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What drives productivity change in the manufacturing sector? Evidence from the metalworking industry in Ethiopia

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Abstract

We employ longitudinal data to explore sources of heterogeneity in productivity among firms in the metalworking industry in Ethiopia. We measure multifactor and labor productivity using non-parametric and regression residual parametric approaches. We find a sizable improvement in both labor productivity and TFP over time, which is also accompanied by large productivity dispersion across firms in the industry. The decomposition of industry-level productivity indicate that productivity increases is mostly explained by the reallocation of market shares across plants in the industry and that firm exit is preceded by declining productivity trends. Our reduced model also indicates that labor productivity and TFP is significantly higher in firms with a large share of workers with vocational training background. Productivity, however, does not differ with firm ownership. These results are robust to the choice of productivity measures.

Key words: metalworking, labor productivity, TFP, exit, entry, human capital
JEL code: O12, D24, J24

1. Introduction

Low level of productivity is one of the key problems facing firms in developing countries (Bloom et al. 2010). Low productivity is often associated with large intra- and inter-industry productivity dispersions. The persistence of large productivity gaps and wide dispersion of productivity across firms could potentially prevent the efficient allocation of labor and capital in these economies (McMillian et al. 2014; Foster et al. 2016; Restuccia and Rogerson 2017).¹ The resulting allocative inefficiency further thwarts pivotal changes in resource allocation, productivity and wage growth that would be crucial for the structural transformation of these economies. A good measurement of productivity, deeper understanding of its sources and drivers is thus vital to identify areas of intervention which could release the growth and productivity potentials of industries in developing countries.

While the sources of large inter-sectoral differences in productivity among firms in developed countries has received a great deal of attention (Foster et al. 2001; Syverson 2004; Bartelsman et al. 2013; Asturias et al. 2017, Bartelsman and Wolf 2017; Decker et al. 2017), there has been limited empirical work on intra-industry productivity differences, particularly in sub-Saharan Africa context. The few studies that analyzed sources of productivity growth and its relationships with firm idiosyncrasies have produced mixed results (e.g., *Van Biesebroeck 2005*; Shiferaw 2007; *Gebreeyesus 2008*; Gelb et al. 2014). Further, most of these studies often focus on aggregate industry level outcomes and rarely conduct systematic within industry productivity studies. Further challenge on such studies is posed by the difficulty involved in collecting input and output information that would permit productivity computation and measurement (Li and Rama 2015).

Unlike previous studies, this paper examines aggregate changes and firm-level drivers of labor and total factor productivity by focusing on one industry. The objective of this paper is thus threefold. First, using various parametric and non-parametric techniques, we show levels and changes in labor and total factor productivity over a nine-year horizon in the metalworking industry in Ethiopia. Second, we highlight sources of productivity change by decomposing aggregate productivity changes into different components related with expansion and contraction of incumbent firms and firm turnover. Third, we explore the main drivers of productivity, considering the impacts of firm ownership, age, size and human capital of workers. Ethiopia and the metalworking industry present an interesting case to examine productivity and earning dynamics over time. Despite recent spurt in growth averaging around 10% in the past decade, the manufacturing sector in Ethiopia has been plagued with low productivity, high labour turnover, and poor competitiveness (Geiger and Moller 2015; Gebreyesus and Demile 2017). For example, manufacturing contribution towards GDP was 6.4% in 1990 and declined to 4.8% in 2015 (African Economic Outlook 2017). Its contribution to GDP growth has also remained less than 0.5% (Geiger and Moller 2015). Similarly, the share of labour force in manufacturing is about 5 % and has barely changed since 1990s reflecting limited contribution towards the structural transformation of the economy (National Bank of Ethiopia 2017). Yet this lacklustre performance is despite the prime importance placed on the manufacturing sector in the various five year development plans, such as the 'Plan for Accelerated and Sustained Development to End Poverty' (PASDEP) and 'Growth and Transformation Plans I and II (GTP I and II). Examining the sources, changes and drivers of productivity in the manufacturing sector

¹ Reflecting this, the structural change that characterized Africa in the five decades of post-colonialism period constitute a movement of labor from low performing agriculture to "an oversized, lower productivity service sector" (Badiane, 2015).

is thus useful to understand key factors that inhibit productivity growth. A richer understanding of the nature and sources of aggregate productivity changes permits policy makers to better target microeconomic forces in designing productivity-enhancing policies.

Our focus on the metalworking industry is also justified on two grounds. First, policy makers in Ethiopia have spent considerable resources and effort to promote the growth of the metalworking industry in the past decade.² In the two recent five year development plans (GTP I and GTP II), for example, the metalworking industry has been considered as one of the strategic sectors with immense potential for ‘technology transfer and skills development’ (National Planning Commission 2016). Yet we are not aware of any systematic study examining the productivity performance of the sector. Second, our narrow focus on the industry allows us to control for many confounders that otherwise make productivity comparison between firms and across industries difficult (see for example Ichniowski et al. 1997). Admittedly, we recognize the limits to generalizability of our study due to the narrow focus on one industry.

The study employs a census of formal metalworking firms employing at least five workers and located in Addis Ababa and its surrounding areas within 100 Km. radius. The baseline data was collected in 2008 with recall information on sales, cost, and investment going back in time up to 2002. Immediate follow-up surveys were conducted in 2009, 2010 and 2011. While these survey waves collected crucial information to compute productivity, they only tracked the same group of enterprises and did not survey new entrants to the industry. In 2017, we tracked all firms that were surveyed in the earlier rounds and also conducted a full census of firms in the industry that are located in Addis Ababa and surrounding areas. In this survey wave, we also collected recall information for the periods 2013, 2014 and 2015. Our analyses thus mostly rely on the comparisons between the 2008 and 2017 survey waves when inference is desired about industry level changes.

We find a substantial output and input expansion in the sector in the nine year horizon between the two survey waves.³ Labor productivity has more than doubled and TFP has increased by about 80% during this period. Our productivity decomposition also shows that most of the gain in productivity is associated with market share reallocation. While the contribution of exit and entry to industry productivity growth is limited, we find that exit is preceded by lower productivity. We also show that the employment of vocational school graduates is significantly and positively related with both TFP and labor productivity attesting to the importance of technical skills in the sector. By contrast, foreign equity participation and higher share of foreign workers in firms is not associated with higher productivity.

The rest of the paper is organized in the following way. The next section presents the related literature. In Section III, we offer a brief overview of the metalworking industry in Ethiopia. Discussion on data and relevant methodological issues of productivity measurement and decompositions is presented in Section IV. In Section V, we present the empirical results. Section VI concludes the paper.

² The government has, for example, set up the Metal Industry Development Institute (MIDI) in 2010 to incubate and imitate foreign technologies and support the industry-wide diffusion of these technologies to the private sector.

³ All variables used to construct productivity levels and changes are deflated using Consumer Price Index (CPI) to account for inflation. The deflator uses 2011 as a base year

2. Related Literature

Studies have documented a wide dispersion of productivity across firms; a few highly productive firms co-exist with a ‘long tail’ of poorly managed and inefficient firms (Olley and Pakes 1996; Syverson 2004; Bloom and Van Reenen 2007; Hsieh and Klenow 2009; Syverson 2010; Gelb et al. 2014). Industry heterogeneities and firm idiosyncrasies shape both changes in aggregate productivity over time and its dispersion across firms within industry. In this section, we briefly review the literature on important drivers of firm and aggregate productivity changes.

Aggregate productivity changes primarily through two microeconomic forces, firm turnover and market reallocation. There are several studies that examined the sources of aggregate productivity changes considering the impacts of industry composition changes related with the entry of new and exit of firms as well as market share reallocation from less to more efficient incumbent firms. The results, however, are largely mixed with some studies reporting relocation to be an important source of aggregate productivity changes, while other studies find firm turnover to be a vital driver of changes in aggregate productivity. Melitz and Polanec (2015) and Pavcnik (2002), for example, respectively find that aggregate productivity change is mainly driven by market share changes by existing incumbent firms in Slovenian and Chilean manufacturing sector. Similarly, Foster et al. (2001) find that firm turnover accounts for only a quarter of productivity growth in the US between 1977 and 1982. By contrast, Aw et al. (2001) find that firm turnover greatly contributes to total factor productivity changes in the Taiwanese manufacturing in 1980's. Similarly, Brandt et al. (2012) show that over two thirds of aggregate productivity growth in Chinese manufacturing during the 1998–2007 period can be explained by firm turnover.

These divergent results reflect heterogeneities in the nature of the firm sample, differences in the productivity measurement and decomposition methodologies and in the structure of industries and economies from which aggregate productivity is measured and decomposed. Differences in country level specificities, often related with the stage of development, further limits the lessons that can be drawn from these studies to other economies. Indeed, *Van Biesebroeck (2005) finds that compared to firms in the US, the largest and productive incumbent firms in Africa ‘contribute disproportionately to aggregate growth’.*

Further, there is limited micro-based evidence on the relative importance of reallocation and firm turnover on aggregate productivity change in the African manufacturing sector. We are aware of three earlier studies, *Van Biesebroeck (2005)*, *Gebreeyesus (2008)* and *Shiferaw (2007)*, that examine sources of aggregate productivity growth employing comprehensive firm-level data from African enterprises. *Van Biesebroeck (2005) study is based on a sample of firms from nine sub-Saharan countries and finds that large firms contribute the greatest to productivity and job creation. Gebreeyesus (2008) and Shiferaw (2007) independently used the annual manufacturing census data from Ethiopia but report somehow very different results. Gebreeyesus (2008) find that aggregate productivity in the manufacturing sector had increased during 1996-2003 period with the increase mostly driven by firm turnover. By contrast, Shiferaw (2007) show that aggregate productivity had declined in the Ethiopian manufacturing sector during 1996–2002 periods and the decline was mostly attributed to productivity deteriorations of incumbent firms, while firm turnover had a very small effect. The opposite results from the two studies using the same manufacturing census data from one country underlie the difficulty of comparing productivity studies using different computational methodologies and the importance of detailed industry-specific evidence to study the topic further.*

Indeed, such differences are not surprising. Even within a single economy, for example, the extent to which aggregate productivity is determined by firm entry and exit or by incumbent firms' market expansion and contraction could be markedly different depending on overall economic performance or business cycle of the country. In a recent study, Asturias et al. (2017), for example, find that while a large fraction of aggregate productivity changes in Chile and Korea is accounted by plant entry and exit during periods of fast growth, the contribution is significantly dampened during periods of slower economic growth. Measuring and decomposing aggregate productivity using recent data from developing country like Ethiopia is thus a useful addition to the available evidence.

Studies have also shown that within-sector productivity differences could be much larger than between-sector differences reflecting the importance of firm level drivers of productivity (Haltiwanger et al. 1999; Foster et al. 2001). There are potentially several factors that can explain the presence of low levels of productivity and high dispersion at the firm level. Some of these factors, such as infrastructure, trade policies, regulation and rule of law, political and macroeconomic stability, are external to the firm. Other factors, such as quality of inputs, management practices, research and development, product and process innovation and access to finance are firm-specific (e.g., Bloom et al. 2010). A key firm-specific determinant of productivity is, for example, firm ownership. To the extent that foreign owned businesses can employ better managerial resources and use higher quality inputs, the participation of foreign capital in the firm could generate a productivity-enhancing effect (Javorcik 2004; Javorcik and Spatareanu 2011; Liang 2017; Abebe et al. 2017).

The quality of workers is also a key determinant of firm productivity. Presumably firms that employ skilled workers can produce more output for given levels of inputs. Black and Lynch (2001), for example, find that a 10 % increase in average education level of workers is associated with a 4% increase in productivity. Similarly, using matched employer-employee micro data, Haltiwanger et al. (1999) find that productivity tended to be higher in firms with a large share of more educated workers in their work force. The positive effect on productivity is partly explained by the direct effect of employing better quality workers that can minimize waste and use inputs efficiently. Partly the effect reflects human capital externalities where knowledge spillovers from high quality workers to the rest within a firm or industry (e.g., Moretti 2004).

A related measure of workers quality relies on their nationality; foreign vs local workers. In economies like Ethiopia where skills shortages are rampant, foreign workers could potentially bring with them better working practices and technical know-how that accelerates technology diffusion. The empirical evidence on the productivity effect of foreign vs local workers, however, is rather thin and mixed. Noor et al. (2011), for example, examine the productivity differential between local and foreign workers in Malaysian manufacturing sector. They find that while the presence of foreign worker is positively and significantly related with firm productivity, its effect is smaller than the effects associated with the employment of skilled local workers. By contrast, Møller et al. (2011) find that the employment of foreigners in Danish firms generates positive productivity shocks that stimulate exporting. In a poor economy that is besieged by skill scarcity, it is reasonable to hypothesize that foreign workers are important source of new knowledge that will enhance firm productivity in the metalworking industry in Ethiopia.⁴

⁴ In addition to differences emanating from firm-level idiosyncrasies, intra-industry productivity dispersion could also be explained by firms' response to other environmental factors related with government policy. Policies that incentivize firms to acquire skills or encourage them to invest in improved technologies are, for example, productivity enhancing. On the other hand, policies that insulate firms from competition prevent the efficient reallocation of resources between firms and attenuate aggregate productivity gains in the industry (Bloom and Van Reenen 2007; Ardagna and Lusardi 2009; Syverson 2010).

3. Overview of the metalworking industry

By its very nature, the metalworking industry is well suited to produce capital products that are used as inputs in production processes in other sectors. The supply of repair and machining services as well as accessories, parts and components lends the sector a critically important role as a hub for technology incubation and diffusion to other sectors. As such innovations in the metalworking industry can potentially spur growth in other sectors that use metalworking products as inputs in their production processes. In short, for developing countries like Ethiopia, the metalworking industry is indispensable for the growth and development of other industries.

Despite its long history in the country, the metalworking industry has, however, experienced limited structural changes over the years.⁵ The sector's value addition has remained paltry and production is confined to low technology and low return production processes with rudimentary technology. Common products in the sector include small-scale manufacturing of motor vehicle parts and components, farm instruments and final-use goods destined for downstream markets, such as corrugated iron, nails and coils for housing construction. In contrast, the productions of capital goods, such as machine tools and equipment that support the growth of other sectors have been limited. To the authors' knowledge, there are several anecdotes, but systematic studies to understand the state of productivity and its evolution over time as well as sources and drivers of productivity growth are absent. This paper thus fills this lacuna in research by examining the sources and drivers productivity in the metalworking industry at the industry and firm level.

4. Data and Methodology

The study employs a primary data collected over several years from the metalworking industry in Addis Ababa, Ethiopia, and its surrounding areas.⁶ The first survey on the metalworking industry was conducted in May and June, 2008. The data was based on a sampling frame constructed using multiple lists obtained from the Ethiopian Association of Basic Metal and Engineering Industries (EABMEI), the then Ministry of Trade and Industry and the trade and industry offices of 10 sub cities in Addis Ababa.^{7,8} Using this information, we selected enterprises that employ more than 5 persons and that are not cooperative- or association-based into our sample.⁹ Subsequently, data on 125 enterprises that employ more than 5 persons in and around Addis Ababa was collected in May, 2008. We solicited information on sales, cost, owner/managers profile and the number of local and foreign technicians employed

⁵ Ethiopia had a long history of iron casting and blacksmithing in the production of agricultural tools, such as plowshares, hoe tips and daggers as well as in the making of swords, spears, jewelries and religious artifacts. For example, the horse cavalries in the 19th century Ethiopia used swords made locally (Shinn and Ofcansky 2013).

⁶ Our sampling area consists of Addis Ababa and areas within 100Km radius from Addis Ababa.

⁷ Ministry of Trade and Ministry was split into Ministry of Trade and Ministry of Industry in October, 2011.

⁸ Addis Ababa is administratively divided into 10 sub cities.

⁹ Cooperatives are enterprises whose establishment is triggered by the state as part of its strategy to reduce urban youth unemployment (Abebe 2015). Their membership typically range from 5 to 15 individuals.

by the firm. In addition, the data set contains the replacement costs of machinery and equipment, total recalled sales and costs from 2002 to 2006.¹⁰ A short summary of the survey waves and the annual data points generated is presented in Table A1 in the Appendix.

Three rounds of annual follow-up surveys were then conducted between 2009 and 2011. These survey rounds, however, collected information only on sales, investment, daily wages and production costs.¹¹ Notably, these three survey waves did not include information on new entrants into the industry.

In June, 2017, we contacted the Ethiopian Association of Basic Metal and Engineering Industries (EABMEI), the Ministry of Industry and the trade and industry offices of 10 sub cities in Addis Ababa to update our list of enterprises. From the combined lists, we discovered that there were a total of 510 firms that were operational in the metalworking industry. Of these 257 met the employment criteria that we set in 2008. During survey implementation, 7 firms refused to respond to our interview. The 2017 survey wave thus collected data from 250 firms including those that were surveyed in the baseline and those that newly appeared in the government lists. We also collected a three year recall data for sales, investment and production costs for 2013-2015 periods. Our data is thus a census of all formal metalworking enterprises that employ five or more workers in Addis Ababa and surrounding areas. When considering industry level changes, we thus mostly rely on comparisons between the 2008 and 2017 survey waves. In all the survey waves, we conducted face-to-face interviews with enterprise operators.

Productivity measurement

Using the primary data, we construct several productivity measures as a check for robustness. Labor productivity is constructed by calculating the value of sales of each worker in the firm annually. To measure overall productivity of the firms (total factor productivity), we employ both parametric and non-parametric methods. Non-parametrically, we implement an index number approach indicated in equation (1) to compute Total Factor Productivity (TFP) (see for example Caves et al. 1982; Aw et al. 2001; Fukao and Kwon 2006).

Accordingly, the TFP index for enterprise i in year t is defined as

$$\ln TFP_{i,t} = (\ln Y_{i,t} - \overline{\ln Y_t}) + \sum_{s=2}^t (\overline{\ln Y_s} - \overline{\ln Y_{s-1}}) - \sum_j \frac{1}{2} (\overline{\alpha_{i,t,j}} + \overline{\alpha_{t,j}}) (\ln X_{i,t,j} - \overline{\ln X_{t,j}}) - \sum_{s=2}^t \sum_j \frac{1}{2} (\overline{\alpha_{s,j}} + \overline{\alpha_{s-1,j}}) (\ln X_{s,j} - \overline{\ln X_{s-1,j}}) \quad (1)$$

¹⁰ More than 80% of the firms in the baseline and follow-up surveys stated that they regularly keep proper records of their business transactions including sales, investment and procurement. Further, among those who do not keep regular records, we learned during our field visits that nearly all enterprises record and compute annual sales revenue and costs for tax declaration purposes (note that all our firms are formal). The recall information is thus mostly drawn from the archives of the firms and hence we do not think that including these data points will bias our result.

¹¹ While these data is useful to estimate production function, we cannot use it to explore drivers of productivity and the differential effect of firm entry and exit on productivity.

where Y is measured by using value of sales, X represents input costs (labor, materials and capital) and $\alpha_{i,t,j}$ is the cost share of input j in period t in enterprise i .⁸ $\overline{\ln Y_t}$ represents the natural log of the average value of sales (output) and hence corresponds to the values of a hypothetical firm to which the value of sales (output) of other enterprises are compared. Similarly, $\overline{\ln X_{t,j}}$ and $\overline{\ln \alpha_{t,j}}$ show the average value of input j and its respective cost shares in the hypothetical enterprise.¹² Therefore, the TFP index captures the relative productivity of enterprise i from our sample of enterprises in the metalworking industry.

A key concern in the computation of productivity is the measurement of capital stock. We collected data on the total value of capital stock only for 2007 and 2016 (in the 2008 and 2017 survey rounds respectively). We have, however, annual investment values for every year including for recalled periods. We thus employ the standard perpetual inventory method indicated in equation 2 to construct an estimate of the value of the capital stock for all the years.

$$K_t = (1 - \delta_t)K_{t-1} + I_t \quad (2)$$

Where K is capital stock, t is time, δ is depreciation rate, which is assumed to be 5%, and I is investment.

Parametrically, we estimate a translog production function of the form

$$\ln Y_{it} = \ln A_{\alpha_i, \beta_i} + \sum_{i=1}^n \alpha_i \ln X_{it} + \left(\frac{1}{2}\right) \sum_{i=1}^n \sum_{j=1}^n \beta_{ij} \ln X_{it} \ln X_{jt} + \varphi_{it} \quad (3)$$

where Y represents value of sales and X vector of inputs including capital stock (k), labor (l) and raw materials (m). $\ln A$ is a measure of levels of technology, which is not observed directly. α and β are parameters to be estimated. The third term on the right presents interactions between inputs. We cluster standard errors at firm levels.

The last term in equation 3, φ_{it} , is given by the sum of two terms; $\omega_{it} + \mu_{it}$. There is a crucial difference between ω_{it} and μ_{it} . The second term, μ_{it} , represents a stochastic and unobserved error term before the firm makes its input choice. The first term, ω_{it} , however, proxy shocks that are potentially observed by the firm when the firm decide on the type and volume of input to use. Shocks, such as electricity outage, supply hold-up, worker turnover and machine breakdown, for example, can be predicted by the firm with reasonable accuracy. These shocks are not, however, observed by the researcher. This poses a major estimation challenge as input choices could be potentially endogenous to this unobserved productivity shock. Under this scenario, the estimated β coefficients are biased and inconsistent.

There are several strategies that can be used to overcome the endogeneity of input choice in estimating equation 3. We employ a range of methods to compute productivity indicators that takes the endogeneity of input choice into account. We briefly discuss some of the conventional methods that can help us employ specifications that are more structural in nature.

¹² Unlike raw materials and labor, we do not have a clean measure of capital cost. We thus proxy the annual cost of capital using the minimum return on saving deposit at the time of data collection, which was 5%.

The first method is inspired by Olley and Pakes' (1996) investment proxy estimator, where productivity is assumed to take a Markov process. Their method relies on the use of investment to proxy capital under the assumption that correlation between input levels and ω_{it} , the unobserved productivity shock, disappears as investment is determined in the earlier period and hence is orthogonal to future changes in ω_{it} conditional on controlling for present levels of investment. A major weakness of this approach is that plants with zero investment will be truncated from the data due to the invertability condition.¹³

Building on the ideas in Olley and Pakes (1996), Levinsohn and Petrin (2003) proposes an alternative estimation strategy that shows that intermediate inputs can be used to remove the correlation between input levels and the unobserved firm-specific productivity shock, ω_{it} . Unlike investment, intermediate inputs are often positive and hence the data truncation problem faced using the Olley and Pakes (1996) methodology can be substantially reduced. Alternatively, the problem of input endogeneity could be overcome by instrumenting for current input levels using lagged differences in inputs (Blundell and Bond, 1998). Yet this specification could also potentially suffer from weak instrument bias.

Despite a voluminous theoretical and empirical research devoted for better identification of firm-level productivity controlling for unobserved shocks, we are not aware of any strategy that is foolproof (see for example Greenstone et al. 2010). Indeed, it is inescapable that one should make an assumption on the nature of the production function to estimate productivity parametrically (Syverson 2010).

Using a range of alternative specifications, we can identify group of firms that will remain productive irrespective of the functional structure of the production function or the way productivity is computed. More precisely, our parametric productivity measures are drawn from the firm residuals obtained from equation 3 using translog, fixed effect, Olley and Pakes (1996), Levinsohn and Petrin (2003) and Blundell and Bond (1998) specifications. We regress these residuals on firm and worker characteristics to identify drivers of productivity. Black and Lynch (2001) and Stoyanov and Zubanov (2012) use a similar approach to drive firm level productivity from production function residuals.

Due to difficulties related with the use of physical output to measure productivity and to take account of product innovation that do not increase volume of output, researchers also typically employ revenue-based productivity measures, such as sales revenue and value added to proxy for productivity. To the extent that prices reflect differences in quality of output, the revenue-based measures of productivity signify the true efficiency differences between firms. However, if price variations instead reflect market power or idiosyncratic demand shift, where some firms are able to charge higher prices for the same type of products, revenue-based measures confound productivity effects with market power. We will construct a measure of industry's concentration using the Herfindahl-Hirschman index and check whether our productivity estimates are robust to the inclusion of a market power proxy.

¹³ In Olley and Pakes framework, investment, i_t , is given by $i_t = i_t(\omega_t, k_t)$. The invertability condition together with the monotonicity assumption allows the firm-specific productivity shock to be modelled as a function of investment and capital, $\omega_t = \omega_t(i_t, k_t)$.

Productivity Decomposition

To better understand the source of productivity growth or decline over time, we also decompose productivity into different components. Using plant level productivity, we first start with a common representation of industry level productivity indicated in equation 4 (Foster et al. 2001).

$$\ln TFP_{it} = \sum_{p \in I} \ln TFP_{pt} S_{pt} \quad (4)$$

Where $\ln TFP$ is log of total factor productivity, i is industry, p is plant and t is time. TFP_{pt} is thus individual firm's productivity at time t . S_{pt} is the output share of plant p at time t . Following Bailey et al. (1992) and Foster et al. (2001), we decompose the changes in productivity over time into different components. Equation (5) outlines this decomposition methodology.

$$\Delta TFP_{it} = \sum_{p \in C} S_{pt-1} \Delta TFP_{pt} + \sum_{p \in C} (TFP_{pt-1} - TFP_{it-1}) \Delta S_{pt} + \sum_{p \in C} \Delta TFP_{pt} \Delta S_{pt} + \sum_{p \in N} S_{pt} (TFP_{pt} - TFP_{it-1}) - \sum_{p \in X} S_{pt-1} (TFP_{pt-1} - TFP_{it-1}) \quad (5)$$

Where ΔTFP_{it} represent change in industry productivity index at time t . C , N and X stand for continuing, entering and exiting firms respectively. The first term in equation 5 shows the within-plant effect, where firm level productivity changes over time are multiplied by fixed output shares from the reference period (baseline). The second expression captures between-plant components given by the product of firm productivity deviation from the industry productivity index in the reference period and change in output shares over time. The third expression is a cross-effect that combines both changes in firm level productivity and changing output shares related with the reallocation of the shares across plants in the industry. The fourth and fifth term capture the productivity contribution of firm entry and exits respectively.

5. Results discussion

We divide our results into three parts. First, we compute productivity indices using both parametric and non-parametric models and examine changes in productivity, earning and other performance indicators over time. Second, we decompose productivity into different components to identify the source of productivity changes. Third, we estimate a reduced form model to identify key drivers of productivity.

5.1. Productivity levels and Changes over time

We start with the basic descriptive of firm characteristics in the two census periods.¹⁴ Table 1 shows that the average firm age in the industry was 21 in 2007 and declined to 15 in 2016 reflecting the entry of a large number of new firms in the industry between the two census periods. The share of firms with foreign equity (either wholly foreign-owned or joint venture with domestic firms) was 9% in 2007 and slightly increased to 10.4 % in 2016. About 16% of the firms have exited in the nine year period between 2007 and 2016. Exiting firms are those that

¹⁴ As indicated in the data section, the two period coincides with the full census of the firms in the metalworking industry in Addis Ababa and its surrounding areas allowing us to explore changes in basic industry performance measures over the 2007-2016 periods. In the 2008 and 2017 survey rounds, we collected information on firm characteristics, output and inputs for the 2007 and 2016 full years respectively.

appeared in the 2008 survey wave but were confirmed to have stopped production during the 2017 survey round.

The industry has also experienced entry of new firms, where 19% and 12% are new entrants in 2007 and 2016 respectively. The firm is defined as a new entrant if it is within the two year window since it started operation at the year of data collection. Reflecting the growth of existing firms, average employment has increased by nearly 40 workers between 2007 and 2016, a change accompanied by substantial increase in standard deviation.

Table 1 also shows that nearly a third of workers in the metalworking firms are high school graduates and one in six had a vocational school background. University graduates constituted about 3.5 % to 5% of the total workforce. Firms also use foreign technicians and supervisors albeit with limited numbers. In 2007 for example, foreigners made up nearly 2% of the workforce in the industry, which declined to less than 1 % in 2016.

Table 1. Basic characteristics of firms in the metalworking industry in 2007 and 2016

	2007		2016	
	Mean	Standard deviation	Mean	Standard deviation
Firm age (years of operation)	20.5	20.4	15.3	15.7
% of FDI	5.6	23.2	6.5	24.6
% of JV	3.4	18.1	3.9	19.4
% that exited	-	-	16	27.2
% that entered	19	39.5	12.4	33
Number of workers	72.2	140.2	111	696
Share of high school graduate workers (%)	33.2	25.1	32.8	20.7
Share of vocational school graduate workers (%)	16.9	18.6	16.5	16.8
Share of university graduate workers (%)	3.5	6.1	4.8	8.8
Share of foreign workers (%)	1.9	13.9	0.8	2.8
Number of observations	125		250	

Source: Authors compilation using the 2008 and 2017 metal industry survey rounds in and around Addis Ababa.

Note. The shares are obtained by dividing the total number of workers in that category by total number of workers in the firm.

Table 2 extends Table 1 by examining changes in the real value of output and inputs over the nine year horizon between 2007 and 2016. More specifically, Table 2 presents changes in value of sales, value added, gross profit, capital and employment. The first three columns respectively present expansion rate, market share of entrants and percentage share of expansion contributed by new entrants. Columns 3 to 6 show contraction rates, market share of exits and percentage share of contraction attributed to exiting firms respectively. Following Davis et al. (1996), we measure expansion and contraction rates as weighted average of the growth rates between 2007 and 2016.¹⁵ The final column shows percentage share of excess reallocation, which is also termed as churning rate (Burgess et al. 2000). Excess reallocation or churning is defined by the arithmetic sum of expansion and contraction minus the absolute value of net change in the sector (Foster et al. 2001) and measures changes in the sector in excess of the level required to accommodate the industry's growth or decline.

Table 2 shows a very large rate of expansion and contraction over the nine year period. Input and output expansion, for example, exceeded 158% for expanding firms. On the other hand, the rate of contraction ranged from 47% for labor input to 418% for profit for contracting firms. Except for profit, the rate of expansion in the industry is higher than the rate of contraction. More importantly, Table 2 shows that output growth has exceeded input growth (both labor and capital) over the nine-year horizon. This presents the first clue on productivity improvement in the metal working industry over time.

Table 2 also shows relatively small market share of entrants, after entry, in 2016 and exits, before exit, in 2007. The corresponding contribution of new entrants and exits to net growth is also limited. The share of employment expansion due to entry is 4 % and contraction due to exit is 6 %. This indicates that gross output and input creation in the metalworking industry is mainly driven by within industry effects of incumbent firms. The final column in Table 2 shows that 48%, 63%, 134% and 70% of excess reallocation in value of sales, value added, gross profit and employment lies within the metalworking industry. This indicates that the large output and input changes observed over the nine-year period is mostly explained by reallocations among firms within the metalworking industry. To explore this more formally, we will shortly decompose productivity measures into several components.

¹⁵ We use output share in the industry as weights.

Table 2. Gross reallocation of value of production, employment and capital stock (nine-year change from 2007-2016)

	Expansion Rate (%)	Market share of entrants (%)	Share of expansion due to entrants (%)	Contraction rate (%)	Market share of exits (%)	Share of contraction due to exits (%)	% of excess reallocation(churning) within the industry
Value of sales	170	13.9	8.2	89.0	17.9	20.0	47.8
Value added	179	11.4	6.4	96.5	30.0	31.0	62.8
Gross Profit	182	12.6	6.87	418	37.9	9.07	134
Employment	158	7.3	4.4	47.0	6.32	12.8	69.6
Capital stock	176	41.4	23.1	92.2	3.97	4.35	37.0

Note. All variables are deflated using Consumer Price Index (CPI) to account for inflation. The deflator uses 2011 as a base year. We also compute the annual growth rates of these variables during the course of the nine year period. We find the rates to be 4.96 (sales growth), 5.04 (value added growth), 7.5 (profit growth), 0.15% (employment growth) and 15.7 % (capital stock growth)

Source: Authors compilation using the 2008 and 2017 metal industry survey rounds in and around Addis Ababa.

5.2. Production function estimation

Table 3 presents production function parameters and mean-industry TFPs computed both non-parametrically and parametrically. Using equation 1, Column 1 computes the non-parametric TFP mean at the industry level. Alternatively, we can compute productivity using a parametric approach. We estimate the translog production function indicated in equation 3 using OLS, fixed effect as well as instrumental variable approaches that rely on Olley and Pakes (1996), Levinson and Petrin (2003) and GMM estimation techniques. By using measures that considers changes over time, these specifications control for unobserved characteristics that may be correlated with input choices. In addition, we use a non-parametric approach by fixing the production parameters to be equal to the input cost (not shown but the results are fairly similar to both the parametric and non-parametric productivity estimates).

A related concern on the use of the value of output as a dependent variable arises if prices reflect market power rather than product quality premium. As a robustness check, we estimate the same model including the Herfindahl-Hirschman index as a regressor. The results indicated in the Appendix Table A2 are very similar to Table 3 indicating that price is not capturing market dominance in the industry.

Column 2 presents input coefficients for a translog production function based on equation 3. We test whether the input interaction terms are jointly equal to zero; a test to confirm whether Cobb-Douglas restrictions are valid. The F-test shows that the interaction terms are different from zero and hence resoundingly rejects the Cobb-Douglas restrictions ($p\text{ value}=0.000$). The translog production function shows that the overall production function has modest increasing returns to scale, with a 1 percent increase in all inputs leading to a 1.7 percent increase in the value of output.

Column 3 presents fixed effect estimations that removes unobserved time-invariant demand shocks that potentially influence input choices and hence productivity levels. As discussed earlier, however, if demand shocks are time variant, fixed effect model produces inconsistent parameters. Columns 4–5 present estimates based on methodologies by Olley and Pakes (1996) and Levinson and Petrin (2003). The two methods use investment and material costs as instruments for capital stock respectively to overcome the correlation between input choice and productivity. Finally, we employ system GMM proposed by Blundell and Bond (1998) where we instrument first differences in inputs using lagged levels and for inputs in levels using all lagged first differences.

The last two rows of Table 3 report mean industry TFP and the correlation with a measure of labor productivity. The simple correlation coefficients are positively related with each other and with sales per workers irrespective of how TFP is measured. The specifications collected from columns 2 to 6 are used to compute the residual for each firm in the sample for each year that the firm is observed. These residuals proxy firm level TFPs (Black and Lynch 2001).

Table 3. Production function coefficients for firm inputs (all years)

VARIABLES	Non-parametric TFP (1)	OLS (Translog) (2)	Fixed effect (3)	Parametric Olley and Pakes (4)	Levinshon and Petrin (5)	System GMM (6)
Capital stock	0.122** (0.061)	0.073*** (0.017)	0.026** (0.012)	0.018 (0.113)	0.016 (0.047)
Number of workers	1.464*** (0.129)	0.456*** (0.055)	0.430*** (0.035)	0.328*** (0.065)	0.436*** (0.125)
Material cost	0.081 (0.054)	0.444*** (0.018)	0.606*** (0.061)	0.752*** (0.223)	0.666*** (0.089)
R-squared		0.925	0.539			
Mean-industry TFP	-0.02	5.26	6.08	4.58	13.6	3.93
Correlation coefficients (with Labor productivity)	0.23	0.05	0.28	0.23	0.28	0.20
Observations	1,324	1,324	1,324	1,417	1,324	737

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. We use all the data points from 2003 to 2017 including recalled period from 2002 to 2006 and from 2013 to 2015. We do not have data points for 2011 and 2012. All variables used to construct TFP are deflated using Consumer Price Index (CPI) to account for inflation. The deflator uses 2011 as a base year

5.3. Basic Decomposition

Table 2 suggests that productivity in the metalworking industry has increased over time. To explore the source of productivity growth, we decompose the overall industry productivity growth computed using equation 4 into different components using equation 5. We weight changes in industry output shares using real value of sales averaged over 2007 and 2016. Table 4 shows the decomposition estimates over these periods and yields several notable results.

First, there is a sizable improvement in both parametric and non-parametric measures of industry productivity. Labor productivity has increased by 139 % over the 9 year period. TFP increment, however, shows wider dispersion ranging from a lower bound of 45% obtained from the translog specification to 110% under non-parametric model. Second, major productivity changes in the industry are attributed to changes in firm-level productivity and market share among incumbent firms. Among the incumbent firms, within firm effect is large and negative. This implies that despite overall industry level growth, there are a large group of firms that experienced deterioration in productivity during 2007-2016 periods.

Third, the between share effect that is indicated in column 3 is negative and large. This implies either a negative growth in output shares between 2007 and 2016 or negative plant levels productivity deviation from industry index in 2007. Fourth, the cross share is positive and very large indicating that market share reallocations in combination with within-plant productivity growth contributes greatly to overall productivity growth. This signifies a rapidly changing distribution of output shares among firms in the metalworking industry. Consistently, between 2007 and 2016, we find that the industry market share of firms at the 90th percentile of the TFP (non-parametric) and labor productivity distribution has increased by 8.5 and 11.0 percentage points respectively indicating also a sharp decline in the market share of less productive firms.¹⁶ Fifth, the productivity effects of net entry and exit components are relatively small. This is partly because of the small number of entrants in the industry in the nine year period.¹⁷ The final column shows that net exit share to productivity growth is positive indicating that the exit of less productivity firms contributes positively to aggregate productivity growth. Overall, these results are consistent with earlier studies that find limited productivity contribution of entry and exit to the aggregate industry (Griliches and Regev 1995; Liu and Tybout 1996; Shiferaw 2007).

Yet these results should be taken with a caution for three reasons. First, while we conducted a census of all metalworking enterprises that employ more than five workers in Addis Ababa and surrounding areas, the census data is only available for two of the survey waves, for 2008 and 2017. We are not thus able to capture entry and exits of firms in the nine year interval between 2008 and 2017. The productivity contributions of exits and new entrants might thus be underestimated. Second, our study covers only Addis Ababa and areas within 100 km radius of Addis Ababa. Our limited geographical coverage weakens our ability to generalize from the results to the wider economy. Third, while our focus on one industry enables us to control for many confounders that bedevil inter-industry productivity comparisons, it also limits the generalizability of our study to other industries even within the manufacturing sector.

¹⁶ In 2008, firms that are at the 90th percentile TFP (labor) distribution commanded a combined market share of 80.5% (65.3 %) of the total industry. In 2017, the market share of firms at the 90th percentile of TFP (labor) distribution has expanded to 89.0 % (76.2%).

¹⁷ Because of the size cutoff we used in sampling, we also do not find small entrants that employ less than five workers in our data set.

Table 4. Decomposition of productivity growth, 2007 -2016

Measure		Overall Productivity Growth (%)	Continuing firm			Entry	Exit
			Within Share	Between share	Cross Share	Entry Share	Exit Share
Non-parametric	Index	110	-0.29	-2.37	3.78	-0.006	0.11
	Labor	139	-0.23	-1.33	2.72	-0.001	0.15
	Translog	45.4	-0.14	-0.63	1.95	0.002	0.17
	Fixed effect	79.3	-0.25	-1.10	2.56	-0.011	0.19
Parametric	Olley and Pakes	78.9	-0.16	-0.63	1.96	-0.007	0.16
	Levinshon and Peterin	109	-0.35	-2.06	3.59	-0.011	0.17
	System GMM	79.4	-0.13	-0.45	1.74	-0.06	0.15

Source: Authors compilation using the 2008 and 2017 metal industry survey rounds in and around Addis Ababa

To formally test the productivity and worker earning differences among cohorts of continuing, entering, and exiting firms, Table 5 presents estimates from a reduced first stage model considering data from 2007, 2009 and 2016.¹⁸ Following Aw et al. (2001), we estimate the productivity indicators on a set of year dummies corresponding to year of entry and exit as well as interactions between the year dummies and entry (exit) status. The year dummies control for the influence of aggregate changes in the productivity distribution over time. The interaction terms capture the differential productivity effect of the firm's entry (exit) status over time. Continuing firms are the excluded group and the intercept captures mean productivity levels of these firms in the base year, 2007.

Large and statistically significant intercept from columns 2 through 7 in Table 5 shows that incumbent (continuing) firms had higher average productivity than entering and exiting firms in 2007. Columns 1 and 5 show that firms in the 2007 entry and exit cohorts have substantially lower TFP than continuing firms. Similarly, column 6 indicates that labor productivity for firms in the 2007 entry is lower than continuing firms by more than 100%. A starker observation is indicated in the interaction between exit and the last year of exit (year 2009). Except for the translog and system GMM TFPs, which are accompanied by higher standard errors, exit is associated with lower and statistically significant productivity differentials. This is consistent with earlier studies that find that lower productivity predict firm exit from the industry (Olley and Pakes 1996; Dwyer 1998, Aw et al. 2001; Gebreeyesus 2008).

To test whether the effects of entry and exits are different from each other and over time, we conduct four tests. The first is a test of the null hypothesis that the productivity effect of entry is not different from exit. The second and third tests check whether the productivity effect of entry subsides over time. The fourth test checks whether exit status of the firm has different productivity effects over time. The first test indicates that there is no meaningful productivity difference between exiting and entering firms with each other; as indicated by the large p-values of the F-test in the table, the tests do not reject equality of the effects. Columns 1, 5 and 7, however, show that the productivity effect of entry depends on entry cohort. The 2007 entry cohort is not only less productive than continuing firms; their productivity levels are also lower than the 2016 entry cohort. By contrast, the 2016 entry cohort has productivity levels that are not statistically different from continuing firms.

These results have three important implications. First, the lower productivity of exiting firms suggest a 'shadow death effect' where firm exit reflects either negative shocks to productivity levels or declining trends in productivity growth over time. This testifies to the important role market selection plays in productivity improvements. Second, the lower productivity of entrant firms compared to continuing firms in 2007 suggests that entry is not necessarily associated with the adoption of new and better technologies. Third, the entry of relatively low productive firms at the 2007 cohort and relatively more productive firms in 2016 is consistent with aggregate productivity improvements in the industry over time. As industry productivity improves, the minimum threshold productivity level that permits entry might have increased. This encourages the entry of firms who have greater productivity potentials and could benefit from learning-by-doing by gradually adopting existing and standardized technologies. Such firms could improve productivity rapidly by eliminating wasteful production processes (Jovanovic 1982).

¹⁸ As discussed earlier, the two census periods consists of a complete industry data for a sampling area in 2007 and 2016. We add 2009 data set to check whether the effect of entry and exit changes over time.

Table 5. Productivity differences among Entering, Exiting and Continuing Firms (2007 and 2016)

VARIABLES	Ln TFP measured by:						Labor productivity measured by
	Non-parametric (1)	Translog (2)	Fixed effect (3)	Olley and Pakes (4)	Levnishon and Petrin (5)	System GMM (6)	Ln Sales per worker (7)
Intercept	0.125 (0.311)	5.373*** (0.043)	6.260*** (0.089)	4.740*** (0.096)	13.828*** (0.231)	4.085*** (0.102)	11.881*** (0.154)
Year 2007* entrant dummy	-1.643** (0.744)	0.029 (0.138)	-0.364* (0.217)	-0.154 (0.154)	-1.421** (0.597)	-0.055 (0.136)	-1.051** (0.411)
Year 2007* exit dummy	-1.877*** (0.444)	0.010 (0.211)	-0.312 (0.284)	-0.194 (0.243)	-1.498*** (0.415)	-0.074 (0.234)	-0.513 (0.405)
Year 2009* entrant dummy	-0.209 (1.140)	-0.036 (0.135)	-0.209 (0.266)	-0.215 (0.180)	-0.300 (0.895)	-0.210 (0.154)	-0.269 (0.524)
Year 2009* exit dummy	-1.807*** (0.322)	-0.113 (0.231)	-0.493** (0.216)	-0.397* (0.229)	-1.489*** (0.236)	-0.302 (0.251)	-0.763** (0.334)
Year 2016* entrant dummy	-0.066 (0.493)	-0.081 (0.158)	-0.076 (0.211)	-0.078 (0.177)	-0.096 (0.435)	-0.075 (0.167)	-0.037 (0.360)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P value of F-test							
Entrant-exit differential	0.75	0.93	0.87	0.87	0.90	0.93	0.29
Entrant differential (2007-2009)	0.29	0.74	0.65	0.80	0.30	0.45	0.24
Entrant differential (2007-2016)	0.08	0.60	0.34	0.75	0.07	0.93	0.06
Exit differential (2007-2009)	0.90	0.69	0.61	0.54	0.99	0.51	0.63
R-squared	0.020	0.012	0.018	0.017	0.023	0.017	0.021
Observations	376	378	378	378	379	378	385

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5.4. Productivity drivers

We now turn to the question what explains productivity differences between firms within the metalworking industry? Table 6 examines the correlation between productivity and firm-characteristics. As indicated in the table, firm age is positively correlated with productivity, where older firms are found to be more productive than younger ones. A one year increase in the firm age leads to about 0.6 % to 2.2 % increase in TFP and 1.2% increase in labor productivity. This is consistent with Jovanovic (1982) model that shows that firms learn about their true efficiency over time and hence more productive firms tend to survive. Older firms also pay slightly higher wages for production workers.

Table 6 also presents clear evidence that shows that larger firms are more productive than smaller firms (micro-firms are the excluded groups). The positive correlation between firm size and productivity (both labor and TFP) is a common finding in the literature (van Biesebroeck 2005; Shiferaw 2007; Yang, 2012). High productivity is often explained by large firms' better access to credit, ability to exploit economies of scale and better managerial capital endowment. Distinguishing the relative role of these factors to large firm's productivity advantage, however, is beyond the scope of this paper.

Table 6 also shows that the presence of foreign equity and foreign national workers in the firm does not lead to a substantial productivity shocks. We also do not find any statistically discernable production workers' wage difference between foreign and local firms. The existence of foreign workers does not also seem to generate wage spillover effects towards domestic production workers. The lack of statistically significant effect on both productivity and wages might be attributed to the limited share of foreign workers in the industry, which was less than 1% in 2017. Further, firms with foreign equity participation do not appear to be different from domestic firms in terms of size, market orientation and productivity levels in the industry.¹⁹

On the other hand, Table 6 shows that a one percent increase in the share of vocational school graduate workers is associated with 28 % to 69 % increase in TFP and 41% increase in labor productivity.²⁰ These results are consistent with earlier studies that show lack of technical skills to be a key barrier for productivity improvement in the Ethiopian manufacturing sector (Geiger and Moller 2015). In other setting, Sala and Silva (2013) find that productivity growth increases by as much as 0.55 percentage points for every extra hour of vocational training of workers in Europe. TVET education promotes effective use of machines and equipment in firms and is thus an important lever for enhancing productivity in the metalworking industry. We also find a similar effect with share of workers with university education but the effect is only significant in two of the six specifications. Labour productivity, however, appears to significantly increase with the share of university educated workers in the firm. In short, these results confirm that the human capital of workers is significantly related with TFP and labour productivity.

¹⁹ FDI and domestic firms are comparably in terms of employment size, capital stock and sales turnover. FDI firms in the metalworking industry thus may not have competitive advantages that are often attributed to foreign capital. Using data from the annual manufacturing census in Ethiopia, Abebe et al. (2017), for example, find that local firms benefit from FDI spillover effects from the entry of large FDI firms, while the entry of smaller firms generate limited effects.

²⁰ The Technical and Vocational Education Strategy was designed to produce technically proficient middle-level workers to enhance labor productivity in the manufacturing sector (Ministry of Education of Ethiopia, 2008).

Table 6. Productivity differences by firm size, ownership and worker characteristics (all years)

VARIABLES	Ln TFP measured by:						Labor productivity measured by
	Non-parametric (1)	Translog (2)	Fixed effect (3)	Olley and Pakes (4)	Levnishon and Petrin (5)	System GMM (6)	Ln Sales per worker (7)
Firm has foreign equity	-0.087 (0.214)	0.093 (0.098)	0.148 (0.118)	0.180 (0.114)	0.049 (0.183)	0.188 (0.115)	-0.041 (0.164)
Years of operation	0.022*** (0.004)	0.007*** (0.003)	0.009*** (0.003)	0.008*** (0.003)	0.020*** (0.004)	0.007*** (0.003)	0.012*** (0.004)
Firm is small	1.669*** (0.236)	-0.085 (0.101)	0.251** (0.117)	0.091 (0.095)	1.296*** (0.200)	-0.014 (0.090)	0.529*** (0.195)
Firm is medium	3.905*** (0.270)	0.040 (0.119)	0.823*** (0.140)	0.438*** (0.118)	3.162*** (0.233)	0.206* (0.114)	1.668*** (0.229)
Firm is large	5.289*** (0.253)	-0.138 (0.118)	0.801*** (0.135)	0.256** (0.115)	3.988*** (0.216)	-0.086 (0.111)	1.673*** (0.206)
Share of foreign workers	0.202 (0.457)	0.049 (0.234)	-0.032 (0.255)	-0.090 (0.237)	0.014 (0.376)	-0.083 (0.234)	0.394 (0.351)
Share of high school workers	-0.455* (0.249)	0.041 (0.128)	-0.091 (0.132)	-0.012 (0.120)	-0.464** (0.225)	0.028 (0.118)	-0.385* (0.210)
Share of vocational school workers	0.686** (0.286)	0.199 (0.128)	0.324** (0.150)	0.297** (0.135)	0.491* (0.253)	0.282** (0.133)	0.408* (0.230)
Share of university workers	1.728** (0.856)	-0.182 (0.323)	0.072 (0.426)	-0.165 (0.356)	1.443* (0.763)	-0.253 (0.338)	1.243* (0.728)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.587	0.028	0.168	0.080	0.521	0.049	0.213
Observations	876	880	880	880	882	880	947

Note: Robust standard errors are in parentheses. Small enterprises employ 6 to 29 workers, medium 30 to 49 and large firm 50 and above. The excluded category of micro enterprises employ at most five workers. We use all the data points from 2003 to 2017 including recalled period from 2006 to 2002 and from 2015 to 2013. We do not have data points for 2011 and 2012. *** p<0.01, ** p<0.05, * p<0.1.

6. Conclusions

Using a longitudinal data collected from the metalworking industry in and around Addis Ababa and a range of computational methodologies, this study quantified productivity changes over time in the industry. To understand sources of productivity growth, we also decomposed industry productivity changes into various components: within plant change, entry and exit effects. We also examined the relationships between key firm characteristics and firm productivity.

We find clear evidence for TFP and labor productivity improvement in the metalworking industry over time. The productivity gain in the industry appears to mostly arise from within firm reallocation effect; that is through the expansion of more productive incumbent firms at the expense of less productive firms. By contrast, firm turnover appears to have limited contribution to aggregate productivity change in the metalworking industry. Firms with declining productivity trends are also more likely to be wedded out of the market. Our results provide further evidence to the crucial role market selection plays in promoting resource allocation from the least to the most productive firms. The importance of reallocation to aggregate productivity is consistent with the growing body of evidence that puts firm capability at the center-stage of productivity improvement efforts. Understanding key constraints that preclude firm's adoption of improved technologies, management practices and marketing techniques is thus vital to improve industry (aggregate) productivity. Policies that are designed to improve aggregate productivity should also operate through the removal of firm entry and exit barriers to facilitate market selection. Reducing sunk costs and entry barriers that shield unproductive incumbents from competition increases the minimum efficiency threshold required to stay operational in the market thereby improving aggregate productivity. Further, our results also indicate that the government's strategy of job creation can yield greater returns if public policies include reforms that boost productivity of existing firms.

Finally, we find strong evidence that confirms that the human capital of workers is significantly related with firm productivity. More notably, the share of workers with vocational education is found to have strong and positive effects on both TFP and labor productivity. To some extent, this validates the claim that the TVET system, which is a key government policy designed to bridge skill gap and enhance productivity in the manufacturing sector, is producing positive results.

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Appendices

Appendix 1. Description of the survey waves and corresponding data points.

Survey waves

Wave	2008						2009	2010	2011	2017				
Data points for the year	2002	2003	2004	2005	2006	<u>2007</u>	2008	2009	2010	2013	2014	2015	<u>2016</u>	2017

Note. The table shows the data points associated with each survey wave. In 2008, for example, complete annual data sets on sales and costs were collected for 2002-2007 periods. In 2017, complete annual data sets were collected for the periods 2013-2016 and only monthly averages for the year 2017. We have a full industry census for the years 2007 and 2016 obtained from the 2008 and 2017 survey waves.

Appendix 2. Production function estimation controlling for market concentration

VARIABLES	Non-parametric	Parametric				
	TFP	OLS (Translog)	Fixed effect	Olley and Pakes	Levinshon and Petrin	System GMM
	(1)	(2)	(3)	(4)	(5)	(6)
Capital stock	0.123** (0.062)	0.072*** (0.017)	0.026 (0.017)	0.018 (0.111)	0.018 (0.048)
Number of workers	1.463*** (0.129)	0.458*** (0.055)	0.429*** (0.036)	0.328*** (0.066)	0.429*** (0.126)
Material cost	0.083 (0.054)	0.444*** (0.018)	0.606*** (0.060)	0.752*** (0.225)	0.668*** (0.089)
Herfindahl-Hirschman Index ^a		0.216 (0.553)	1.402** (0.623)	0.857 (1.378)	0.418 (0.742)	1.271 (1.083)
R-squared		0.906	0.616			
Mean-industry TFP	-0.02	5.24	6.14	4.58	13.6	3.80
Correlation coefficients (with Labor productivity)	0.23	0.05	0.28	0.23	0.28	0.19
Observations	1,324	1,324	1,324	1,417	1,324	737

Note. ^a we construct the HHI index using the output share of the firm in the industry. We use all the data points from 2002 to 2016 including recalled period from 2006 to 2002 and from 2015 to 2013. We do not have data points for 2011 and 2012. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

