Productivity Determinants in the Manufacturing Sector in Ethiopia: Evidence from the Textile and Garment Industries

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Abstract

The study aims at exploring the determinants of productivity using a census data of medium and large firms in the textile and garment industries in Ethiopia. The study reveals that labour and material inputs drive firm level outputs while the elasticity of output to capital input is weak. This could be due to the labour and material intensive nature of the textile and garment sector. Moreover, the analysis uncovers that human capital, agglomeration effects and incentive systems to be core drivers of productivity. To overcome endogeneity caused by potential simultaneous determination productivity shocks and labour input, the Levishom-Petrin estimator was used on two-year panel-data constructed using a recall data for 2015. The cross-sectional and panel data estimators yield qualitatively similar results in our study.

Keywords: TFP, Labour Productivity, Textile and Garment, Ethiopia

JEL Classification: D22, D24, L25

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1 Introduction

Firm productivity is an essential indicator of the strength of firms to stay in operation, expand, and compete in local and international markets and thereby contribute to employment, income, and generating essential foreign currency.

The textile and garment industries are some of the key strategic sectors the government of Ethiopia selected and provided a special attention in the successive five years plans of the country particularly since the launch of PASDEP in 2005, and further underlined in GTP I and GTP II. This is due to their strong linkage with the agriculture sector as well as their labour and material intensive nature, which potentially give the country a comparative advantage and competitive edge in the global market. Despite the potential gains of the textile and garment industries, actual benefits accrued in terms of growth of firms; employment generation; and export revenue have been under par. According to a report by the National Planning Commission (NPC, 2016), the textile and garment industries heavily underperformed in terms of export earnings and employment generation during GTP I period (2010-2015). At the end of the plan period, export earnings stood at USD 98.9 million (about 10 percent of the target USD 1 billion). It was also set to create job opportunities for 40,000 citizens in the sector during the same period, but only 50% of the target was achieved.

Hence, a comprehensive study on the state of productivity of the textile and garment industries and its determinants can help inform policy makers, academics, and the firms themselves to effectively address the challenges that hold the growth of the sector at bay. Some attempts have been made by several researchers to study the determinants of productivity in the manufacturing sector in Ethiopia (e.g., Bigsten

& Gebreeyesus, 2007; Gebreeyesus; 2008; Rijkers, Söderbom and. Loening, 2010). However, a careful scrutiny of the textile and garment industries is warranted to addresses specificities of the industries that one cannot learn from general studies of the manufacturing sector.

The currents study aims to contribute to bridge the research gap in the textile and garment industries by analysing the source and determinants of TFP and labor productivity in the sector.

The rest of the paper is organized as follows. A conceptual framework and a brief review of related literature is given in section two while section three provides an overview of the textile and garment industries in Ethiopia. Section four briefly describes the 2016 census survey of the textile and garments industry and presents a preliminary descriptive statistics based on the survey. Section five discusses the empirical strategy and estimation results. The study concludes in section six.

2 Related Literature

In this section, we briefly review the concept of productivity, its measurement, and a brief empirical review of the source and determinants of TFP and labor productivity.

2.1 Firm Productivity Measurement

Productivity, the efficiency with which inputs are converted into outputs, is a fundamental concept in economic analysis. Productivity growth is the basis for improvements in real income and welfare. The measures of levels and growth of productivity, therefore, represent important economic performance indicators.

The economic theory of productivity measurement dates back to the works of Jan Tinbergen (1942, as cited in OECD Productivity Manual, 2001) and Robert Solow (1957). They developed productivity measures in the framework of a production function relating to the analysis of economic growth. The literature on the subject has made a remarkable progress since then and the concern of productivity has become pervasive in today's globalized world.

According to the OECD (2001), the objectives of productivity measurement can be summaries as follows:

Technology: A frequently stated objective of measuring productivity growth is to trace technical change.

Efficiency gains: A firm's internal efficiency is an important factor for its economic viability – efficiency both in terms of the use of inputs, given technology (i.e. technical efficiency), and in combining its inputs, given technology and market prices (i.e. allocative or price efficiency). Technical efficiency refers to the "ability of firms to maximize output from a given combination of inputs and technology", i.e. the effectiveness with which resources are being used (Hill and Kalirajan, 1993). It occurs when a firm makes the best use of its inputs, given technology (i.e. operating on the production frontier). Allocative efficiency, on the other hand, occurs when a firm uses its inputs in 'optimal' proportion, given technology and prices (i.e. operating at the optimal point on the production frontier or using optimal levels of inputs).

Benchmarking production processes: Productivity measures can be used to compare a given production process across firms in the same industry (firms using similar inputs to produce similar output). Firms can then use this result to know their position in terms of productivity in the industry and work accordingly.

Living standards: Productivity matters because it is the main determinant of national living standards.

Measures of Productivity:

The literature provides several productivity measures. The choice between these measures depends on the purpose of the measurement and the availability of data. Productivity measures can broadly be classified as *single factor* productivity measures and *multi-factor* productivity measures (also known as *total factor productivity*). The former reflect units of output produced per unit of a given input, the later relates to a measure of output to multiple inputs (OECD, 2001; Schreyer and Pilat, 2002). This distinction applies to both macro level and industry or firm level productivity analysis. Another distinction of particular relevance at the industry or firm level is between productivity measures that relate gross output to one or several inputs and those, which use a value-added concept to capture movements of output.

The single factor productivity levels are likely to be influenced by the intensity of use of the omitted factor inputs. It is possible that two producers having the same production technology may have different labor productivity levels if one happens to use capital much more intensively than the other due, for instance, to differences in factor prices (Syverson, 2011).

Cognizant of this, researchers often use a productivity measure that is invariant to the intensity of use of observable factor inputs, namely total factor productivity (TFP). The idea is that variations in TFP reflect shifts in the isoquants of a production function indicating that producers with higher TFP will produce greater amounts of output with the same set of observable inputs than those with lower TFP (Syverson, 2011). Unlike in the case of single factor productivity, TFP is less likely to be affected by difference in factor prices because it induces movements along isoquants rather than shifts in isoquants.

In this paper, we focus on two types of productivity measures: Total factor productivity (TFP) and labour productivity. Both are crucial measures of production efficiency and thus important indicators for policymakers at both macro and industry or firm levels. In particular, there is special interest in labour productivity measures as they also represent welfare and development levels (Heshmati & Rashidghalam, 2016). Hence, in what follows, we briefly discuss these measures .

2.2 Overview of the Determinants of Firm Productivity: Empirical Review

Recent studies such as Syverson (2011) revealed that one of the significant findings in the productivity literature is the existence of widespread variations in productivity and efficiency levels across establishments and firms. Abegaz (2013), in his study of technical efficiency and total factor productivity (TFP) in the Ethiopian manufacturing sector, found wide dispersion of efficiency and TFP levels among firms. Similarly, Hailu & Tanaka (2015) presented evidence of substantial technical efficiency variations in the sector. This prompts the question, what explains such productivity differentials among firms. The literature provides various factors affecting productivity and productivity growth of firms. These include factors internal and external to the firm. In what follows, we discuss the main factors affecting productivity.

Human capital: Human capital, as measured by educational attainment, plays a crucial role in determining firm's performance such as output, productivity and profit (Honig 2001). Recently, Raggl (2015) investigated the relationship between human capital and total factor productivity in the Middle East and North Africa region covering the period between 1980 and 2009. His findings suggest that human capital plays an important role in changing the efficiency in which existing input factors are used. The author emphasizes the need to achieve certain threshold level of educational attainment if domestic innovations are to be efficient. World Bank (2012) studied the investment situation of Chinese FDI in Ethiopia. The study found labor productivity to be very low due to inadequate education. Hailu & Tanaka (2015) also showed that despite Ethiopia's abundant human resources, the quality of the labor force is generally low. There is a lack of practical, systematic, and targeted worker training programs and implementation methods that can improve workers' production efficiency and productivity in the companies.

Export orientation: Bigsten & Gebreeyesus (2009) studied the relationship between export and firm productivity using firm-level panel data for the Ethiopian manufacturing sector and reported that productivity appears to be strongly associated with exporting. They concluded that exporting firms pay higher wages, have more workers and have more capital per worker. Van Biesebroeck (2005) also reported similar findings for Sub-Saharan African manufacturing firms. In an earlier study, Bernard & Jensen (1999) also found that US firms increased their productivity after entering international market. Using data of Slovenian manufacturing firms operating in the period 1994–2000, De Loecker (2007), explored the effect of exporting on productivity. He found that exporting firms received higher productivity gains than non-exporting firms and that productivity increases further overtime.

Management practice: Several studies, (Bloom et al., 2013; Mano et al., 2012 and Syverson, 2011), show management practices play an important role on firm productivity. Bloom et al. (2013) investigated whether managerial skill explains productivity differential among Indian textile firms using a randomized field experiment. The researchers provided free consulting on management practices to randomly chosen treatment plants and compared their performance to a set of control plants. Their finding shows that adopting these management practices "raised productivity by 17% in the first year through improved quality and efficiency and reduced inventory, and within three years led to the opening of more production plants. A cross-country study by Bloom et al. (2005) looking at medium sized manufacturing firms in Europe and the US found that good managerial practices are strongly associated with superior firm performance in terms of productivity, return on capital employed and sales growth. Goldfarb & Xiao (2011) assessed the effect of managerial capability on firm performance in the US telephone services providers. The authors found that enterprises run by high ability managers were more likely to survive and have higher revenue. Using longitudinal data in the metalworking sector in Addis Ababa, Abebe (2012) finds that foreign owned firms had better productivity due to their superior management practices.

Firm size: Leung et al. (2008) explored the importance of the relationship between firm size and productivity using a Canadian administrative dataset during the 1984-1997 period. The authors also tried to gauge the magnitude of the firm size-productivity relationship and found a significant size-productivity relationship in terms of both labor productivity and TFP. The size-labor productivity relationship is stronger in the manufacturing sector while a positive and stronger relationship between firm size and TFP was found in non-manufacturing. Evidence from Van Biesebroeck (2005) also indicated significant variation in the TFP distributions of large and small African manufacturing firms. Using data on publicly-traded manufacturing firms, Lee and Tang (2001) found that firms with more than 500 employees and firms employing between 100 and 500 employees are 17 percent and 15 percent more productive than firms with less than 100 employees in Canada, respectively. On the contrary, Taymaz (2002) found a negative relationship between productivity growth rates and firm size.

Firm age: A study by Jenson et al. (2001) on productivity levels of different age cohorts suggests that new entrants are more productive compared to established firms. According to the authors, surviving cohorts tend to increase productivity levels over time, while productivity levels of entering cohorts is observed to converge after five to ten years. In line with this, Taymaz (2002) argues that new firms are likely to experience higher productivity growth rates than existing firms. Other studies (Celikkol, 2003) found positive relationship between age and firm productivity growth rates in the U.S. food and kindred products industries.

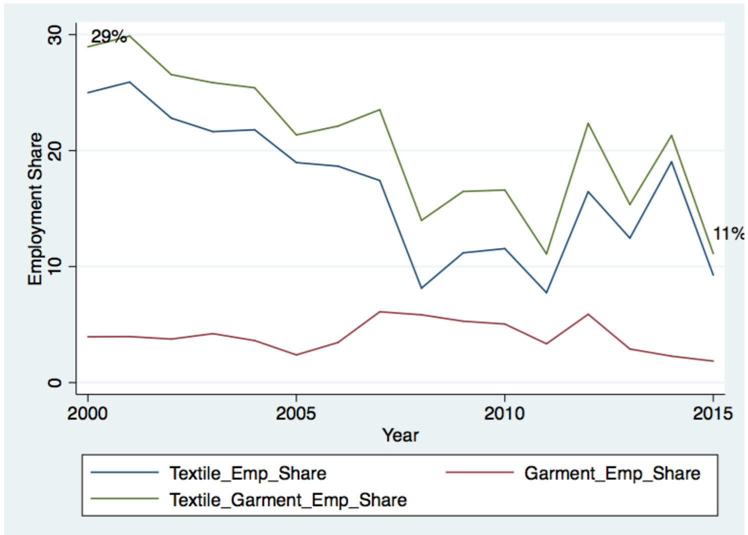
Other firm productivity determinants, which are external to the firm, include firm infrastructure facilities, regulations, trade policies, development and access to finance (Bloom et al., 2010).

3 Overview of the Textile and Garment Industries in Ethiopia

The establishment of Dire-Dawa Textile Factory in 1939 marked the beginning of modern textile industry in Ethiopia. Since then the textile and garment has evolved into having one of the largest shares in employment and value-added in the manufacturing sector. However, like most sectors in the manufacturing industry of the country, its growth has been slow, if not stagnant, in most decades.

The textile and garment sector includes spinning, weaving and finishing of textiles, manufacture of cordage, rope, twine, netting, knitting mills and manufacturing of wearing apparel. The major products of the sector include cotton and woolen fabrics, nylon fabrics, acrylic and cotton yarn, blanket, bed sheet, shirts, carpets, gunny bags, wearing apparels, and sewing thread.

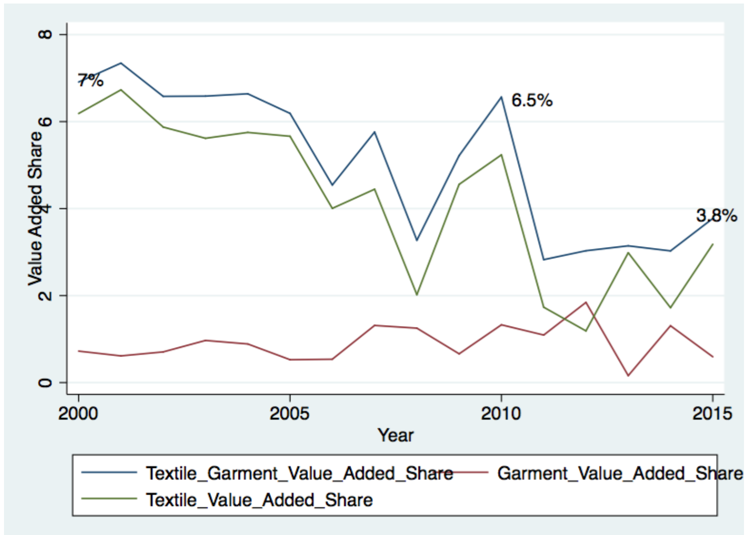
The textile and garment industry was one of the largest employers in medium and large manufacturing sector. However, its share of employment in the country's



Source: Source: Authors' computation using CSA Large and Medium Industries Survey.

Figure 1: **Employment Share of the Textile and Garment Industry in Medium and Large Manufacturing**

medium and large manufacturing sector declined from about 29% in 2000 to 21% in 2014 and 11% in 2015 (See Figure 1. The fluctuation in the share of employment (especially after 2007) is dictated by the textile industry while garment had relatively stable share of employment in the manufacturing sector overtime. Similarly, the share of value-added of the textile and garment industry in medium and large manufacturing sector declined from about 7% in 2000 to 4% in 2015 (Figure 2. Hence, it is evident the textile and garment industry underperformed compared to other forms of manufacturing in the last 15 years.



Source: Source: Authors' computation using CSA Large and Medium Industries Survey.

Figure 2: **Value Added Share of the Textile and Garment Industry in Medium and Large Manufacturing**

4 Data and Descriptive Statistics

4.1 Data

To address the aforementioned objective, primary data was collected in 2016 from 137 textile and/or garment enterprises located throughout the country using a structured survey instrument. This is a census survey of all firms in the textile and garment industries that employed 25 or more workers. Before the survey was conducted, an enterprise mapping exercise was conducted. The exercise was intended to identify as many as possible of the formal sector businesses operating in the garment and textile industries that would constitute a sampling frame. The enterprise mapping arm of the study was successfully completed by generating a list of firms that consists of 164 enterprises with their location and contact detail, year of establishment, market orientation, number of workers and installed production capacity. The list of the 164 textile and garment enterprises is collected in the first instance from secondary sources such as the Ministry for Industry and the Textile Industry Development Institute. Ultimately we conducted a ground truth validation and found only 137 active garment and textile enterprises employing more than 25 workers, which were all in operation in 2016 in all the regions.

We collect census data from the entire 137 textile and/or garment enterprises of which 33 are from the textile industry, 72 from the garment industry and the rest from the integrated industry. In what follows we briefly describe the profile of all the 137 firms ,their owners and/or managers as well as their worker composition while we use only information collected from the 88 firms for the econometric estimation.

4.2 Descriptive Statistics

Firms and Owner/Manager Profiles

About 85% of respondents hold a college diploma and above. About 33% of respondents are owner-manager, while 21% are human resource managers. The rest are president/manger (13%), vice-president /deputy manager (8%), production manager (8%), while the remaining 17% hold other positions. Detailed profile of respondents disaggregated by sub-sector is provided in Table A1 of the appendix.

Table 1 provides some key characteristics of the surveyed firms such as ownership and legal status at industry level. More than a quarter of the firms are part of a larger firm. Similarly, slightly more than a quarter are located in an industrial zone. On the average the firms have been operating for about 11 years with firms in the textile industry being in operation for longer compared to their garment

Table 1: Firm Characteristics by Industry

	Textile	Garment	Integrated	All
N	33	72	20	137
General Characteristics				
Firms that are part of larger establishment (%)	33.3	20.8	25	27
Firms, which are located in an industrial zones (%)	27.3	31.9	15	26.3
The av. years firms started operation	1998/9	2009/10	2004/5	2005/6
Firms' legal status (%)				
Public Limited Company	12.1	12.5	0	10.2
Private Limited Company	78.8	70.8	70	74.5
Sole Proprietorship	0	12.5	10	8
Partnership	9.1	4.2	10	5.8
Government enterprise	0	0	10	1.5
Ownership form of firms (%)				
Domestic private	58.4	76.9	49.2	70.1
Foreign Private	39.8	21.7	40	27.1
State owned	1.8	1.4	10.8	2.8
Firms' av. no. of major owners	2.4	2.2	2.3	2.4
The average largest share of one person within a firm (%)	62.8	73.5	73.8	70.3

Source: Authors' computation using 2016 EDRI Textile and Garment survey data

and integrated counter-parts. A large proportion (75%) of the firms are private limited companies; it is striking that partnership is rare in the industry. Domestic private firms dominate in number accounting for 70% followed by foreign private firms (27%) and domestic state owned (3%). Foreign ownership is relatively more widespread in the textile and integrated than the garment sector.

Overview of Firm Performance: Sales Turnover and Export Shares

Table 2 shows that firms in the integrated industry have fared better than their counterparts in the textile and garment in terms of sales revenues and export shares. The sales revenues are in real terms as the nominal sales have been deflated using the GDP deflator using 2011 as a base year. One the one hand, the textile industry registered the biggest growth in sales between 2013/14 and 2014/15 among the three industrial groups. On the other hand, the firms in the garment sector not only had relatively smaller sales revenues in both 2013/14 and 2014/15, but the growth rate of sales was negative between 2013/14 and 2014/15. Moreover, the average export share grew between in 2014/15 from its level in 2013/14 for firms in all

Table 2: Sales Turnover and Export Shares

Values in '000 ETB	Textile		Garment		Integrated		All	
Year	2013/14	2014/15	2013/14	2014/15	2013/14	2014/15	2013/14	2014/15
N	27	30	41	58	19	16	94	118
Total annual sales	32436.5	47756.7	9246.6	8277.4	69085.1	64658.5	27470.9	28498.8
Sales growth		47.2		-10.5		-6.4		3.7
Av. share of export from total sales (%)	10.2	12.8	15.6	17.3	27.7	35.4	14.4	17.2

Annual sales and sales growth are in real terms (nominal values deflated by GDP deflator)
The 'all' category in the last column includes firms in the 'other' category such as ginners
Source: Authors' computation using 2016 EDRI Textile and Garment survey data

three-industry groups.

5 Empirical Strategy, Estimation, and Discussion of Results

This section focuses on measuring productivity and its determinants. The first part of this section uses various estimations methods to compute firm level productivity. The second part addresses the determinants of firm-level productivity

5.1 Firm Level Productivity Estimation and Discussion

As discussed in the preceding sections, the productivity of firms can be measured either using total factor productivity (TFP) or through partial productivity measures by taking account of the contribution of a specific input, such as labor or capital. In this study, we measure firm productivity using both TFP and labour productivity. First, we compute TFP at firm level as a residual from augmented Cobb-Douglas production function. We use OLS and Levinsohn-Petrin estimators to compute TFP at firm level. Secondly, we compute labour productivity as the ratio of the value of output produced (proxied by the value of sales) and the number of workers involved.

To compute firm-level TFP we use information on output, labour, intermediate goods (materials) and capital inputs at the firm level for firms with such information among the 137 firms engaged in the textile, garment, and integrated industries.

Assuming the production technology to be Cobb-Douglas

$$Y_{it} = \beta_l L_{it} + \beta_k K_{it} + \beta_m M_{it} + \gamma_s + \omega_{it} + \epsilon_{it} \tag{1}$$

Where Y_{it} is the logarithm of the firm's output measured as the value of gross sales; L_{it}, K_{it} and M_{it} are the logarithms of the values of firm i's costs of labour, capital, and materials in period t respectively. β is a vector of input elasticities of firms. γ is a vector of industry-specific effects. ω_{it} represents firm i's total factor productivity in logs in period t while ϵ_{it} denotes an i.i.d component capturing idiosyncratic deviations from the mean due to unexpected events such as measurement errors or external factor. We estimate (1) to solve ω_i. Hence, we estimate log of TFP (ω_i) as follows.

$$\hat{\omega_{it}} = Y_{it} - \hat{\beta_l} L_{it} - \hat{\beta_k} K_{it} - \hat{\beta_m} M_{it} - \hat{\gamma_s} \tag{2}$$

Estimated TFP in level can then be computed as the exponential of ω_{it} as $\hat{\Omega}_{it} = e^{\hat{\omega}_{it}}$ Since the choice variable inputs, especially labour, may depend on productivity shocks, OLS estimation of (1) can be biased due to endogeneity arising from simultaneous determination of the choices of labour input and the level of productivity, which is captured by the error term. To deal with this problem, we use the Levinsohn-Petrin estimator, which addresses the potential simultaneity problem by using intermediate inputs such as materials as instruments for productivity shocks.[1] Unlike Olley and Pakes (1996) who suggest investment as an instrument for productivity shocks, Levinsohn and Petrin (2003) argue that intermediate goods respond more smoothly to such shocks (See Levinsohn and Petrin (2003) for the

[1] For a review of methods developed over the years to tackle firm-level productivity estimations such as endogeneity of inputs, see Beveren (2010).

theoretical basis of this estimator which is in the spirit of the model developed by Olley and Pakes (1996) to deal with simultaneity). Additionally, the non-zero investment condition in Olley and Pakes (1996) substantially truncates the data when actual annual investment is zero. On the other hand, the use of materials as instruments for unobserved productivity preempts data truncation as material costs in operational firms is rarely zero.

We use panel fixed and random effect estimators complementing OLS and Levinsohn and Petrin (2003) estimators to compute the total factor productivity. Even though the survey was conducted for 2016 only, we have recall information on inputs and output variables for the previous year.[2] Hence, we are able to conduct panel and Levinsohn-Petrin estimations in addition to OLS.[3] In addition to the Levinsohn-Petrin estimator, the panel fixed estimator also attenuates simultaneity problem by using the with-in variation in the sample if unobserved productivity shocks is to be firm specific, but time invariant (Pavcnik, 2002; Ackerberg et al., 2007). However, Wooldridge (2009) argues that the strict exogeneity of inputs assumed in panel fixed effect estimators are not tenable in practice. We also thus employ the IV approach to overcome the endogeneity concern.

Summary Statistics and a short description of the variables used to estimate TFP based models 1 and 2 are given in Table 3.

Table 4 provides the estimated input elasticities based on estimation of (1) using conventional OLS, random and fixed effect panel estimators, and the Levinsohn-

[2]Our sample of firms keeps records of their business transactions and hence we do not believe that recall bias is a serious concern in our analysis.

[3]For the panel and Levinsohn-Petrin estimators we use data for 2016 and recall data for 2015.

Table 3: Summary Statistics for the Estimation of Total Factor Productivity

Variable	Description	N	Mean	SD	Min	Max
lsales	Log of Sales Value	88	9.36	1.90	5.47	13.27
lcapital	Log of Capital Value	88	8.67	2.19	3.37	14.22
llabour	Log of Labour Cost	88	7.45	1.71	3.37	11.62
lmaterial	Log of Material Cost	88	8.85	1.98	3.99	12.96

Source: Authors' computation using 2016 EDRI Textile and Garment survey data

Table 4: Input Elasticities and Firm-level TFP

Estimator	OLS	OLS	Panel FE	Panel RE	Levinsohn-Petrin
Dep. Variable	Log (sales)	Log (sales)	Log (sales)	Log (sales)	Log (sales)
log capital	-0.05	-0.03	0.03	-0.02	0.00
log labour	0.28***	0.30***	0.51***	0.37***	0.28***
log material	0.71***	0.72***	0.40***	0.59***	1.00***
Industry FE: Base: Textile					
Garment	-0.33				
Integrated	-0.11				
Others	-0.05				
Constant	1.48***	1.00***	1.81	1.53***	
Obs.	88	88	147	147	147
R-sq	0.880	0.876	0.500		
TFP	1.23	1.25			0.87

Note
***, **, * indicate Significance at 1%, 5%, 10% level
Source: Authors' computation using 2016 EDRI Textile and Garment survey data

Petrin method.

The input elasticities estimated by the various estimators are essentially similar. There is a very high correlation among the estimated TFPs. For example, the simple correlation between the log of TFP obtained by OLS and Levinsohn-Petrin is 0.74. This is in line with the high correlation between TFPs estimated using a number of methods in the literature (See, for example, Beveren, 2010) enhancing our confidence in the estimates.

To account for industry level heterogeneity, we controlled for industry fixed effects provided in the first column of Table 9. We find insignificant industry fixed effects pointing to similar response of output to changes in inputs among the textile, gar-

Source: Source: Authors' computation using CSA Large and Medium Industries Survey.

Figure 3: **Correlation between TFP computed by OLS and labour productivity**

ment, integrated, and the "other' category of industries.[4]

The elasticity of production to capital input comes out as insignificant in all specifications provided in Table 4. The potential explanation for this seemingly anomalous result is that unless capital has been accumulated heavily already, the use of obsolete or less productive technologies may not enhance productivity. Melaku (2013) and Hailu and Tanaka (2015) found a similar result for the manufacturing sector in Ethiopia. Moreover, this could be explained by the very nature of the textile and garment industries, which are generally labour and material intensive. Thus, the need for capital saturates quickly implying that further accumulation of physical capital is not adding to production.

Similarly, in line with the findings of Melaku (2013) and Hailu and Tanaka (2015) ,

[4]This is confirmed by industry – level estimates not reported her,e but are available up on request.

we find that output in the textile and garment industries are highly responsive to intermediate inputs (materials) followed by labour. In labour -abundant country like Ethiopia, the high elasticity of the textile and garment industries is awelcome news and points to the high potential of the sector to absorb more labour input.

5.2 Determinants of Productivity: Estimation and Results

5.2.1 Empirical Specification and Estimation

Research has documented substantial productivity differences among firms within an industry (See for example, Syverson, 2004 for the US manufacturing; Hsieh and Klenow, 2009 for India and China, among others). In addition research uncovers enormous disparity in the evolution of firms through time. While some firms grow and survive others stagnate or even cease to exit. Cases in point are the findings by Ábrahám and White (2006) and Foster et al (2008). Hence, studying the determinants of productivity has been at the center of research and policy dialogue. In this section, we analyze the determinants of firm-level productivity (both TFP and labor productivity) that we estimated in the previous section.

We regress log of TFP, ω_{it}, computed from (2) and labour productivity on a number of potential determinants of productivity based on past empirical literature. These include measures of human capital, agglomeration effects, openness to international trade, incentive systems and management practices, and firm age and size.
We regress log of TFP, computed from (2)

$$\hat{\omega}_{it} = \tau_i + \theta^{'} X_{it} + \varepsilon_{it} \tag{3}$$

where ω_{it} represents the log of TFP or labour productivity, τ_i captures industry

Table 5: **Summary Statistics for the Estimation of Total Factor Productivity**

Variable	Description	Mean	SD	Min	Max
ln_TFP_OLS	Log of TFP by OLS estimator	0.01	0.66	-1.90	2.01
Ln_TFP_LP	Log of TFP by Levishom-Petrin Estimator	-1.54	0.87	-3.67	1.18
llabour_productivity	Lof of labour Productivity	4.32	1.33	-0.33	7.06
lpercent_high_skilled	Log of the percentage of high skilled workers	2.65	0.92	0.51	4.19
Industrial Park	Dummy '1' if located in an industrial park, 0 otherwise	0.27	0.45	0.00	1.00
lave_salary_low_skilled	Log of average salary of low skilled workers	6.76	0.30	5.99	7.47
lave_salary_mid_skilled	Log of average salary of mid skilled workers	7.13	0.37	6.21	8.02
lave_salary_high_skilled	Log of average salary of high skilled workers	7.61	0.57	6.62	9.55
talent_management	An index whether the firm identifies perfromance, has a reward system				4.00
	for managers and non-managers, has performance identification	2.42	1.57	0.00	4.00
performance_tracking	Dummy '1' if more than 2 KPsI, '0' otheriwse	0.31	0.46	0.00	1.00
export	Dummy '1' if exports, '0' otherwise	0.32	0.47	0.00	1.00
export xFirmSize	Interaction term for export and firm size	1.24	1.94	0.00	5.00

Source: Authors' computation using 2016 EDRI Textile and Garment survey data

specific effects, and X is a vector of covariates.

Data on the major determinants of productivity studied in literature such as human capital, managerial practices, firm size, firm ages, ownership structure, exposure to foreign technology are given for one year only in our survey. Hence, we rely on the productivity estimates of the OLS given in the first column of Table 9 in the previous section. Since the productivity estimates from the various specifications and estimators were largely similar, relying on OLS is also preferable based on efficiency of the estimates. Summary statistics for the main variables of interest for the estimation of the determinants of productivity are given in Table 5.

Table 6 provides estimates of the determinants TFP while Table 7 reports the determinants of labour productivity. In both tables the first columns represent estimations for all the four industry categories while second columns show estimations restricted to garment and integrated. The third columns in both tables focus on the garment industry only. The number of observations in the textile industry is small, so separate regression is not possible due to limited degrees of freedom. In what follows we discuss the estimations results of the determinants of firm productivity based on Tables 6 and 7 .

Table 6: **Determinants of TFP**

	All Four Industries	Garment and Integrated	Garment
Estimator	OLS	OLS	OLS
Dep. Variable	Log TFP	Log TFP	Log TFP
Human Capital			
lpercent_high_skilled	0.192*	0.262	0.450**
Agglomeration			
Industrial Zones	0.342**	0.367	0.189
Incentives and Management Practices			
laverage_salary_low_skilled	0.188	0.232	0.464
laverage_salary_mid_skilled	-0.426	-0.645	-1.288*
laverage_salary_high_skilled	0.445*	0.793*	1.726***
talent_management	-0.000	0.031	0.003
performance_tracking	0.031	0.072	0.238
Exposure to Foreign Markets			
export	-0.856	-0.663	-0.832
export x firmsize	0.147	0.067	0.160
Firm Age and Size			
firm_age			
2nd Quantile	0.609***	0.699**	0.593*
3rd Quantile	0.204	-0.001	0.276
4th Quantile	0.818***	0.859**	0.344
5th Quantile	0.440*	0.434	0.048
Firm Size			
2nd Quantile	0.174	0.293	0.797**
3rd Quantile	0.401*	0.692**	1.185***
4th Quantile	0.655**	1.001**	1.171**
5th Quantile	0.152	0.497	0.796
Constant	-2.880	-4.718	-9.278**
Obs.	88	59	47
R-sq	0.281	0.379	0.567
F	1.61 (0.084)	1.47 (0.153)	2.23 (0.027)

Note
***, **, * indicate Significance at 1%, 5%, 10% level
Source: Authors' computation using 2016 EDRI Textile and Garment survey data

Table 7: **Determinants of Labour Productivity**

Estimator	OLS	OLS	OLS
Dep. Variable	Labour Productivity	Labour Productivity	Labour Productivity
Human Capital			
lpercent_high_skilled	0.404**	0.153	0.145
Agglomeration			
Industrail Zones	0.014	-0.104	-0.085
Incentives and Management Practices			
laverage_salary_low_skilled	0.346	-0.321	-0.597
laverage_salary_mid_skilled	-1.387*	-0.442	-0.252
laverage_salary_high_skilled	1.504***	0.647	1.485
talent_managment	0.075	0.113	0.152
performance_tracking	-0.218	-0.500	-0.260
Exposure to Foreign Markets			
export	-0.608	-0.355	-0.912
export x firmsize	0.114	-0.004	0.228
firm_age			
2nd Quartile	1.040**	2.013***	1.737***
3rd Quartile	1.083*	2.234***	2.424*
4th Quartile	0.938*	2.093***	1.489**
5th Quartile	1.116**	2.401***	2.331***
Firm Size			
2nd Quartile	0.538	0.209	0.719
3rd Quartile	0.533	0.594	0.802
4th Quartile	1.205**	0.113	0.176
5th Quartile	0.451	0.798	-0.051
Constant	-2.115	1.916	-3.911
Obs.	88	64	47
R-sq	0.303	0.537	0.564
F	1.79 (0.047)	3.13 (0.001)	2.21 (0.029)

Note
***, **, * indicate Significance at 1%, 5%, 10% level
Source: Authors' computation using 2016 EDRI Textile and Garment survey data

5.2.2 Determinants of Productivity: Discussion of Results

The Role of Human capital on Productivity

We find that human capital, measured by the percentage of high-skilled employees, comes as one of the most significant and robust determinants of both TFP and labour productivity. The role of human capita in enhancing productivity is an empirical regularity in both macro and micro studies of productivity. Examples of studies that find a significant role of human capital on productivity include Ilmakunnas et al., (2004) for Finland and Raggle (2005) for Middle East and North Africa.

Agglomeration Effect of Industrial Parks/ Clusters

Industrial parks or clusters enhance productivity through learning from neighboring firms and cost effectiveness due to lower transaction costs of doing business. We find a strong positive impact of being located in industrial zone/or clusters on TFP. This is in line with Lin et al., (2011) who find significant productivity gains from agglomeration for China.

Exporting behavior and Productivity

We fail to detect a significant correlation between exporting behavior of firms and productivity. This contradicts several studies such as Bigsten & Gebreyesus for Ethiopia; Van Biesebroeck (2005) for Sub-Sahara Africa, and De Loecker (2007 for Slovenia that find a productivity-enhancing role of exporting or participating in international market in general. Our findings are mostly closely related to the strand of literature, which emphasize that exporting per se doesn't play a significant role in boosting productivity, but rather productive firms self-select into exporting (See, for example, Arnold and Hussinger, 2005). However, since our results are based on cross-sectional analysis with limited number of observation, they are only indicative and provoke a need for further research to investigate why exporting fails to enhance productivity in the textile and garment industries.

Incentive Systems and Management Practices

Another determinant of firm productivity is the incentive system in place. Several works by Edward Lazear has shown that monetary and non-monetary rewards enhance productivity (see, for example, Lazear (2000)). One aspect of an effective incentive system is the level of remuneration to workers. We find that the level of pay to high- skill workers has a significant positive role in enhancing TFP and labour productivity in most specifications. The role of pay in productivity for mid and low skilled workers is inconclusive in our model.

Another determinant of firm productivity is the quality of management practices in firms. Notable works in this field include Bloom and Van Reenen (2010) and Bloom et al., (2012) among others that find a robust significant positive role of quality management in enhancing productivity. We model two indices of management practice that capture talent management and performance tracking to measure the quality of management system in the textile and garment industry. We measure talent management by an index composed of whether the firm identified top performers, has a reward system for managers and non-managers, and whether it actually rewards when the firm achieves production targets. We measure performance tracking by whether the firm has more than two key performance indicators (KPIs) or not. We find no significant role of theses practices on productivity in our analysis. However, this could be due to lack of variation in the measures and the 'yes or 'no' nature of the questions. The impact of management practices may be detected with more comprehensive measures of management practices in the manner Bloom and Van

Reenen (2007) did where a team of researchers score the management practices based on responses to a range of questions.

Firm Age and Size

The correlation between firm size and productivity is one of the most widely studied aspects of firm productivity. Similarly, the role of firm age and productivity has attracted the attention of productivity researcher for decades. We measure firm age and size by dividing the firm's age into five quantiles and using the first Quantiles as base.

We find a significant positive relationship between firm age and TFP in most specifications suggesting the positive role of learning by doing. Our results indicate a concave relationship between firm size and TFP. Firms in both tails of the size spectra are less productive than their counter parts in the middle.

6 Conclusions and Policy Implications

The current study has analyzed the determinants of firm-level productivity in the textile and garment industries in Ethiopia using a census data for 137 firms collected in 2016. It particularly focused on the status of total factor and labour productivities and their determinants.

This study has relied on a cross-section of firm level survey collected in 2016. A two-year panel-data was constructed and analyzed for parts of the research using a recall data for 2015 in order to employ panel data models particularly the Levishom-Petrin estimator to address endogeneity caused by potential simultaneous determination of productivity and labour input. Our results are largely consistent and robust across most specifications. However, despite this we cannot claim we have fully established a clean causal relationship between the variables of interest. Hence, a panel data with a reasonable time span can better identify causality in future work when and if additional rounds of survey are conducted.

We find significant elasticities of output to labour and material inputs while the response of output to capital is weak. Thus, labour and material inputs drive firm level outputs in the textile and garment industries in Ethiopia. The labour and material intensive nature of the textile and garment industries could be behind this finding. Our analysis also reveals that human capital, agglomeration effects and incentive systems to be the core drivers of productivity in the textile and garment industry.

The findings that human capital came out as one of the strong correlates of productivity is in line with empirical research in field. Close interaction between the private sector and the government to identify the skill gap in the economy and improve labour-market information systems can help better matching of supply of and demand for skills. Revisiting the higher education policy especially TVET centres to enable them to produce an adequately trainable workforce is also desirable. On-the-job trianing subsidies can minimise the disincentive effect on the side of firms due to high labour turnover

The positive relationship between productivity and location in industrial zone (clusters) indicates a productivity-enhancing role of agglomeration effect. This is good news as construction of industrial parks in the country is undergoing in earnest. Encouraging participation of domestic firms in the industrial parks can enhance productivity through technology diffusion

Another factor that consistently appeared as a significant correlate of productivity in most specifications is the positive role of incentives on productivity. The average salary of high-skilled labour and productivity was particularly apparent. Reasonable incentive system in place not only boosts firm productivity as evidenced by our analysis, but also can also potentially help retain labour.

Future work based on panel data with a reasonable time can help overcome omitted variable biased arising from unobserved firm-specific heterogeneity. Moreover, reasonably spanned panel data enables one to analyze dynamics such as firm growth, productivity trends, entry and exit aspects of firms.

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