010 to 2017, which is less than 2% per annum. As productivity is the linear combination of catch-up and frontier shift, firms need to balance these factors in order to improve productivity.

Furthermore, we observed that the total technical efficiency scores computed by a constant return to scale model show considerable variations among the sub-sectors under consideration. To understand the determinant factors that can cause a firm to be more efficient or less efficient, a censored Tobit regression was run and the results showed that capital expenditure ratio and account book ratio has a significant positive effect on technical efficiency. The capital expenditure ratio indicates long-term investments that can increase a firm`s future cash flow, which in turn improves technical efficiency. On the other hand, the account book ratio reflects firm internal control practice which involves financial management practices and how business transactions are recorded, maintained, and processed into information helpful to decision-makers in planning, directing, and controlling activities. It can be inferred that a firm that designs an effective

Table 8. The Malmquist index summary of annual means

Year	TE	TeChE	PTE	SE	TFP
2011	1.062	1.201	1.12	0.948	1.276
2012	1.544	0.869	1.767	0.873	1.341
2013	0.744	1.225	0.68	1.094	0.911
2014	0.957	1.354	1.036	0.925	1.296
2015	0.948	0.873	0.827	1.147	0.828
2016	0.931	1.46	1.236	0.754	1.36
2017	1.132	0.912	0.876	1.292	1.033
Mean	**1.022**	**1.105**	**1.032**	**0.991**	**1.13**

Note: All Malmquist indexes represent geometric means (Coelli, 1996). *TE-total technical efficiency; TeChE-technological change; PTE-pure technical efficiency; SE- scale efficiency; TFP-total factor productivity.*

accounting system and financial management practices more likely to be efficient. The coefficient of capital intensity is positive but not statically strong. This study also finds public-owned sub-sectors are less efficient than privately owned sub-sectors.

Even though the sector shows total productivity progress, it is still insignificant when compared to other industries. For example, the sector's net contribution to GDP in 2016/17 was 1.1%, while agriculture and services accounted for 36.3% and 39.3%, respectively (CSA, 2018). Growth in the manufacturing sector is expected to be a positive function of the GDP. To meet these expectations, the sector needs to be efficient. Efficiency in the sector can be improved by strengthening the corporate governance structure (Bris et al., 2008), enhancing R&D, innovations, and utilization of information technology. Finally, human resource development is another aspect that needs to be addressed. The skills of personnel working in manufacturing should match the changing requirements of these industries, which are forced upon us by globalization. Without a competent workforce, it is difficult to compete, particularly in this type of knowledge-based industry.

6. Practical implications of the study

The findings of the study would have implications for policymakers and firm owners in that it offers an insight into the source of productivity growth, competitiveness, and areas for further improving the manufacturing sector. Policymakers would also use the findings in designing strategic plans towards increasing the productivity of the sector. The main source of productivity is internal factors which involve optimal usage of existing resources or producing the optimal production from the existing input resources. Thus, considerable due attention should be given to the productivity-driven growth strategy than the foreign direct investment-driven growth strategy of the sector.

7. Limitations and future research directions

Our study has two potential limitations. First, our analysis focuses mainly on medium and large-scale firms, excluding small manufacturing firms that make up a large percentage of the sector. Future research may focus on small and medium enterprises (SME) in developing countries like Ethiopia. Second, the limitations in the data also forced us to use sectoral data instead of firm data, which would have allowed a deeper and more interesting or novel analysis. There are several factors recommended in the empirical literature (Alvarez & Crespi, 2003) like export performance, firm owner education level, import performance, research & development, but we could not include these variables in the model due to data unavailability.

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