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**Article**

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# Comparison of Recent Developments in Productivity Estimation: Application on Ethiopian Manufacturing Sector

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**Abstract**

The objective of this paper is to estimate total factor productivity of manufacturing firms in Ethiopian under alternative estimation approaches. Six methods are compared in the estimated total factor productivity namely ordinary least square, fixed effects, Olley and Pakes (1996), Levinsohn and Petrin (2003, Robinson (1988) and Wooldridge (2009). The estimated input elasticities in all the models are statistically strongly appealing and have the theoretically expected sign yet they differ in magnitude. Though there is significant variation in the mean total factor productivity estimates ranging from 6.38 in the ordinary least square estimate to 4012.21 in Olley and Pakes, there is strong positive correlation among the methods except the Olley and Pakes approach. The correlation (excluding Olley and Pakes) ranges from 92.71% between Levinsohn and Petrin and fixed effects to 99.97% between Robinson and Wooldridge. Taking Wooldridge as the appropriate estimator since it has the additional advantage of producing more efficient estimates and tackles potential serial correlation and heteroscedasticity, output on average increases by 0.25% for 1% increase in labor input, other factors unchanged, it increases by 0.11% when a firm increases its capital user cost and also it increase by 61% as a firm increases its raw material usage by 1%. Productivity estimates of the manufacturing sector vary significantly across industrial groups ranging from 41.52 in the non-metallic to 937.77 in the wood category. The variation is higher even within the top three performers 937.77, 198.42 and 132.72 respectively for wood leather and textile industries. Exporting firms are more productive across ownership types and firm size. Therefore, there is a need to raise capital productivity, export participation and learning across industrial groups in order to build strong manufacturing base which enhance the aggregate economic growth to sustain and to improve social wellbeing.

**Key words**

Total factor productivity, manufacturing, Ethiopian industry, productivity

**JEL Codes**: D24, D22



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## 1. Introduction

Industrial development is considered as a pre-requisite for structural transformation and sustained growth in the economy as it uses resources in such a way that produce higher value added (Mbate, 2016). The manufacturing sector take the priority in industrial development policy debates because it has linkages with other sectors, utilizes scale economies, is source of innovation and technological repercussion effect both within it premise and across sectors (McMillan *et al.*, 2017; Rodrik, 2004; 2013). The aim of measuring productivity in output[1] oriented approach is to estimate the variation in output which is not contributed by the variation in input. Measuring productivity enables to evaluate performance level and change overtime of production unit as well as assessing the effect of policy shocks, for instance trade liberalization, research and development investment (Van Biesebroeck, 2008). Productivity level differential is assumed by scholars as cause for variation in income level across economies (Syverson, 2011).

In Ethiopia several researches are conducted in relation to productivity. For instance, Bigsten *et al.* (2009) conducted a research on liberalization and firm productivity using establishment level panel data on covering the period 1997 to 2005 and found that reduction in tariff rate increases firm level TFP. This is confirmed recently by Friorini *et al.* (2017) who further studied the effect of infrastructure improvement on realization of the effect of trade liberalization on productivity improvement and found positive result. Tekleselassie *et al.* (2018) studied the determining factors of productivity of textile and garment firms and found that human capital, agglomeration and policy incentives positively affect productivity. Gebreeyesus (2008) examined the effect of firm entry and exit (*turnover*) on firm level productivity. His result showed that firm turnover leads to high productivity growth among the surviving firms mainly due to resource reallocation from the

[1] Output oriented approach is one which maximizes output for a given set of inputs whereas input oriented producing a given level of output using a minimum possible input combination (Coelli *et al.*, 2005; Kumbhakar and Lovell, 2000; Kumbhakar *et al.*, 2018; Kumbhakar *et al.*, 2015)

leaving to the newly entering (from the less productive to high productive establishments). Bigsten and Gebreeyesus (2007) conducted a research on firm age, size and labor productivity level as factors determining firm growth and found that small enterprises have higher growth rate than the large sized counter parts. Older firms grow faster than younger firms and labor productivity positively affects firm growth. Bigsten and Gebreeyesus (2009) examined the relationship between export participation by firms and their productivity in which they found both self-selection of more productive firm to exporting and learning by exporting have contributed to productivity improvement. These and other papers conducted so far on the Ethiopian manufacturing firm productivity are confined only on few issues such as export, import, trade liberalization firm age and size where the whole pattern of productivity measurement and growth structure is not comprehensively addressed.

Abegaz (2013) conducted a research on productivity and Efficiency on Ethiopian large and medium scale manufacturing establishments using data from 1996 to 2009 a survey of the central statistical authority (CSA). He did great job in decomposing TFP in to source component namely: Technical progress, scale efficiency change and technical efficiency change. He used wage bill as measure of labor and net capital stock as measuring the labor and capital inputs respectively. However, to tackle the potential measurement error in the inputs which cause correlation with the residual term, in this paper full time equivalent number of employees (Schreyer, 2011) and deflated depreciation are used. Moreover, as far as our knowledge is concerned, there is no study on TFP using the period of the first growth and transformation period (2011 to 2015) which is very important from policy view point. In terms of estimation methods of TFP level recently developed methods Wooldridge (2009), Olley and Pakes (1996), Levinsohn and Petrin (2003), Robinson (1988) are compared along with the benchmark of fixed effects and ordinary least square (OLS).

The objective of this paper is to estimate total factor productivity (TFP) level of large and medium scale manufacturing establishments in Ethiopia covering the period 2011 to 2015. The period is very important from policy perspective as it the first growth and transformation plan completed and the second one is on progress. There is a need to evaluate the first period in order policy intervention for the successive plans will be effective.

## 2. Literature review

The availability of data and the aim of measuring productivity determine the type of its measure to be adopted. As such productivity can be measured either based on a single input or composed from multiple input. The other productivity measure classification is on the basis of gross output or value added (Schreyer, 2001). Among the several ways of classifying the methods of total factor productivity (TFP) estimation, the non-parametric and parametric approaches are common in the productivity literature. The non-parametric method includes Malmquist, Divisia indices and data envelopment analysis (DEA). Since index number approach assumes that all firms are fully efficient, DEA is most commonly used in the non-parametric context (Coelli *et al.*, 2005). DEA, which was introduced first by Farrell (1957), attracted the attention of scholars after Charnes *et al.* (1978) came up with a paper in which the structure of production was assumed to follow constant returns to scale. The term DEA was used for the first time in this paper (Coelli *et al*., 2005). Following this, Fare *et al.* (1983) and Banker *et al*. (1984) extended it in such a way that it accounts for variable returns. DEA uses mathematical programming technique of analysis (Kumbhakar *et al.*, 2018). In this case, productivity is calculated as a ratio of the *linear combination of output in to linear combination of inputs.* The most performer unit is considered as 100% efficient. Then, solution is obtained for each individual firm. (Van Biesebroeck, 2008). The advantage of the non-parametric technique is that it doesn't require functional form of the deterministic part of the production technology and no distributional assumption is imposed on the inefficiency term (Greene, 2008; Kumbhakar *et al.*, 2018; Mattsson *et al.*, 2018). However, it has serious limitations in that first it interprets any deviation from the production possibility set as inefficiency. This means all factors which affect firm performance are considered as under the control of the firm. The consequence of this is that the estimated inefficiency is biased because of exogenous factors such as measurement error (Kumbhakar and Lovell, 2000). The second limitation is that it measures inefficiency relative to the best performing unit among the observations which makes its result liable to be biased due to outliers (Coelli *et al*., 2005).

The parametric measures can further be classified in to deterministic (average measures) which was implemented fir instance by Solow (1957) and stochastic frontier which was first introduced independently but within same period by Aigner *et al.* (1977), Meeusen and van den Broeck (1977) and Battese and Corra (1977). The stochastic frontier (econometric) approach in addition to the inefficiency effects, it explicitly introduces the stochastic error component to capture the effects of exogenous factors which are beyond the control of the production unit (Kumbhakar and Lovell, 2000). It is specified for a Cobb. Douglas production technology using panel data set as follows:

$$Y_{it} = f(X_{it}, t;\ \beta)e^{u_{it}}e^{v_{it}} \tag{1}$$

Where i = 1,2, …n represents individual firm, t = 1,2, …,T firm observed at time period, $Y_{it}$ = denotes the output of firm i at time t, $X_{it}$ is a vector of input factors of firm i at time t, β represents vector of parameters including the intercept, $u_{it}$ = captures technical inefficiency component of the composed error which is considered here as time varying and individual firm specific, $v_{it}$ the statistical noise which measures the effects of exogenous factors such as classical measurement error and other random behavioral factors.

Though the stochastic frontier approach is criticised for its prior functional form for the production technology and its restrictive assumption on the inefficiency effect, it is commonly used particularly when the need arises to decompose TFP growth in to components.

Firms decide their input demand depending on the level of productivity they face. That is when productivity is positive; they decide to expand output which requires them to increase their variable input demand (Van Biesebroeck, 2012) and the reverse holds when the productivity shock is negative. This implies that input demand is not an exogenous decision because the residual (productivity) and inputs are decided simultaneously which creates correlation between the observable inputs and unobservable (to the researcher) productivity term arising from the simultaneity endogeneity. Thus, ordinary least square method produces biased estimated of productivity (Mollisi and Rovigatti, 2017). The other source of endogeneity is attrition of firms in a panel data case where the more productive units sustain and the less productive ones exit and this leads to selection bias if balanced panel is considered (Olley and Pakes, 1996). Thus, there is a need to work on unbalanced panel data set (Ackerberg *et al.*, 2015). In order to solve the endogeneity problem, several scholars worked on the development of other methods such as fixed effects estimator, generalized method of moments (GMM) or instrumental variables and input control function approaches (Ackerberg *et al.*, 2015; Mollisi and Rovigatti, 2017).

For the control function approach Olley and Pakes (1996) developed a semi-parametric algorithm which follows *a tow step* procedure using investment as a proxy variable for time varying (dynamic) productivity shock (Ackerberg *et al.*, 2015). The limitation of this estimator is its assumption of investment as monotonically increasing function of productivity. However, firms might not make positive investment during each time period which indicates that investment is not perfectly elastic to changes in productivity. This leads to drop out of many firms from the sample data set because they don't satisfy the strictly increasing presumption (il Kim *et al.*, 2016; Levisohn and Petrin, 2003). Levinsohn and Petrin (2003) modified this method using intermediate inputs as proxy instead of investment and following a two-step procedure similar to the Olley and Pakes. In the first step of both approaches, the coefficient of the variable factor (labor) is estimated non-parametrically (Ackerberg *et al.*, 2015) and in the second step, the elasticity of the fixed input (capital) is identified (Petrin and Poi, 2004; Yasar *et al.*, 2008). Ackerberg *et al.* (2015) criticised both Olley and Pakes (1996) and Levinsohn and Petrin (2003) on the ground that the first stage estimation has potentially the labor input face functional dependency on the non-parametric part of the inverted productivity function. This leaves the labor coefficient unidentified because the labor demand function is taken as unconditional on the non-parametric inverted function. They designed a new data generating mechanism that inverts the proxy variable conditional on the labor demand function yet following a two-step estimation procedure.

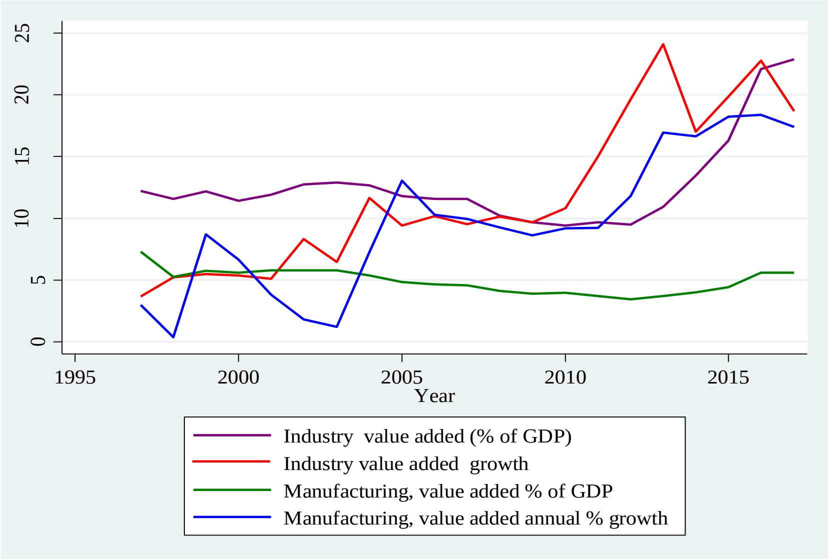
Wooldridge (2009) developed a system-GMM single step technique which gives consistent and efficient[2] coefficients of labor and capital simultaneously in such a way that solves the problems associated with contemporaneous correlations of error terms across the two equations serial correlation and heteroscedasticity. So far the alternative and competing estimation methods are reviewed which should be followed by the question to address regarding the choice which method. System-GMM gives out more robust estimates in the presence of technological heterogeneity and measurement error and if measurement error is limited even if heterogeneity in technology prevails, the non-parametric approach is preferred (Van Beveren, 2012).

*1. Industrial performance trends in Ethiopia*

Based on figure 1 below industry value added as percentage of GDP (the purple line), growth rate of industry value added (the red line) and manufacturing growth rate (the blue line) face repeated up and downs over the time span of 1997-2017 though all show growth on average. The proportion of industrial value added out of total GDP started with about 13% in 1997, fallen below just 10% between 2007 and 2011 and raised to reach about 23% by 2017. The growth of industrial value added started from below 3.68% in 1997 and continued to grow but facing repeated fluctuations up to a peak of 24.1% in 2013 after which it remained below it and reached 18.68% during 2017. The average industrial share of GDP is 11.81%. The manufacturing value added growth showed more oscillation up and down starting at 2.97% in 1997 and down to its trough of 0.3% immediately the next year and continuing in such fluctuation reached 17.41% in 2017. On average, it has

[2] Efficiency is one of the desirable properties of parameter estimates of parameter implies where the variances are minimum (Gujarati, 2009)

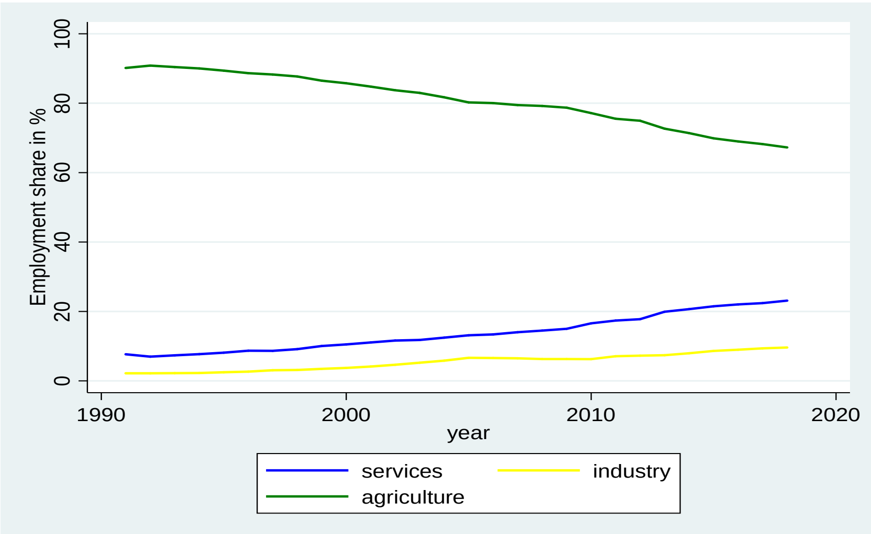
grown by about 9.61% over the 21 period. On the other hand, the GDP share of manufacturing value added remained almost stable. In the initial year, it was 7.3% which fall down to about 5.26% in 1998. For seven years starting from 1998, this share remained below 6% and above 5% after which it fall further below 5% and from 2009-2014 even below 4%. During the last 3 years it showed recovery from 4.4% to 5.9%. The question to be addressed at this point is that given this 4.9% average manufacturing contribution to GDP, which other sector contributes to 11.81% industrial share to GDP. Majority of the industry value added is contributed from the recent upsurge of the construction sector in the country (World Bank, 2019).




***Source:*** Own sketch using World Bank WDI (2019)

*Figure 1.* Industry value added to GDP ratio and growth (1997 to 2017)

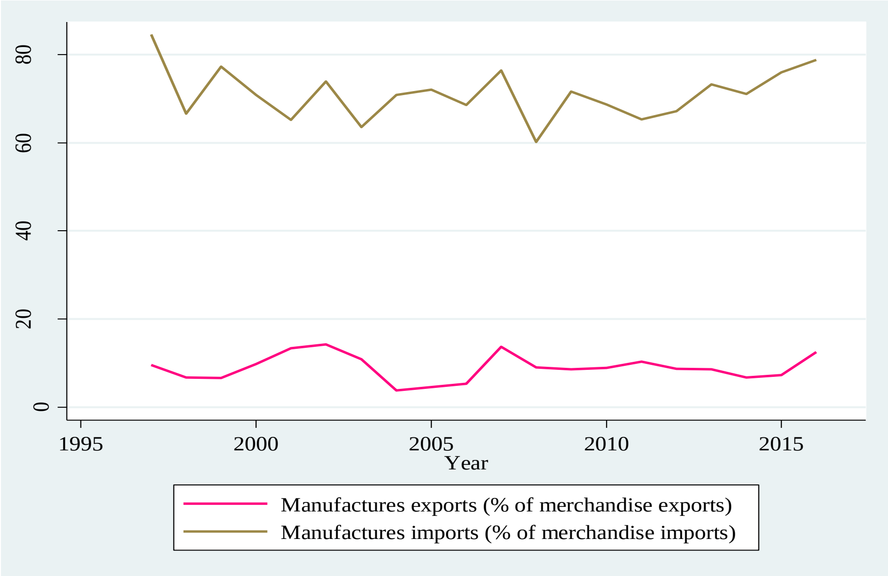
As can be observed from figure 2 below, though the employment share of the agricultural sector (the green line) shows steadily declining trend yet it accounts for the majority proportion. It was 90.16% in 1991 and it became 67.27% in 2018. The employment share of the service (blue line) and the industrial (yellow line) sectors depict a growing trend where the service lays above the industrial sector. However, the gap between the two diverged since 2007. In 2017, the gap was 7.52 but in 2018 it reached 13.5 which close to double within a 12 years period. This result indicates that though the industrial share of employment is increasing, it is still very small with a mean of 5.44% whereas much of the decline in employment share of agriculture is captured by the service sector whose mean is 13.69%. The share of the service sector was 7.66% in 1991 to reach 23.11% in 2018 while the industry started with 2.18% and reached 9.62%.




***Source:*** Own sketch using World Bank WDI data (2019)

*Figure 2:* Employment performance by sector in Ethiopia (1991-2017)

Based on the observations from figure 3 below, there is significant gap between the proportions of manufacturing import out of total merchandise import (green line) and its export contribution (pink line). It continued widening the divergence particularly after 2010. Hence, the manufacturing sector instead of contributing to foreign exchange earnings, it is putting burden on it unless its imports being capital goods may help the productive capacity of the sector to improve exportable commodities in the long run.




***Source***: Own sketch Using World Bank data (2019)

*Figure 3*. Import export performance of Manufacturing in Ethiopia (1997-2017)

To summarize, the industrial sector has limited contribution in terms of value added as percentage of GDP, employment share and export earnings. It implies that there should be strategic intervention so that the country would reap the potential contribution from industrialization and the sustainable development commitment (SDG 9) will be realized.

## 3. Methodology of research

The data is obtained from central statistical authority (CSA) annual survey over the period 2011 to 2015 which is unbalanced panel. The period is of particular interest from policy perspective because it represents the era of the first growth and transformation plan implementation period.

3.1. Methods of data analysis

Two methods are adopted for this research. First, to estimate TFP level and examine its average growth over time, the Wooldridge (2009) estimator is used because it has several desirable properties such as consistent and efficient parameters estimation by using the single step of system-GMM approach. Here, lagged values are used as instruments in order to solve the potential endogeneity issue. In addition, it addresses heteroscedasticity and serial correlation problems (Ackerberg *et al.*, 2015; Mollisi and Rovigatti, 2017; Wooldridge, 2009). Second, to decompose the growth in to its component parts namely: Technical progress, scale efficiency change and technical efficiency change, the step by step version of stochastic frontier model developed by Kumbhakar, Wang and Horncastle (2015) including technical efficiency change as driver of TFP growth.

Model specification

$$Y_{it} = A_{it}K_{it}^{B_k} L_{it}{}^{\beta_l} M_{it}^{\beta_m} \qquad (2)$$

Where: $Y_{it}$ denotes real sales value of firm i at time t; $K_{it}$ represents depreciation allowance in real terms as a proxy for capital user service cost (Tingum, 2014); $L_{it}$ is the full time equivalent number of employees; $M_{it}$ = refers to the raw material input cost (real).

Transforming equation (1) into natural logarithm, it becomes:

$$lnY_{it} = lnA_{it} + B_k lnK_{it} + \beta_l lnL_{it} + \beta_m lnM_{it} \qquad (3)$$

Letting small cases for the natural logarithm and decomposing as $lnA_{it} = \beta_0 + \varepsilon_{it}$:

$$y_{it} = \beta_0 + B_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \varepsilon_{it} \tag{4}$$

Here, $\beta_0$ measures the mean efficiency of firms over time and across firms (van Beveren, 2012) and $\varepsilon_{it}$ captures variations from the mean which considered as individual specific and time varying one. $\varepsilon_{it}$ can be further decomposed in to two components as Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) did for cross-sectional data in to the statistical white noise ($v_{it}$) caused by classical measurement error plus other unpredictable exogenous shocks and the part which measures technical inefficiency of firms ($u_{it}$) arising managerial capability and so on which are internal to the decision making unit. In the panel data literature, $v_{it}$ is referred to as the idiosyncratic error component.

$$y_{it} = \beta_0 + B_k k_{it} + \delta t + \beta_p l_{pit} + \beta_n l_{nit} + \beta_m m_{it} - u_{it} + v_{it} \tag{5}$$

Here time trend t is included as regressor in order to let the research account technical change as a driving factor for TFP growth (Kumbhakar *et al.*, 2018). The question to be addressed at this point is that which method (fixed effects, instrumental variable approach or control function approach) should be employed so that equation (4) is estimated consistently and without bias. For this thesis, the control function approach developed by Mollisi and Rovigatti (2017) and their stata code prodest will be applied with special emphasis on the modification made on Wooldridge (2009). Hence, $u_{it}$ is considered to take first order Markov process (Mollisi and Rovigatti, 2017)[3].

3.1.1. Estimate of Total Factor productivity (TFP) level

By estimating the parameters in equation (4), the basis for estimating total factor productivity level will be obtained as:

$$\hat{\omega}_{it} = \hat{\beta}_0 + \hat{u}_{it} = y_{it} - \hat{B}_k k_{it} - \hat{\beta}_p l_{pit} - \hat{\beta}_n l_{nit} - \hat{\beta}_m m_{it} \tag{6}$$

Since $\omega_{it}$ is lnTFP, to get the productivity level one should transform it in to natural exponential function (anti-log). This means $e^{\omega it}$ = TFP (Bils and Klenow, 2000).

### 5. Results and discussions

This section presents the main findings of the research in relation to TFP level and growth by introducing using some descriptive statistics.

*Table 1.* Summary of variables

| Variable | Obs | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| Full time equivalent labor | 8495 | 89.005 | 261.918 | 5 | 6157 |
| Real sales | 8495 | 327,000 | 1,320,000 | 38.78 | 3.70e+07 |
| Real raw | 8495 | 156,000 | 545,000 | 1.03 | 1.06e+07 |
| Real depreciation | 8495 | 18,097.63 | 188,000 | 1.01 | 1.40e+07 |
| Real wages | 8488 | 16,670.91 | 98,929.32 | 76.022 | 5,550,000 |
| Real Value Added | 8495 | 171,425 | 956,753.1 | 17.80414 | 3.64e+07 |

***Source:*** own computation using CSA raw data

Table 1 above presents the summary of variables used in the analysis. The mean number of full time equivalent employees is 89 ranging from 5 to 6175. Though the CSA (for example 2015) survey report states that large and medium enterprises are those which employ 10 and above workers, the minimum in terms of full time equivalent workers is 5 (208 establishment with five full time equivalent employees). This may be due to either there is labor turn over and the survey is conducted during season with less job activities or the nature of job requires more seasonal and temporary workers and hence the weighted number full time equivalent workers is less. In terms of variability (standard deviation is 261.92); it is smaller as compared with other variables. The mean real sales value is 327,000 birr per year but with large variability (1,320,000) ranging from 38.78 to 37,000,000. The mean real raw material input is 156,000 close to half of the real sales value and it shows similar pattern with real sales by measure of standard deviation, the minimum and maximum values. This indicates that firms are highly heterogeneous in their real sales revenue. On the other hand, the mean depreciation

[3] Markov process is named after the Russian mathematician Andrey Markov (1856-1922). First order Markov process refers to first order autoregressive process, i.e. the probability of a random variable depends only on its immediate previous value. e.g. $\omega_{it} = E(\omega_{it} | \Omega_{it-1}) + \xi it = E(\omega_{it} | \omega_{it-1}) + \xi_{it} = g(\omega_{it-1}) + \xi_{it}$ (Mollisi and Rovigatti, 2017)

allowance in real terms is 18,097.63 having large variability of 188,000 which about 10.4 times higher relative to its mean value. Both raw material input and depreciation allowance show large range from very small to very large values. The mean real value added (171,425) is much higher than the mean wage cost (16,670.91). Taking value added as source of remuneration among the factors of production, capital and organization take a larger share of value added because the mean share of labor is approximately 9.73% of mean value added. In terms of variability both show similar pattern as standard deviation of wage is 5.58 times its mean and standard deviation of real value added is 5.58 times its mean though they significantly differ in their respective minimum and maximum values.

Table 2 below shows the input elasticities from Cobb-Douglas production function estimated using six estimators. The models are ordinary least square estimator (OLS) included here a bench mark for comparison otherwise since endogeneity is critical issue, OLS coefficients are inconsistent; the fixed effects estimator (FE) which tackles the correlation between the residual productivity term and any or more of the input factors; Wooldridge (2009) system-GMM estimator denoted by WRDG; the Robinson (ROB) estimator; the Olley and Pakes (1996) estimator represented by OP and the Levinsohn and Petrin (2003) estimator symbolized by LP. The purpose of comparing various estimators is to evaluate the conclusions that might be drawn based each thereby the policy distortion that may arise due to various estimations (Van Beveren, 2012). As the Wooldridge (2009) method of estimation has several advantages over the others such as it solves potential serial correlation, heteroscedasticity as well as the endogeneity due to simultaneity and attrition by adopting a single step estimation using lagged values as instrument (Ackerberg *et al.*, 2015). The last four methods are estimated using the *prodest* user written status command which allows correction for attrition developed by Mollisi and Rovigatti (2017). These methods are recognized in the following discussion as competing models because they are the hot debating techniques in the productivity estimation literature. Observation of this table shows that all the input coefficients are positive (in line with a priori expectation) and statistically significant at 1% level of significance.

*Table 2.* Comparison of Productivity Estimators

| Variable | OLS | FE | WRDG | ROB | OP | LP |
|---|---|---|---|---|---|---|
| lnL_fulltime | 0.2961 (0141) | 0.2534 | 0.2538 | 0.2453 | 0.2003 | 0.2004 |
| | | (0.0369) | (0.0128) | (0.0220) | (0.0066) | (0.0088) |
| lnreal_depreciation | 0.1756 | 0.0906 | 0.1078 | 0.1091 | 0.3633 | 0.1407 |
| | (0.0088) | (0.0149) | (0.0100) | (0.0144) | (0.0339) | (0.0091) |
| lnRaw | 0.5285 | 0.5608 | 0.6114 | 0.6185 | | 0.6288 |
| | (0.0113) | (0.0318) | (0.0102) | (0.0230) | | (0.0268) |
| _cons | 3.2475 | 3.6636 | | | | |
| | (0.0605) | (0.2484) | | | | |

***Source:*** Own Computation using CSA raw data

***Legend:*** standard errors in parenthesis

The labor coefficient value range from 0.2961%[4] in OLS to 0.2003% in Olley and Pakes (1996) method. In the same manner, the elasticity of the capital service (proxied by depreciation allowance) ranges from 0.3633% for Olley and Pakes (1996) method to 0.0906% in case of the fixed effects model. Olley and Pakes (1996) gave by far a larger coefficient of capital service but the lowest in labor coefficient. The raw material input elasticity ranges from 0.6288% in Levinsohn and Petrin (2003) method to 0.5285% in OLS. As Olley and Pakes (1996) uses investment as proxy, it does not have coefficient for raw material.

The interpretation of the input elasticities is made using the Wooldridge (2009) estimator results. On average when a typical firm increases, other factors kept unchanged, its full time equivalent labor by 1%, real sales value in that firm increases by 0.2538% and if it increases the capital service usage by 1%, real sales value increases by 0.1078% but if the firm increases the raw material input by 1%, its sales value in real terms increases by 0.5608%. These coefficient elasticities show that the manufacturing sector in Ethiopia is more dependent on raw material than on capital services. This finding is in line with the various study results in Ethiopia where output is less elastic in comparison with other inputs. Abegaz (2013), for instance, using panel data from 1996 to 2009 found that for all of his 10 industrial groups the elasticity of real raw material input was more than 0.62% ranging from 0.799% for food to 0.622% for beverages. Gebreyesus (2008) employing data from 1996 to 2003 found similar pattern regarding elasticity of input. Here, however, in five[5] out of ten industrial groups the elasticity of capital was negative but insignificant.

[4]Since the parameters are estimated from log transformed Cobb-Douglas production function, they represent percent values.
[5] Non-metallic (I think it is to mean non-metallic minerals), rubber & plastic, wood & furniture, textile & apparel, and food & beverage.

Similarly, Tekleselassie *et al.* (2018) for the textile and garment industrial group using various models for comparison found out different values in terms of magnitude but similar in pattern. The elasticity of capital in this result is negative for OLS, Corrected OLS and RE but positive for FE and Levinsohn and Petrin (2003) and insignificant for all the five models. The size of the raw material elasticity ranged from 0.40% in FE to 1% in Levinsohn and Petrin (2003) and significant in all the models. On the other hand, Lemi and Wright (2018) using World Bank enterprise surveys data found that the elasticity of output to changes in capital input, though positive in sign, its magnitude is statistically insignificant. The high degree of responsiveness to raw material indicates that value added by firms is less. In all of the group cases, the elasticity of real capital input is less than the labor and raw material elasticities. Moreover, Hailu and Tanaka (2015) using panel data from 2000 to 2009 found that the capital elasticity of output is insignificant (with negative sign for wearing apparel, paper and printing, chemicals and fabricated metals) at 5% significance level. Even, the interaction with other inputs is not satisfactory. The reason forwarded for the less responsiveness of output to capital input is that firms employ old capital with less latest technology embodied and may be due to capital maturity[6] is reached. The result of this paper is significant, though small relative to the other inputs, may be due to the recent efforts to improve the performance of the manufacturing sector since the data used in the previous literature before the onset of the first growth and transformation plan of the country.

*Table 3*. Summary of TFP for the six models

| Variable | Obs | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| TFPols | 8324 | 6.381 | 239.816 | 0.019 | 21089.36 |
| TFPfe | 8324 | 8.152 | 352.739 | 0.034 | 31020.26 |
| TFPwrdg | 8324 | 239.582 | 11187.39 | 0.876 | 990000 |
| TFProb | 8324 | 239.148 | 11272.65 | 0.878 | 998000 |
| TFPop | 8324 | 4012.205 | 12495.04 | 0.797 | 567000 |
| TFPlp | 8324 | 212.006 | 9907.399 | 0.782 | 877000 |

***Source:*** own summary using estimated TFP

Table 3 above provides the summary of TFP in which one can see that there is significant variation in the size of the estimated mean TFP. However, three of the methods (Wooldridge, Robinson and Levinsohn and Petrin) give closely similar results 239.58, 239.15 and 212.01 respectively. The Olley and Pakes (1996) estimator is an outlier which equals to 4,012.21. Since the Wooldridge (2009) approach incorporated a modification to Robinson (1988), the results in all respects (in input elasticities and mean, minimum and maximum TFP) are highly similar. The mean TFP of OLS and fixed effects estimator are much lower than the other four but they are close to each other.

Table 4 below presents the spearman rank correlation among the six estimation methods and except in case of Olley and Pakes (1996) approach, estimated TFP is strongly positively correlated across estimators. It ranges from 0.9271 between Levinsohn and Petrin (2003) and fixed effects to 0.9997 between Robinson (1988) and Wooldridge (2009). This high level of rank correlation is in line with other researchers like Van Beveren (2012) who compared OLS, fixed effects (both for balanced and unbalanced), Wooldridge Levinsohn and Petrin, and Olley and Pakes (for the basic and with correction for survival analysis) and drawn a conclusion that even if the estimation algorithms differ their assumptions and tactics, the estimated TFP is highly correlated to each other and from policy perspective, they don't significantly differ. Similarly, Van Biesebroeck (2008) compared five techniques of productivity estimation namely: index numbers, data envelopment analysis, instrumental variable approach, stochastic frontier analysis and semi-parametric methods. The first two methods are non-parametric ones. His findings show that the estimated TFP is similar across methods and there is no significant difference in the conclusion to be drawn and the policy effects for that matter.

The less correlation of Olley and Pakes (1996) with the rest of the approaches particularly the recently developed ones may be due to its use of investment as proxy for the productivity term with an assumption of monotonous relationship between the two. In the data we employed here, 3,424 out of 8,495 (about 40.31%) firms have zero record of investment which violates the monotonocity assumption. Hence, in the presence of high non-response of firms to productivity by investing immediately, Olley and Pakes method may not give comparable results and policy conclusions. Van Beveren (2012) and Van Biesebroeck (2008) obtained comparable result may be due to less zeros in the investment of the data they used.

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

*Table 4.* Spearman rank Correlation of TFP among competing estimators

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| (1) TFPols | 1.000 | | | | | |
| (2) TFPfe | 0.9291* | 1.000 | | | | |
| (3) TFPwrdg | 0.9694* | 0.9685* | 1.000 | | | |
| (4) TFProb | 0.9677* | 0.9685* | 0.9997* | 1.000 | | |
| (5) TFPop | 0.6730* | 0.7390* | 0.6274 | 0.6164 | 1.000 | |
| (6) TFPlp | 0.9672* | 0.9271* | 0.9865* | 0.9896* | 0.5809 | 1.000 |

***Source:*** own computation using estimated productivity levels

Table 5 below presents the mean TFP estimated by using Wooldridge (2009) for ten industrial groups. The top three productive industries are the wood products (including furniture) industry (937.77), the leather products and foot wear industry (198.42) and the textile and wearing apparel industry (132.72) respectively. The first ranked industry (by productivity measure) is more than 4.7 fold of the second and the second about 1.5 fold of the third. The least performer in this regard is the non-metallic group (41.52) which is much smaller than the mean TFP (239.58), i.e. the mean TFP is about 5.77 times more than the least and the highest performer is approximately 3.9 times larger than the mean. This all shows that there is high variation among the various industries of the manufacturing sector in TFP performance.

Therefore, firm managers and the public sector should work as a coordinated team to reap the potential productivity of the high performer industry disseminate lessons form group in order that those lagging behind should cope with it.

*Table 5.* TFP by Group of Establishments as per Wooldridge (2009)

| Industrial group | TFP |
|---|---|
| Food and Beverages (15[7]) | 127.615 |
| Textiles and wearing apparel (17, 18) | 132.732 |
| Leather, leather products and footwear (19) | 198.416 |
| Wood products including furniture (20, 36) | 937.774 |
| Paper, Paper product, printing and publishing (21, 22) | 66.547 |
| Chemical and Chemical products (24) | 121.819 |
| Rubber and Plastic products (25) | 123.384 |
| Non-metallic mineral products (26) | 41.517 |
| Basic and Fabricated Metals, Machinery and Equipment (27, 28, 29) | 51.043 |
| Others (16, 23, 30, 31, 32, 34, 37, 40,41) | 46.647 |

***Source:*** Authors' computation

Table 6 below shows that there is significant variation in productivity across ownership type. The largest mean TFP (409.41) privately owned firm which participate in the global market by exporting their output and medium in size. The next highest (357.98) performing establishments are those under public ownership with medium size and participants in the export market. Medium sized firms are more productive when they are engaged in exporting of their products. The productivity of these firms varies not only due their export status but also the ownership structure such that irrespective of size and export status, privately owned firms are more productive.

*Table 6.* TFP of firms by ownership export participation and firm size

| | Ownership | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Private | | | | Public | | | | Joint | | | |
| | Exporting | | Not exporting | | Exporting | | Not exporting | | Exporting | | Not exporting | |
| | Large | Medium | Large | Medium | Large | Medium | Large | Medium | Large | Medium | Large | Medium |
| Mean TFP Using Wooldridge 2009 | 354.318 | 409.414 | 25.844 | 25.676 | 43.159 | 357.010 | 37.979 | 31.537 | 35.919 | 165.655 | 39.961 | 18.023 |

***Source:*** Authors' computation using estimated TFP

[7] The numbers in Parentheses denote the two digit ISIC (international standard industrial classification) that each group is comprised of.

Among non-exporting establishments, large size ones are found to be more productive. However, medium exporting firms are much more productive than large firms. In all the cases, exporting firms are more productive. This is in line with the findings previous literature (e.g. Bigsten and Gebreeyesus, 2009; Van Biesebroeck, 2005) that exporting firms are more productive because of two reasons. First, more productive firms self-select to exporting their product which means that exporting firms are more productive before participating in the global market by exporting. Second, there is evidence that firms learn from exporting.

## 6. Summary and conclusions

The objective of this paper is to estimate productivity level of Ethiopian large and medium scale manufacturing firms by comparing different methods. The development of estimating total factor productivity (TFP) is an on-going process. The methods implemented so far deal with solving the problems related to identifying the coefficient parameters (input elasticities) and the productivity there of. The problems are caused by, among others, simultaneity bias, selection bias (due to attrition) and measurement error in input factors. In this paper, six different methods - Ordinary least square (OLS), fixed effect estimator, Olley and Pakes (1996), Levinsohn and Petrin (2003), Robinson (1988) and Wooldridge (2009) - are compared. While Olley and Pakes and Levisohn and Petrin employ a two-step semi-parametric procedure to identify the input elasticities, Robinson and Wooldridge use a single step GMM estimation technique using lagged values as instruments. The OLS and fixed effects estimators are adjusted to give robust estimates tackling the potential problems arising from heteroscedasticity. The Wooldridge estimator is preferred in the literature because in addition to consistent estimates, it gives out more efficient and it accounts for serial correlation and heteroscedasticity at the same time.

The result shows that the parameter estimates strongly significant from statistical point of view in all the six methods. The direction of relationship between inputs and outputs is also in line with theoretical expectations in all the cases. The labor coefficient is lowest and the capital coefficient is highest in case of the Olley and Pakes method. The labor coefficient ranges from 0.20% in Olley and Pakes to 0.296% in OLS. The capital input elasticity falls in the range of 0.091% in fixed effects to 0.363% in Olley and Pakes. Raw material input elasticity goes from 0.529% in OLS to 0.629% in Levinsohn and Petrin.

When we compare the estimated mean TFP across the methods of estimation, there is large variation in magnitude where the Olley and Pakes approach gives the outlier in the ceiling edge (4012.201) and the floor is the OLS estimator (6.38). Even the fixed effect estimator is (8.15) is close to OLS. The rest three methods are close to each other being 239.58, 239.15 and 212.01 respectively in Wooldridge, Robinson and Levinsohn and Petrin. Even if they differ in the size of the estimated mean TFP, they are highly correlated with each other except Olley and Pakes. The highest correlation (99.97%) is between Wooldridge and Robinson as per our expectation since they has similar estimation procedure and method. All correlation between each of the five methods (Excluding Olley and Pakes) is above 92% (between Levinsohn and Petrin and fixed effects). The Olley and Pakes estimator, however, has less correlation with all the other methods, the maximum being 73.9% with the fixed effects model and the next highest correlation is 67.3% with OLS. The reason for the low correlation particularly with the recent estimators may be due to its use of investment as proxy where about 40.31% in the data used in this paper has zero investment value. This violates the core assumption of Olley and Pakes which states that firm level productivity is strictly increasing with investment (monotonocity assumption). Van Beveren (2012) and Biesebroeck (2008) concluded that there is high degree of correlation among the methods (including Olley and Pakes, 1996). However, the data they used might have comparatively less zeros of investment.

Taking the result from Wooldridge (2009), the coefficients are interpreted in view of factor elasticities as: on average when a firm raises its labor input by 1%, its real output (sales value) increases 0.259%, other inputs and the technology kept unchanged. On the other hand, if the firm increases its usage of capital service (proxied by depreciation allowance) by 1%, real output increases by 0.108% and if, using same other factors and technology, it increases the raw material input by 1%, real output increases by 0.561%. Thus, the manufacturing firms are much more responsive to changes in raw material usage as compared with other input factors. This is an indication that Ethiopian large and medium scale manufacturing firms are more dependent on raw material which further indicates that value addition by the firms is very limited. This result is similar with the findings of previously conducted researches in Ethiopia (e.g. Abegaz, 2013). Comparing the various industries within the manufacturing premise showed that the three most productive groups are wood products including furniture (937.77), leather products and foot wear (198.42) and textile and garment (132.72). This shows that there is significant variation in performance not only among all the industrial groups but even with in the top performance. A comparison of productivity performance using ownership structure, export status and firm size as factors showed that exporting firms are more productive in all the ownership and size categories. This is in line with expectations from intuition as well as literature (Bigsten and Gebreeyesus, 2009).

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## Policy implications

In order to secure the sustainability of the recent economic growth, there is a need to enhance industrial productivity and broaden its base so that the backward and forward linkages effectively put in place. To realize this, the manufacturing sector should be given priority in practice. The manufacturing sector is more dependent on raw material which implies that value addition is limited as a result there is a need to induce the use of labor and capital inputs in more productive way. Particularly, the capital input elasticity is very small leading to the marginal[8] productivity of capital smaller. To increase the marginal productivity of capital, there is a need to utilize the full capacity because low level of capital responsiveness arises from capital maturity which means that there is excess installed capital and adding to it may not lead to more production. According to central statistical agency of Ethiopia (2015), about 50% of the firms reported that they are exploiting the full installed capacity. The public sector which is responsible to promote the manufacturing sector and the private companies themselves should coordinate their efforts to score real change in the sector. Also it is necessary to update the capital stock to new technology embodied one because a mere capital stock may not help rather it requires some sophistication.

Lessons can be taken among the various industrial groups because there is a prevalent variation in productivity performance. Though the nature of each group may be peculiar yet it is possible to learn from each other their management practice, marketing, international experience, human resource management, etc. This will augment the use of resources in a productive manner. Moreover, private ownership and participation in the export market are drivers of productivity. Then all concerned body should incentivise the exporting process and the policy framework in place should be evaluated in its implementation to bring more firms to the export sector. This should be aimed not only raise the productivity of a production unit but it has an implication to improving the current accounts balance.

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[8] Marginal productivity of a factor of production is given by input elasticity*average productivity of the factor, i.e. $\beta_W * \frac{VA_{it}}{W_{it}}$; Where $\beta_W$ is input elasticity of input $W$, $VA_{it}$ value added of firm i at time t, and $W_{it}$ an input of firm i at time t.

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