Revisiting the Export-Productivity Relation:

Market power shifts or technical efficiency differences?

Evidence from Ethiopian manufacturing firms

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ABSTRACT

This paper examines whether the empirical regularity that exporters are more productive than non-exporters is at least partly explained by price heterogeneity and demand differences across firms. This is motivated by the view that exporters may face different demand and competitions in international markets, and we would expect them to set different prices than non-exporters. Thus, the tradition of estimating export premium based on sales deflated by a common industry price would confound technical efficiency and price heterogeneities. In order to separate these two components of export premium, we first compare the revenue and physical productivity of exporters and non-exporters by using Ethiopian manufacturing firm's data. We further compute demand shocks and prices, and then investigate whether these demand components play roles in explaining export-productivity links. We find that exporters are more productive than non-exporters not only because they are technically efficient, but also face positive demand shocks and charge higher prices than non-exporters.

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1. Introduction

Following the pioneering study by Bernard and Jensen (1995), a surge of interest in microeconometrics of international trade and productivity has yielded numerous studies on the link between trade activities and various aspects of firm characteristics, such as employment, capital intensity and productivity. A key issue in this literature is whether exporters are different from non-exporters in terms of their characteristics, the main being productivity. Subsequent studies for a large number of countries have found that exporters are larger, more capital intensive, and more productive than non-exporters (See Greenaway and Kneller, 2007; Wagner, 2007, 2012, for surveys and ISGEP, 2008 for international comparisons). Bigsten et al. (1999) are among the first to provide evidence on the export – productivity relationship in the African context. By using firm-level data, Bigsten et al. (1999) examined the relationship between exporting and productivity in four African countries (Cameroon, Kenya, Ghana and Zimbabwe) and find that exporters are indeed more productive than non-exporters. Subsequent studies for other African countries also find a significant positive correlation between exporting and productivity (See for example, Bigsten et al. (2004), Van Biesebroeck (2005), and Amakom (2012) for Sub-Saharan Africa, and Bigsten and Gebreeyesus (2009) for Ethiopia).

Along with such empirical findings, Melitz (2003), among the others, introduced theoretical explanations for the positive correlations between exporting and productivity. Exporters are more productive than non-exporters because, on the one hand, foreign market entry entails substantial sunk costs and thus only more efficient firms self-select into export markets (Clerides et al., 1998; Bernard et al., 2003, Melitz 2003). Hence, the existence of sunk foreign market entry costs and productivity heterogeneity across firms explain why more productive firms get into export markets. On the other, exporters are more productive than non-exporters because contact in foreign markets reduces inefficiencies and increase their productivity[1].

The productivity measures that are used to draw the conclusion that exporters are more productive than non-exporters are often based on a production function estimated by using deflated sales. Studies, for example, that use total factor productivity (TFP) as a measure of

[1] In this paper while we abstract from identifying the direction of causality between exporting and productivity, we see whether revenue and physical productivity measures gives different results as a possible expansion point for future work.

productivity often use firm-level sales deflated by a common industry prices as a proxy for real output and estimate TFP from the residual of a production function[2]. However, this approach of computing real output is based on the implicit assumptions that firms in the same industry produce a homogeneous product and face perfectly competitive markets. In case where these assumptions are violated, productivity estimated from the residuals of a production function may reflect not only productivity, but also price and demand components. De Loecker and Goldberg (2013) argue that productivity measures based on deflated-sales is closely related to profitability as its computation involves the difference between sales and expenditures. They pointed out that this productivity, thus, comprises physical efficiency and price components and reflects product differentiation, mark-ups and costs. It is widely acknowledged that firms operating in the same industry do not face perfectly elastic demand, and thus the assumption of a common industry price results in a biased productivity estimates (Klette and Griliches,1996).

The issue of price heterogeneity across firms is particularly interesting in examining the export-productivity link. Firms that sale in international markets are faced with different markets and would change their pricing behaviour. If exporters have different prices than non-exporters, then the export premium we observe in the data may not only reflect higher physical efficiency (output per unit of input) by exporters, but also different degree of market powers. Thus, export-productivity link analysis that relies on sales deflated by common industry deflator would combine the separate effects of technical efficiency and price heterogeneity. Consequently, the export premium observed in the data may capture price differences, not necessarily efficiency differences. Yet, the effect of price heterogeneity across firms on productivity estimates and a subsequent analysis of its implication on export-productivity link have been largely neglected.

One exception in this regard, at least to my review, is a recent study by Smeets and Warzynski (2013) for Danish manufacturing firms. They compute productivity based on sales deflated by common industry price and sales deflated by firm specific price, and then compare the resulting trade premium in the two productivity measures. Smeets and Warzynski (2013) find that trade premium is larger when output is deflated by firm-level price than average industry price. This result is interpreted based Melitz and Ottaviano (2008)

[2] The few studies that use physical output for their analysis, at least to my knowledge, are Eslava et.al (2004) which focuses on market reform and firm dynamics; Syverson (2004), which focuses on explaining productivity differences across producers; and Foster et.al (2008) which focuses on market selection and productivity growth.

prediction that more efficient firms charge lower prices than less efficient firms. Specifically, they claim that exporters are on average more productive than non-exporters, and thus would charge lower prices. Consequently, deflating sales by common industry price, results in over-deflation of exporters' output. Although, these explanations are undoubtedly important and are consistent with the theoretical prediction of the inverse relation between price and productivity, we contend that a closer investigation of the pricing behaviour of exporters and non-exporters (rather than more efficient and less efficient firms) is essential to fully understand the role of price heterogeneity in explaining the productivity differences between exporters and non-exporters.

Due to pro-competitive effects in international markets, one would expect that exporting firms reduce their prices. At the same time, exporting firms are faced with more demands that will allow them to charge higher prices than non-exporters. The theoretical prediction of Hallak and Sivadasan (2009) shows that conditional on size, exporters are expected to sale higher quality products at higher prices. As a result, selling in global markets would have countervailing effects on prices and hence, whether exporters charge higher or lower prices than non-exporters depends on the counterfactual effects of competition and demand forces, among the others. However, the characteristics of the source and destination countries of exports may also affect the pricing of exporters. Schott (2004) and Hummels and Klenow (2005) noted that export prices are systematically correlated with source country characteristics, such as per capita income. Based on detail Chinese custom data Manova and Zhang (2012), for example, find that exporting firms charge higher prices in richer and larger countries and earn bigger revenues.

Besides, despite the recent interest in trade and firm heterogeneity, empirical analysis has been centered in developed countries, probably due to limited availability of firm level data in the developing world, such as Africa. The purpose of this paper is to examine whether the real productivity premium of exporters is different from their revenue productivity (which combines technical efficiency and demand component). We then attempt to disentangle the export premium that arises due to technical efficiency differences from the premium due to price and demand differences. To this end we use Ethiopian manufacturing firm-level data over the period 2000 to 2009. This data has information on sales values and physical outputs. The unique feature of the data allows controlling price heterogeneity by estimating physical productivity or deflating sales by firm-level prices. In order to compare our findings to earlier studies, we also estimate productivity based on sales deflated by common industry deflator. Furthermore, as the country considered here is one of the least developed countries, the study reveals the features of exporting firms and their characteristics in the context of less industrialized developing countries.

Our analysis uncovers a wealth of interesting results. We find that, on average, revenue productivity is larger than physical productivity. While physical productivity is inversely related with firm price, the traditional revenue productivity and price correlate positively. The negative price-physical productivity supports the view that more efficient firms pass their cost advantage to buyers and charge lower price than less efficient ones. Whereas, the positive price-revenue productivity relationship is consistent with our claim that revenue productivity confounded price and physical efficiency components and, thus, firms that charge higher price would have large revenue productivity.

In terms of exporting and productivity, irrespective of productivity measures, we find that exporters are more productive than non-exporters. This is consistent with the empirical regularity in this literature. The most interesting result is, however, the export premium sharply drops when we use physical productivity as compared with the traditional revenue productivity. This result suggests that exporters are indeed more productive than non-exporters, but the relative productivity of exporters is overstated in the traditional revenue based productivity measures. We further our analysis to explore whether price variations and demand shocks explain some part of the export premium. We estimate demand shocks as a disturbance from the expected sales of firms and analyse its correlation with exporting. Price and demand shock differences across exporting and non-exporting firms emerge: exporters face positive demand shocks and tend to set higher prices than non-exporters. This implies that the tradition of deflating sales by industry average price results in under-deflation of exporters' revenue, and thus higher revenue productivity. These findings reinforce our earlier finding that revenue productivity overstates export premium. We find consistent result by employing quantile regression technique that characterizes the relationships between exporting and productivity at different points of the productivity and takes into account outliers.

Combining all the pieces of our findings, we claim that exporters are more productive than non-exporters not only because they are technically efficient, but also face positive demand shocks and charge higher prices than non-exporters. This conclusion is consistent across different levels of productivity. Thus studies that explain export-productivity links based on revenue based productivity may overstate real productivity of exporters and understate the demand components that accompany firms export participation.

The remainder of this paper is organized as follows. Section 2 provides the description of the data we used. Section 3 reviews the methodological issues and estimation of production function. Section 4 presents the discussion of the results. Section 5 concludes.

2. The Data and Construction of variables

2.1. Data description

The data used for the analysis come from the annual Ethiopian manufacturing survey carried out by the Central Statistical Agency of Ethiopia (CSA). The census covers all major manufacturing sectors of Ethiopia based on 4-digits international standard industrial classification (ISIC). The unit of observation in our sample is the firm. All firms are uniquely identified and information such as production quantity, production value, sales quantity and sales value (in both the domestic and foreign markets), value of fixed assets, employment, intermediate inputs and investment are available.

Table 1: Sample coverage

	Food and Beverage		Textile and Apparel		Leather and Tanning		Total	
Year	Number of firms	Share of firms (%)	Number of firms	Share of firms (%)	Number of firms	Share of firms (%)	Number of firms	Share of firms (%)
2000	130	56.5	53	22.5	52	22.1	235	7.8
2001	128	55.8	52	22.7	49	21.3	229	7.6
2002	145	57.0	58	22.8	51	20.0	254	8.4
2003	149	55.8	62	23.2	56	20.9	267	8.9
2004	160	55.5	67	23.2	61	21.1	288	9.6
2005	162	58.0	60	21.5	57	20.4	279	9.3
2006	191	60.4	68	21.5	57	18.0	316	10.5
2007	192	58.7	66	20.1	69	21.1	327	10.9
2008	246	66.4	50	13.5	74	20.0	370	12.3
2009	273	65.1	60	16.2	78	18.6	419	14.0
Total	1776	59.5	604	20.2	604	20.2	2984	100

We limit our analysis to firms operating in the food, beverage, textile, wearing apparel and leather and footwear sectors. We stick to these sectors, which relatively produce physically homogeneous products, in order to reduce measurement problem in using physical output and to make our physical productivity estimates comparable across firms. Furthermore, these sectors are perhaps the most important ones in the manufacturing sectors of Ethiopia as about 89 percent of exporting firms are concentrated in these sectors (See Appendix A for details). Firms that did not have complete record of sales, outputs and inputs were also dropped. The remaining analysis is, therefore, based on an unbalanced panel of 2984 observations (firm-years) from 2000 to 2009 (inclusive).

Table 1 shows the summary of our sample and the number of firms used in this analysis. We grouped firms into three broad sectors: food and beverage, textile and apparel and leather and tanning. Looking at the proportion of firms in our sample, food and beverage sector accounts the largest share (60 %) while the other two sectors take the remaining share equally (20 % each). The time series property of the sample shows an increase in the number of firms in all sectors over time, except some fluctuations in the leather and tanning sector. It is important to note that the sample of observations comprises only 14 percent of the Ethiopian manufacturing firms over the sample period, and thus the interpretation of our analysis needs caution to represent the whole Ethiopian manufacturing firms (See Appendix C for the summery statistics of the entire manufacturing sector).

2.2. Variable Construction

We use three measures of output. Our first measure of output is sales deflated by industry-level price (Y_IP). This is the traditional measure of real output where we deflate sales by a common industrial deflator at the two-digit level of industrial classification obtained from CSA. Our second measure of output is sales deflated by firm-level prices (Y_FP). To account price heterogeneity, we compute average firm level prices (as discussed below) from the reported sales value and sales quantity and then use it to deflate firm level sales. Our third measure of output is physical output (Y_Q). This is the physical output reported by firms with some adjustments in the units of measurement.

We use the number of permanent employees as a measure of labour inputs. Intermediate inputs are measured as the sum of costs of electricity, fuel, water and other inputs deflated by their respective deflators obtained from CSA.

Capital stock is computed using the perpetual inventory method from the stock value of tangible assets as follows $K_{it} = K_{it-1} + \frac{I_t}{P_t} - \delta K_{it-1} - sK_{it}$, where K_{it} is the stock of capital of firm i at the beginning of the year, $\frac{I_t}{P_t}$ is deflated investments in fixed assets during year t, sK_{it} is total capital sold or disposed during the year and δK_{it-1} is total depreciation of capital[3]. We then take the average of capital stocks at the beginning and the end of each year to construct the series of capital.

We construct product level prices by dividing the sales value for each product by its respective quantity. The firm level price is then computed as a weighted average of product level prices; $P_{it} = \sum_{h=1} W_{hit} P_{hit}$ where P_{it} is the average price of firm i at time t, W_{hit} is the shares in sales of product h of firm i at time t, and P_{hit} is the average price of product h of firm i at time t.

Table 2 provides the summary statistics of the main variables used in the analysis. The statistics are computed based on the samples used for the analysis. Here, there is little variation in the mean output and inputs across sectors. However, as indicated by the standard deviations, there are reasonable variations in both inputs and output across firms with in each sector. Comparing the averages of revenue and quantity based measures of output; the quantity based measure of output is less than the revenue based measures across all sectors. It is interesting to note that the standard deviations for the industry deflated output are lower than outputs deflated by firm-level prices and physical output. This result is consistent with the view that, the use of common industry level price deflator to compute real output would reduce the variation of output across firms.

Table 2: Summary statistics of output and inputs by sector, 2000-2009

variables	*Food and Beverage*		*Textile and Apparel*		*Leather and Tanning*	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Y_{it}_IP	14.68	2.09	14.55	2.19	14.50	1.85
Y_{it}_FP	16.66	2.74	15.76	2.93	16.23	2.37
Y_{it}_Q	11.08	2.71	10.52	3.02	12.19	2.07
L_{it}	3.69	1.39	4.39	1.78	3.89	1.26
K_{it}	14.64	2.38	13.51	3.48	15.21	1.94
M_{it}	12.27	2.11	11.66	2.63	12.26	1.90

Note: all values are in logs. L_{it} is labour, K is capital and M is intermediate inputs.

[3] We use different rate of depreciation for different fixed assets: 8 percept for machinery and equipment, 5 percept for buildings, and 10 percept for furniture and fixtures.

3. Empirical Framework

This section provides the review of methodological issues and estimation results of productivity measures that we use in the subsequent analysis.

3.1.Methodological issues in Estimating input coefficients

The analysis of this study mainly relies on total factor productivity (TFP) estimated from production function. However, we also employ labour productivity (LP) measured by output to labour ratio ($\frac{Y_{it}}{L_{it}}$) as a robustness checks. In order to calculate $TFP,$ we considered that firms are producing according to the following Cobb-Douglas production function:

$$Y_{it} = A_{it}K_{it}^{\beta_k}L_{it}^{\beta_l}M_{it}^{\beta_m} \tag{3.1}$$

Where Y_{it} measures the real output of firm i at time t, K_{it} denotes capital $, L_{it}$ denotes labor, and M_{it} denotes intermediate inputs. A_{it}captures total factor productivity, and is additivly separable into two components: $lnA_{it} = \omega_{it} + \varepsilon_{it},$ where ω_{it} captures the part of the productivity shocks that is known to firms, but not to econometricians and thus affects input decisions, whereas ε_{it} captures random productivity shocks unobservable for both econometricians and firms and hence does not affect firm's input decisions. A logarithmic transformation of equation (1) yields

$$\mathrm{y_{it}} = \beta_k \mathrm{k_{it}} + \beta_l \mathrm{l_{it}} + \beta_m \mathrm{m_{it}} + \omega_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \tag{3.2}$$

Where y_{it} is the log of the real output of a firm i at time t. $k_{it}$is the log of capital input, l_{it} is the log of labour input, and m_{it} is the log of intermediate inputs. ω_{it} captures firm-specific productivity shocks and ε_{it} is the standard i.i.d. error term and captures any unforeseen shocks or measurement errors. The total factor productivity (TFP) is then computed as the difference between firms actual production and predicted output:

$$\mathrm{TFP_{it}} = \mathrm{y_{it}} - \widehat{\beta_k} k_{it} - \widehat{\beta_l} l_{it} - \widehat{\beta_m} m_{it} \tag{3.3}$$

Where $\widehat{\beta_k}$,$\widehat{\beta_l}$ and $\widehat{\beta_m}$, are ,respectively, the estimated coefficients of capital, labour and intermediate inputs.

A simple OLS estimation of equation (3.2) yields biased estimates of input coefficients due to the well-known simultaneity and selection biases[4]. One potential solution to simultaneity bias is to use instrumental variable (IV) estimates. However, the practical difficulty to find valid instruments for inputs makes IV estimation impractical in empirical studies. Olley and Pakes (1996) proposed an innovative method to deal with the endogeneity problem by using investment function as a proxy for productivity and to apply a semi-parametric estimation. Levinsohn and Petrin (2003) extended this approach and propose to use intermediate input demand as a proxy for productivity rather than investment. To identify input coefficients, the Olley and Pakes (1996) approach requires all firms to invest in all periods. Given the fact that firms in our sample do not invest in all periods, this method is inappropriate for our analysis. On the other hand, Levinsohn and Petrin (2003) approach assumes demand for inputs is monotonically increasing in productivity. However, this assumption may not hold if high productive firms manage to reduce their inefficiency in the use of intermediate inputs.

Arellano and Bond (1991) developed a generalized method of moments (GMM) estimation where past values of repressors are used to instrument repressors themselves. In this approach, once time-invariant components of the error are wiped-out by taking first differences, the lags of the dependent and independent variables can be used as instrument in the first difference equations, and referred as first-difference GMM estimation. However, Blundell and Bond (1998) emphasized that the validity of instruments in first-difference GMM estimation depends on the persistence of inputs and outputs variables overtime: if inputs and outputs are highly persistent, their past values will be weak instruments and results in large finite sample biases. They introduced more moment conditions and develop the system-GMM estimator. System-GMM uses lagged first-difference of inputs and outputs in addition to the lags in levels and yields efficient estimators.[5]

The other practical problem in estimating productivity, often not discussed in the literature, is the omitted variable bias that arises due to unavailability of information on physical output and price of intermediate inputs. Klette and Griliches (1996) and Levinsohn,

[4] The simultaneity problem arises due to potential correlations between firm-specific productivity shocks and demand for inputs: when firms observe productivity shocks, they often adjust their demand for inputs. The sample selection problem arises because firms' exit decision is partly explained by their perception about their future productivity (See Olley and Pakes, 1996 for the discussion of these problems).

[5] See Eberhardt and Helmers (2010) for further discussion and empirical implementations of the GMM, Olley and Pakes (1996), and Levinsohn and Petrin (2003) production function estimation techniques.

and Melitz, (2002) discuss the bias in input coefficient estimates arises due to omitted firm-level price variable. More recently De Loecker (2007) and De Loecker and Goldberg (2013) extend the analysis to multi-product firms and introduce unobserved demand shocks that are likely to be correlated with price and other demand shifting factors.

Since physical output and intermediate inputs price are often unavailable in a typical firm-level data, the common practice in empirical literature is, thus, to substitute real output (Y_{it} in equation 3.1) by sales ($Y_{it}P_{it}$), where P_{it} is firm-level price. In order to obtain real output, $Y_{it}P_{it}$ is then deflated by common industry price (PI_t). Similarly, intermediate input (M_{it}, in equation 3.1) is also replaced by total expenditures on intermediate inputs ($M_{it}\Upsilon_{it}$), where Υ_{it} is firm-specific input price. Real raw material is then captured by $M_{it}\Upsilon_{it}$ deflated by common input deflator (ΥI_t). The dependent variable in equation (3. 1) is then become $\frac{Y_{it}P_{it}}{PI_t}$ as well the material input variable is replaced by $\frac{M_{it}\Upsilon_{it}}{\Upsilon I_t}$. When we use commonly deflated sales and deflated expenditures, the log-linear transformation of the equation (3.1) yields

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \eta_{it} \quad (3.4)$$

where $\eta_{it} = (P_{it} - PI_t) - \beta_m(\Upsilon_{it} - \Upsilon I_{it}) + \varepsilon_{it}$. Thus the error term in equation (3.4) captures not only the disturbance term (ε_{it}), but also the deviation of firm specific prices from the average index used to deflate sales and raw material expenditures. Klette and Griliches (1996) noted that because the price of output and intermediate inputs affects the optimal choice of factors, the repressors in equation (3.4) are likely to be correlated with η_{it} and this results in biased estimates of input coefficients. Specifically, Klette and Griliches (1996) claim that using deflated sales as a measure of real output creates a downward bias in production function estimates. However, De Loecker and Goldberg (2013) argue that the omitted price might cause upward or downward bias depending on the correlation between firm's price and levels of input.

In order to correct omitted price bias, for example, Klette and Griliches (1996) suggest introducing growth in industry output in firm-level production function estimation. Based on the same framework, Ornaghi (2008) suggests replacing the unobserved prices by observed labour costs. In this analysis, however, we directly control price heterogeneity across firms by using the unusual frim reported physical output rather than deflated sales.

However, it is important to note that availability of detail data by itself is not a panacea to deal with price heterogeneity across firms. One challenge is that, in a strict sense 'prices' derived by dividing sale values by quantities are unit values, but not prices. Since firms produce more than one product, the quantities and sales reported by firms might include different variety of products and the composition of these varieties might vary across firms. Thus differences in the computed 'prices' might reflect differences in qualities and measurement errors rather than differences in prices for homogenous products[6]. The other challenge is associated with using physical output in estimating productivity. This is because, unit of measurements may vary across firms and the difference in quantity may have quality components. Recent papers address this issue by focusing on sectors which produce homogeneous products (See for example Syverson , 2004; Eslava et.al., 2004,and Foster et.al, 2008)[7]. Following the same strategy, we limit our analysis to food, beverage, textile, wearing apparel and leather and footwear sectors (with some adjustment in the units of measurement), which relatively produce physically homogeneous products. This allows us to reduce measurement problem in using physical output and to make our physical productivity estimates comparable across firms. We have not been able to unravel the biases due to input price variations across firms. However, earlier studies that estimate physical productivity assume that input prices do not vary across firms that produce relatively homogenous products. This is a plausible assumption in our analysis. Furthermore, we should notice that Ethiopian manufacturing sector is dominated by small firms and largely depends on imported raw inputs. Thus, it gives sense to assume that input price variations within the same industry are moderate.

3.2.Estimation strategy and results of production function estimates

The main analysis of this paper relies on TFP estimated from a Cobb-Douglas production function by using Blundell and Bond (1998) system-GMM estimator, while using labour productivity (LP) defined as output per labour as a robustness checks. The data permit estimation of three versions of productivity measures : (1) real physical productivity

[6] To correct prices for quality differences and measurement errors, we follow Deaton (1997) approach that involves regression of unit values on firms' asset and characteristics. This exercise is based on the assumption that quality differences are correlated with firms' asset levels and other characteristics. Unit values corrected for quality-biases and measurement error (that capture the actual prices) are then obtained by removing the coefficients of assets and firm characteristics. Our results for the subsequent analysis are also robust when we use the price corrected for quality differences and measurement error.

[7] For example Foster et.al, (2008) focus the analysis on the following products: boxes, bread, carbon black, coffee, concrete, hardwood flooring, gasoline, block ice, processed ice, plywood and sugar. .

(TFP_Q) which is estimated by using physical output (Y_Q) as a dependent variable; (2) firm-level price productivity (TFP_FP) which is estimated by using sales deflated by firm-level price (Y_FP) as a dependent variable; and (3) industry-price deflated productivity (TFP_IP) which is estimated by using the common approach of sales deflated by industry-deflator (Y_IP) as a dependent variable. Similarly, we measure three versions of labor productivity: real labour productivity (LP_Q) defined as Y_Q per unit labour, firm-level price deflated labour productivity (LP_FP) defined as Y_FP per unit labour, and industry price deflated labour productivity defined as Y_IP per unit labour.

We estimate the production function by using different instruments using system-GMM estimator and report the result which passed the necessary tests. Tables from B1 to B3 report the input coefficient estimates for the three versions of the production function. To take into account the biases of estimated input coefficients due to heterogeneity of production technology across sectors, we estimate the production function at 2- ISIC digits level: food and beverage, textile and apparel, and leather and tannin. Furthermore, we account the presence of common shocks by including year dummies in all models. For comparison reason we present OLS and within estimates.

4. Discussion of Results

In this section we first provide some basic descriptive statistics of our productivity measures and their relationships with prices. Then we revisit the export-productivity correlations by using revenue and physical productivity measures and draw the implications of omitted price bias in this literature. We next estimate productivity shocks and introduce it into the export-productivity analysis.

4.1. Comparing revenue and physical productivity.

An important question is whether production functions estimated based on industry-deflated sales and physical output result in different productivity estimates. However, given the significant differences between the revenue based and physical output based input coefficient estimates; it would be somewhat surprising if this were not the case. To highlight this issue, we begin by computing the simple statistics for revenue and physical productivity. Table 2 provides the summery statistics of TFP and LP based on deflated sales and physical output.

Table 2: Summary statistics of productivity measures

	Mean	Std.Dev.	Min	Max	Obs
			TFP		
TFP_IP	8.737	1.238	3.309	12.345	2984
TFP_FP	9.560	2.430	-1.575	17.563	2960
TFP_Q	6.729	2.033	-1.481	13.823	2975
			Labour productivity		
LP_IP	10.741	1.291	5.502	16.637	2984
LP_FP	12.513	2.319	3.473	20.966	2960
LP_Q	7.317	2.053	-0.693	14.440	2975

Notes: all values are in logs.

The averages of revenue productivity (both TFP_IP and TFP_FP) are higher compared to physical productivity (TFP_Q). Labor productivity also provides consistent result where the averages of revenue labour productivity (both LP_IP and LP_FP) are larger than physical labour productivity (LP_Q). It is also interesting to note that physical productivity is dispersed than revenue productivity. These results are consistent with our output statistics reported in Table (2).

Since one of our objective is to figure out how unobserved price variations across firms result in productivity differences, we compute simple correlation of prices with revenue and physical productivity. Table 3 reports the outcome of this exercise. We find that the traditional revenue based productivity (TFP_IP) is positively correlated with firm level prices, whereas TFP_FP and TFP_Q are negatively correlated with prices. We also observe consistent evidence when we consider the correlations between labour productivity and prices.

Our results are consistent to findings by Foster, et.al (2008) that firm's price is negatively correlated with true productivity. This result reflects the theoretical prediction that more physically productive firms pass their cost advantage to buyers by selling their products at lower prices. The positive correlation between price and TFP_IP supports our claim that industry-deflated sales understates price variations across firms and those firms that charge higher price may show high revenue productivity. We observe positive and high (more than 80 percent) correlations between TFP and respective labour productivity measures. TFP_Q and LP_Q, for example, have 88 percent correlation. Furthermore, price-productivity relationships observed in TFP measures also hold for labour productivities.

Table 3: Correlations between price and productivity

	TFP_IP	TFP_FP	TFP_Q	LP_IP	LP_FP	LP_Q	Price
TFP_IP	1.000						
TFP_FP	0.286	1.000					
TFP_Q	0.460	0.467	1.000				
LP_IP	0.874	0.259	0.360	1.000			
LP_FP	0.375	0.808	0.472	0.457	1.000		
LP_Q	0.404	0.282	0.883	0.448	0.550	1.000	
Price	0.128	-0.739	-0.337	0.125	-0.781	-0.339	1.000
Std. Dev.	1.238	2.430	2.033	1.291	2.319	2.053	1.917

Notes: all variables are in logs.

This simple price-productivity correlation analysis, however, is crude in the sense that it does not show whether the price bias affects productivity gains associated with exporting. The literature on trade and firm heterogeneity (often by using revenue productivity) emphasized that exporters are more productive than non-exporters. But it is important to examine to what extent exporting and real productivity are correlated. To stage for further analysis, we next examine export-productivity links based on revenue and physical productivity measures.

4.2.Productivity and price heterogeneity

Our primary focus is to analyse the link between exporting and productivity by controlling for biases due to price variations across firms. The rational for this analysis is that, access to foreign markets, for example, may provide large demand for exporters and we would expect them to charge higher price. In the meantime, exporting firms may benefit from increase in efficiency due to their contact in foreign markets. These imply that, productivity improvements associated with exporting would have both physical efficiency and demand components. Thus, the positive correlation between exporting and productivity found in earlier studies could overstate real productivity gains as the revenue based productivity confined technical efficiency and market power shift effects.

4.2.1 Mean productivity differences between exporters and non-exporters

To give first impression on the unconditional mean differences in revenue and physical productivities between exporting and non-exporting firms, we provide a summary statistics of productivities, prices and inputs in table 4.

Table4: Differences in productivity, inputs and prices between exporters and non-exporters (Averages, 2000-2009)

	Exporter		*Non-exporter*	
	Mean	Dtd.Dev.	Mean	Std.Dev.
LP_IP	11.30	1.20	10.64	1.28
LP_FP	12.65	2.04	12.48	2.36
LP_Q	8.13	1.88	7.17	2.04
TFP_IP	9.62	1.09	8.58	1.19
TFP_FP	9.71	2.44	9.53	2.42
TFP_Q	7.90	1.85	6.52	1.99
Capital	16.54	1.71	14.18	2.60
Raw materials	13.90	1.99	11.84	2.09
Employment	503.27	675.21	108.61	260.13
Price	21.65	223.25	5.122	174.04

Notes: productivity measures, capital and raw materials are in logs. Employment and price are in labels.

Table 4 presents the relative performance of exporting and non-exporting firms. Without holding other factors constant, exporters are found to be more productive than non-exporters. The better performance of exporting firms is reflected irrespective of whether output is measured by deflated sales or physical quantity. However, comparing the revenue productivity and physical productivity, quantity based measures of productivity measures (both TFP_Q and LP_Q) are lower than revenue based productivity measure. It is also interesting to note that exporters, on average, charge higher prices than non-exporters. These results hint that caution needs to be used in interpreting the correlation between exporting and productivity when productivity is estimated using industry deflated sales. For both exporting and non-exporting firms, physical productivity is more dispersed than industry-price deflated productivity, but less dispersed than firm-price-deflated productivity. This result might partly reflect output price variations across firms. Considering factor inputs, on average, exporters employ both more capital and labour relative to non-exporters. However, this productivity difference between exporters and non-exporters can be explained by firm specific effects uncontrolled in this analysis. We explore this issue in the next sections by estimating the correlation between exporting and productivity conditional on other firm characteristics.

4.2.2 Productivity and price heterogeneity within exporters and non-exporters

In order to examine the heterogeneity across firms within the group of exporters and non-exporters, we provide productivity and price distributions at selected percentiles (See Appendix C). It is interesting to note that firms within exporters and non-exporters are highly heterogeneous with regard to productivity and prices. Considering the revenue productivity (TFP_IP) distributions of exporters, the lower 1 percentile of firms are 234 times less productive than the upper 99 percentile of firms. Whereas, TFP_IP of non-exporters seems to be less dispersed than TFP_IP of exporters: the lower 1 percentiles of non-exporters are 198 times less productive than the upper 99 percentiles of non-exporters. One explanation for this difference can be because TFP_IP is measured based on common industry price deflator, it may understate productivity heterogeneity across firms. This claim is further reinforced by the observation that, in terms of physical productivity (TFP_Q), the upper 99 percentile of exporters (non-exporters) is 3732(7447) times more productive than the lower 1 percentile of exporters (non-exporters). Among exporters price varies between 0.0024 (the lowest) and 3773.206 (the largest). Similarly, price varies between 0.00018 (the lowest) and 8713.553 (the largest) for non-exporters.

Despite this heterogeneity, exporters are more productive and charge higher price than non-exporters at all the quantiles of the distributions. We test the stochastic dominance of exporters over non-exporters by using Kolmogorov-Smirnov test. The lower panel of Tables C1 to C4 show the p-values of this test. We reject the equality of the productivity and price distributions of exporters and non-exporters at the conventional levels of significance in favour of the dominance of exporters over on-exporters. This result is consistent in all physical and revenue productivity measures. However, a comparison of the physical and revenue productivity distribution of exporters reveals that their revenue productivity is higher than physical productivity. In general, the average and entire distribution comparison of the productivity of exporters and non-exporters support the claim that exporters are more productive and charge higher prices than non-exporters. Because this unconditional correlation can be explained by other firm characteristics, in the next sections, we examine the relationship between exporting and conditional productivity distributions by controlling for firm characteristics. Outliers are also controlled by using quantile regression.

4.2.3. *Exporting and revenue productivity versus exporting and physical productivity*

In order to investigate the extent to which export participation is correlated with productivity, we follow the standard approach of regressing productivity measures on the export dummy and other control variables:

$$lnX_{it} = \alpha_0 + \alpha_1 EX_{it} + \gamma \mathrm{Controls_{it}} + \sum_k \theta_k \mathrm{Ind_k} + \sum_t \lambda_t \mathrm{year_t} + \xi_{it} \qquad (4.1)$$

Where lnX_{it} Captures the log of the different characteristics (TFP, $employment$ and $capital$) of firm i at time t. EX_{it} is dummy for current export status and equals to one if the firm exports, zero otherwise. Controls are firm characteristics that are widely used in the literature: size and age[8]. We also controls for industries (ind), and year ($year$) effects. Non-exporters are the reference groups. The coefficient on the export dummy thus measures the average differences between TFP, employment and capital of exporting and non-exporting firms.

For the sake of comparison with earlier findings in the literature, we first follow the tradition of estimating the effect of exporting on TFP_IP using pooled OL and fixed effects (FE) model. However, the identification of coefficients in fixed effects estimation is based on the variations of the variables within a firm over time. For example, to identify the coefficient of export status based on within estimation, firms should often change their export status. Thus, the fixed effects estimation requires a large within variation of variables over time. The within variations of productivity measures, export status and employment are, however, smaller than the variations between firms (See Appendix D). Thus, the application of fixed effect for this analysis seems inappropriate, and thus our subsequent analysis is based on pooled OLS estimates. For comparison, yet, we provide the fixed effect estimates alongside the OLS estimates. The outcome of this exercise is reported in table 5.

Considering the OLS estimates, we find that exporting firms have higher revenue productivity (TFP_IP and TFP_FP), physical productivity (TFP_Q), and employ more labour and capital than non-exporting firms. Exporting positively and significantly explains all the productivity measures. This finding is consistent with the earlier empirical regularities in this literature where exporters outperform non-exporters.

What is interesting here is that the export premium sharply drops when we use physical productivity relative to the traditional revenue productivity. Specifically, the physical productivity (TFP_Q) export premium is about 31 percent less than revenue productivity (TFP_IP). When we use labour productivity, similar patterns hold, but the magnitude of difference between revenue productivity and physical productivity is larger, about 55 percent.

[8] Size is not controlled when employment is used as a dependent variable.

Table 5: Export status and firm characteristics: pooled OLS and within estimates

Dependent variables	*Sector, size, age & year controlled Export premium*			
	OLS	Se	FE	Se
TFP_IP	0.913**	(0.063)	0.262**	(0.088)
TFP_FP	0.588**	(0.116)	0.159	(0.178)
TFP_Q	0.596**	(0.101)	0.083	(0.122)
LP_IP	1.146**	(0.073)	0.336**	(0.104)
LP_FP	0.490**	(0.121)	0.218	(0.191)
LP_Q	0.593**	(0.108)	0.124	(0.130)
Employment	2.965**	(0.065)	0.222	(0.080)
Capital	0.587**	(0.035)	0.479*	(0.082)
Raw material	1.820**	(0.094)	0.164	(0,134)
Price	0.793**	(0.104)	0.048	(0.174)
Demand Shocks	3.53**	(0.412)	0.090	(0.671)

Notes: The dependent variables are in logs. The reported values are export premium computed as $exp\ (coefficients) - 1$. Estimators employed are pooled OLS and FE- firm fixed effects (within). All models include year dummies, sector dummies size, and age (coefficients not reported). Cluster-robust standard error in parentheses, **, * indicate statistical significance at 1% and 5% level respectively.

Our results seem to be in contrast to the recent findings of Smeets and Warzynski (2013) for Danish manufacturing firms that trade premium is larger when output is deflated by firm-level price than when it is deflated by average industry price. They argue that since exporters are more efficient than non-exporters, they would set lower prices. Thus, deflating revenue by common industry price over-deflates exporter's revenue, and results in lower export premium. This claim is based on a theoretical prediction on the inverse relation between prices and efficiency without a close look at the price differences between exporters and non-exporters. However, in our case, we have seen that exporters indeed charge higher prices than non-exporters. Hence, deflating sales by a common industry price leads to under-deflating exporters sales, rather than over-deflating.

In contrast to the claim that international market competition forces exporting firms to reduce their prices, the evidence for Ethiopian firms is in favour of exporters. In other words, exporters tend to charge higher prices than firms that sale solely into domestic markets. This evidence can be explained by the income difference between the source of exports and the destination countries. Given the fact that a large proportion of Ethiopian manufacturing firms export to developed countries, it seems reasonable to expect exporting allows exporters to charge higher prices than selling in domestic market[9]. This is because; while the low per-capita income of the domestic economy hinders firms from charging a higher price in the domestic market, exporting to developed economies would allow them to charge higher prices. This result is consistent to the finding of Manova and Zhang (2012) based on Chinese detail custom data where exporting firms charge higher prices in richer and larger countries. Further explanations can be associated with large export market entry costs. As noted by Bigsten and Soderbom (2010), African firms incur large entry costs associated with exporting. Thus, if exporting firms could not find certain price advantages in foreign markets at least to cover this additional market entry costs, they may rather sell in domestic markets. The finding that exporting and demand shocks are positively and significantly correlated strengthens our claim that exporters tend to face larger demand than non-exporters and thus charge higher prices (we shall discuss this in the next section in details).

The findings that exporters have higher revenue productivity than physical productivity, and charge higher price than non-exporters suggest additional channels through which international market participation affects firm's productivity. Thus, we argue that part of the reasons that exporters are more productive than non-exporters are due to the fact that exporters face positive demand shocks and charge higher prices, not only because they are more technically efficient than non-exporters. In the next section we explicitly explore the two channels through which exporting affects productivity: physical efficiency and demand components. Towards this end, we next estimate demand shocks and use it for the subsequent analysis.

4.2.4 Estimating demand shocks

It happens that participation in export markets leads to positive demand shocks, and firms that are facing high demand are likely to set higher prices than low-demand firms. This price advantage in turn may result in large revenue and consequently large revenue productivity even if exporters are not physically more efficient than low- demand firms. Our aim is thus to separate the effect of demand shifts from technical efficiency in explaining export productivity links. Keeping this in mind, in this section we estimate the idiosyncratic demand shocks from a demand function following Eslva et.al. (2004) and Foster et.al (2008),

[9] A large proportion of Ethiopian manufactured goods are exported to developed countries. For example, in 2000, about 60 percent of Ethiopian manufacturing exports were exported to developed countries. However this figure drops to 52 percent in 2009.

and use it for our subsequent analysis[10]. Consider a firm facing the following demand function:

$$Q_{it} = P_{it}^{-\xi} M_{it}^{\Upsilon} \tag{4.2}$$

Where Q_{it} is the physical output of firm i at time t, P_{it} is price, M_{it} is income, and $-\xi$ and Υ , respectively, capture price and income of elasticity of demand.

The firm level price is defined as in section 2.2; $P_{it} = \sum_{h=1} W_{hit} P_{hit}$ where P_{it} is the average price of firm i at time t , W_{hit} is the shares in sales of product h of firm i at time t, and P_{hit} is the average price of product h of firm i at time t.

Income is defined as the weighted average income of the domestic economy and the top ten destinations of Ethiopian exports[11]. Specifically, $M_{it} = DS_{it}(MD_t) + FS_{it}(MF_t)$, where DS_{it} is the share of output of firm i sold in domestic markets at time t, MD_t is Ethiopian per capita income at time t; FS_{it} is the export intensity of firm i at time ; MF_t is the mean per capita income of the top ten export destinations of Ethiopia at time t.

We estimate the log of equation 4.2 controlling for a set of demand shifters: year ($year_t$), and age (Age_{it}) and size ($size_{it}$) of firm i at time t:

$$q_{it} = \alpha - \xi p_{it} + \Upsilon m_{it} + \sum_t \lambda_t \, \mathrm{year}_t + \beta size_{it} + \acute{a} Age_{it} + \eta_{it,} \tag{4.3}$$

Where q_{it}, p_{it} and m_{it} , respectively, capture the log of real output, price and the weighted average income. η_{it} captures the error term. The log of demand shock of firm i at time t (d_{it}) is then computed as the disturbance in the expected sales of a firm. Thus, we recover it as a residual from regression equation (4.3) and adding back the contribution of income.

The estimated demand shocks are peculiar to each firm and capture the shifts in demand once we control movements on the demand due to productivity variations. The problem for estimation of specification (4.3) using simple OLS regression arises from a plausible claim that firms decide on their choice of price based on the realized demand shocks included in the disturbance term: a favourable demand shift for a particular product

[10] Foster et.al (2008) use demand shock estimates to analyse the effect of demand shocks on selection and growth of industries.
[11] Despite some changes in their order over time, the main top Ethiopian export destinations in the sample period remain Italy, Great Britain, Germany, the USA, Netherlands, China, Saudi Arabia, United Arab Emirates, Sudan and South Africa.

might induce firms to set a higher price where as a negative shock might induce to reduce their price. So elasticities estimates will be smaller (absolute value) than the true elasticities. To eliminate this bias, we propose TFP_Q as an instrument for price since TFP_Q is positively correlated with price but less likely to respond for demand shocks. We estimate the demand function at 2-digit sectors including year dummies to control common shocks, and age to control market experience.

Table 6: Price and income elasticity estimates by sector

Sector	OLS		IV	
	Price	Income	Price	Income
Food and Beverage	-0.35**	0.68**	-3.10**	1.23**
	(0.030)	(0.077)	(0.195)	(0.218)
Textile and Apparel	-0.39**	0.72**	-6.12**	0.18
	(0.070)	(0.093)	(0.976)	(0.311)
Leather and Tanning	-0.30**	0.496**	-4.87**	1.13**
	(0.065)	(0.036)	(0.724)	(0.133)
Year, size and age		controlled in all models		

Notes: estimators employed are OLS and 2sls- IV (instrumental variable). All models include year dummies, size, and age (coefficients not reported). Robust standard error in parentheses, **, * indicate statistical significance at 1% and 5% level respectively.

Table 6 presents the results. The first two columns show the OLS estimates. Price and income, respectively, have negative and positive statistically significant coefficients, as expected. The last two columns report the results of the IV regression. Both price and income have the expected signs. Price has statistically significant explanatory power on demand in all sectors. Income also has positive significant coefficient in all sectors, but insignificant in textile and apparel. The IV estimates differ significantly from the OLS estimates, and relative to the IV, the OLS estimates are upward biased, as expected. For example, considering leather and tanning sector the coefficient of price has IV estimates of -4.87, greatly different from the OLS estimates of -0.30. This is a strong evidence that price is endogenous. However, we see a loss of efficiency in using IV, as the standard error of price is higher in IV than OLS estimates.

Despite the efficiency loss, we consider the IV results as preferred estimates for the subsequent analysis. The demand shock is thus computed as a residual from the IV regression plus the contribution of income.

4.2.5. The role of Price variations and Demand shocks in trade-productivity links

Turning to the main focus of our analysis, our earlier finding where exporters have higher revenue productivity than physical productivity and face positive demand shocks and charge higher price than non-exporters already warns us that caution needs in interpreting export-productivity links. In this section, we closely investigate the price and demand shock exporters relative to non-exporters, and examine the role of these demand components in explaining the correlation between exporting and productivity.

To further our analysis towards separating the true efficiency effect of exporting from demand side effects (namely price and demand shock effects), we re-estimate equation (4.1) by introducing demand shocks and prices as follows:

$$lnX_{it} = \alpha_0 + \alpha_1 EX_{it} + \pi DD_{it} + \gamma \mathrm{Controls_{it}} + \sum_{k} \theta_k \mathrm{Ind_k} + \sum_{t} \lambda_t \mathrm{year_t} + \xi_{it} \qquad (4.4)$$

Whre lnX_{it} is revenue productivity (TFP_IP, TFP_FP, LP_IP, LP_FP) or physical productivity (TFP_Q, LP_Q). EX_{it} is a dummy to capture the current export status of each firm i. DD_{it} captures firm price or demand shocks in a separate regression. This is because, the computation of demand shock largely depends on price, and price and demand shocks are highly correlated (about 77 percent), controlling for both of them may results in multi-collenearity problem. The model also includes industry and year dummies; $ind\ and\ year$, respectively. The omitted reference group is non-exporting firms and the coefficients are interpreted as the average differences between exporting and non-exporting firms.

Introducing prices or demand shocks in the specification is based on the following claims.: if productivity differences of exporting firms in the revenue productivity and physical productivity arises due to price or demand shock effects, we expect that a specification of physical productivity that includes prices or demand shocks results in higher coefficients for export status than the one without controlling price or demand shocks. Similarly, we expect that controlling prices or demand shocks in revenue productivity results in a lower productivity of exporting firms relative to a specification without controlling prices or demand shocks.

The estimates of equation (4.4) are reported in table 7. The first four columns report the OLS and within estimates when we control for prices and the next four columns report the OLS and within estimates controlling for demand shocks.

Table7: Export-productivity relations: controlling for prices and demand shocks.

	Price controlled				*Demand shock controlled*			
Dependent	*Export premium*		*Price coeff.*		*Export premium*		*DD-shock coeff.*	
Variable	OLS	FE	OLS	FE	OLS	FE	OLS	FE
TFP_IP	0.873**	0.241*	0.078**	0.039**	0.800**	0 .244**	0.023**	0.014**
	(0.063)	(0.089)	(0.010)	(0.013)	(0.063)	(0.089)	(0.002)	(0.002)
TFP_FP	1.238**	0.187*	-0.906**	-0.964**	0.523**	0.122	-0.155**	-0.164**
	(0.062)	(0.085)	(0.010)	(0.013)	(0.084)	(0.127)	(0.003)	(0.007)
TFP_Q	0.831**	0.068	-0.395**	-0.459**	0.749**	0.043	-0.036**	-0.045**
	(0.097)	(0.119)	(0.016)	(0.040)	(0.103)	(0.129)	(0.003)	(0.009)
LP_IP	1.087**	0.316**	0.097**	0.026	0.989**	0.319**	0.028**	0.012**
	(0.073)	(0.105)	(0.012)	(0.015)	(0.072)	(0.105)	(0.002)	(0.003)
LP_FP	1.093**	0.256*	-0.892**	-0.973**	1.356**	0.185	-0.152**	-0.165**
	(0.073)	(0.096)	(0.012)	(0.014)	(0.093)	(0.136)	(0.003)	(0.007)
LP_Q	0.803**	0.109	-0.382**	-0.465**	0.721**	0.085	-0.033**	-0.046**
	(0.105)	(0.123)	(0.017)	(0.040)	(0.111)	(0.135)	(0.004)	(0.009)
Year, sector, size and age	Controlled in all models							

Notes: The reported values for export are export premium computed as $exp(coefficient) - 1$. Estimators employed are OLS and FE- firm fixed effects (within). All models include year dummies, sector dummies size, and age (coefficients not reported). Robust standard error in parentheses, **, * indicate statistical significance at 1% and 5% level respectively.

We find that all the general patterns we observed without controlling prices or demand shocks hold for when we control price or demand shocks. In all measures of productivity, exporters outperform non-exporters. Consistent with our earlier finding, exporters have higher revenue productivity (TFP_IP or TFP_FP) than physical productivity (TFP_Q). This result is robust when we employ labour productivity instead of TFP. The most interesting result emerges when we compare these results with results reported in Table 5 (the results without controlling either price or demand shocks). As compared with results presented in Table 5, including price and demand shocks in the model significantly reduces the traditional revenue based productivity (TFP_IP) of exporting firms while it increases their physical productivity (TFP_Q) and firm-price deflated productivity (TFP_FP). When we control price heterogeneity, for example, TFP_Q export premium rises by around 22 percent while exporting effect on TFP_IP drops by around 4 percent. Similarly, controlling demand shocks leads to about 15 percent rise of TFP_Q export premium and about 11 percent drop of TFP_IP export premium.

Our finding is consistent with the idea that productivity differences between exporters and non-exporters are partly attributed to price variation between exporting and non-exporting firms and positive demand shocks associated with exporting. This is further confirmed by a statistically significant coefficient of price and demand shocks in all specifications. The signs of price and demand shocks show the same pattern: positive for TFP_IP and negative for TFP_FP and TFP_Q. This pattern is robust for labour productivity measures.

To summarize, the traditional revenue based measures of productivity confined both physical efficiency and demand components. Thus, the decomposition of these two components helps for the understanding of the real productivity effects of exporting. Separating prices and demand effects from the revenue based measures of productivity significantly reduces the presumed effects of exporting.

4..2.6 Quantile regression: For which firm does exporting matter?

The analysis of export-productivity links based OLS estimates provides only a partial view of the relationships: how on average exporting is correlated with productivity. Furthermore, OLS estimator is sensitive to outliers and would results in biased estimates when variables have long-tailed distributions. As described in the detailed summery statistics of productivity measures (Appendix C), exporters themselves are highly heterogeneous and some observations are far from the mean of the sample. The average relationships, thus, may miss crucial questions whether exporting is correlated with productivity differently at a different level of productivity and whether the export-productivity correlations are driven by outliers. Quantile regression (QR) provides a richer understanding of the relationships at different levels of productivity by characterizing the relationships between exporting and productivity on the full distribution and helps to control outliers. This technique is more appropriate for heterogeneous firm analysis as it avoids assumptions about parametric distribution of regression errors.

As described in Koenker and Bassett (1978), the estimation of q^{th} regression quantile is computed by minimizing the following absolute deviation equation:

$$min_{\beta \in \mathbb{R}^k} \left[\sum_{i \epsilon \{i: Y_{it} \geq X_{it}^{'}\beta\}} q \left| Y_{it} - X_{it}^{'}\beta \right| + \sum_{i \in \{i: Y_{it} < X_{it}^{'}\beta\}} (1-q) \left| Y_{it} - X_{it}^{'}\beta \right| \right] \qquad (4.5)$$

Where Y_{it} is the dependent variable, X_{it} is the K by 1 vector of explanatory variables, β is the coefficient vector and q is the quantile to be estimated, and $0 < q < 1$. The coefficient vector β is peculiar to each quantile being estimated. The objective function is a weighted sum of absolute deviations, which gives a robust measure of location, so that the estimated coefficient vector is not sensitive to outlier observations on the dependent variables. QR, thus, provides more robust estimates in the presence of outliers. The estimated linear quantile regression can be written as:

$$Q^q(y_{it}|X_{it}) = \beta_0^{(q)} + \beta_i^{(q)} X_{it} + \varepsilon_{it},\ 0 < q < 1 \qquad (4.6)$$

Where $Q^q(Y_{it}|X_{it})$ denotes the q^{th} conditional quantile of y_{it} (log of dependent variables) given X_{it} (explanatory variables). $\beta_s^{(q)}$ represent the coefficients of the explanatory variables at the q^{th} quanrtile. We run a separate regression for the following independent variables:TFP_IP ,$TFP\_FP, TFP\_Q, LP\_IP, LP\_FP, and\ LP\_Q$. The explanatory variables are: EX_{it} a dummy to capture the current export status of each firm i and equals to one if the firm is exports, zero otherwise, $industry\ and\ year\ dummies, size$ and age. ε_{it} captures the error term. Non-exporters are the reference groups.

In order to make the quantile regression more informative about export-productivity correlations, we estimate the model at nine quantiles: 0.01, 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95 and 0.99. We also present the OLS estimates for comparison. In order to obtain a consistent estimate of the standard errors, we use bootstrap standard errors based on 400 replications. Table E1 reports the results. The lower panel of the table presents the Wald test statistics to test the null hypothesis that coefficients across different quantiles are equal. For brevity, we only present test results for equality of selected quantiles and joint equality of the nine quantiles.

The export-productivity correlations at each quantile differ from the mean correlation obtained from OLS regression. Considering the specification based on TFP_IP, export coefficients are all significantly different from zero across all quantiles, and the export premiums are larger at the lower and upper end of the productivity distribution. These findings match Wagner (2011) findings where the productivity premium of exporters on the upper and lower end of the distribution is larger than the median and it results in a U-shaped export-productivity links across quantiles. Another interesting result emerges when we consider physical productivity (TFP_Q) and exporting correlations. At the lower end of the distribution, the coefficient of export is negative and insignificant; however, they are positive and significant at the median, 0.75 and 0.99 quantiles. This suggests that, in terms of physical productivity, least productive exporting firms are not different from non-exporting firms. These results are consistent when we consider models estimated based on TFP_IP, LP_Q and LP_IP. In all models, however, we failed to reject the null hypothesis that coefficients are equal across all the nine quantiles, at the conventional levels of significance.

A comparison of the revenue and physical productivity of exporters reinforce our earlier finding that physical productivity of exporters is less than their revenue productivity. In general, although it is statistically insignificant, there are variations in the export-productivity correlations across the different points of the conditional productivity distribution.

5. Conclusions

In this paper we provide empirical evidence on the relationships between exporting and productivity based on data from Ethiopian manufacturing sectors that produce relatively homogeneous products over the period 2000 to 2009. Unlike earlier studies in this literature, we estimate revenue and physical output based productivities, and examine whether omitted firm-level prices and demand shocks result in a bias on export premium estimates. We further decompose the revenue productivity of exporters into its demand and physical efficiency components by introducing prices or demand shocks in the standard regression. To fully understand whether export premium is sensitive to outliers and varies across different levels of productivity distribution, we run quantile regressions.

We find that exporters are more productive than non-exporters. However, exporters found to have higher revenue productivity than physical productivity. Furthermore, it is evident that exporters face positive demand shocks and charge higher price than non-exporters. These results are consistent when we employing quantile regression technique that characterizes the relationships between exporting and productivity at different points of the productivity and takes into account outliers. Thus, the tradition of using industry deflated sales to capture real output could overstates the true productivity of exporters (by under deflating their revenue) and understates the demand side roles. Thus, decomposition of revenue productivity in to real productivity and price components would help for deeper understanding of export-productivity links. Understanding the extent to which exporting is associated with real efficiency would have important implications for industrial policy. Because, exporting firms that earn higher revenue productivity are likely to have smaller long-term industrial development impact compared to firms that gain real efficiency improvements through foreign market exposure.

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Appendix A. Summary statistics of Ethiopian manufacturing firms (2000-2009)

Table A1: Summary of Ethiopian manufacturing firms by year (2000-2009)

Year	*Number of firms*	*Number of exporters*	*share of exporters*
2000	739	40	5.41
2001	722	38	5.26
2002	883	32	3.62
2003	939	41	4.36
2004	997	46	4.61
2005	763	50	6.55
2006	1153	56	4.85
2007	1339	57	4.25
2008	1734	62	3.57
2009	1948	77	3.95
Total	12667	563	4.28

Table A2: Summary of Ethiopian manufacturing firms by sector (2000-2009)

Sector	*Number of firms*	*Number of exporters*	*share of exporters*
Food	3143	96	3.05
Beverage	350	57	16.2
Wearing & Apparel	756	136	17.9
Leather &tanning	183	174	95.08
Foot wear	544	37	6.80
Furniture	1955	12	0.81
Wood industry	285	1	0.35
Publishing & Printing	795	2	0.25
Detergent & cosmetic	293	4	1.36
Basic Metal	511	0	0
Others	3852	44	1.14
Total	12667	563	4.28

Appendix B. Production function estimates

Table B1: Production function estimates – Sales deflated by industry deflator

	Food and beverage			*Textile and Apparel*			*Leather and Tanning*		
Sales deflated by Industry deflator	OLS Coeff (Se.)	FE Coeff (Se.)	GMM Coeff (Se.)	OLS Coeff (Se.)	FE Coeff (Se.)	GMM Coeff (Se.)	OLS Coeff (Se.)	FE Coeff (Se.)	GMM Coeff (Se.)
lnL_{it}	0.277***	0.288***	0.312**	0.222***	0.373***	0.268**	0.243***	0.211**	0.335**
	(0.054)	(0.076)	(0.145)	(0.082)	(0.092)	(0.115)	(0.084)	(0.086)	(0.140)
lnK_{it}	0.091**	0.004	0.076*	0.100**	0.065	0.181***	0.069	-0.001	0.197**
	(0.047)	(0.024)	(0.044)	(0.051)	(0.063)	(0.063)	(0.043)	(0.048)	(0.092)
lnM_{it}	0.285***	0.233***	0.282***	0.175***	0.136***	0.227***	0.076**	0.112***	0.128**
	(0.031)	(0.430)	(0.082)	(0.039)	(0.047)	(0.054)	(0.035)	(0.039)	(0.054)
Year dummies	*Included in all models*								
AB Test AR(1)			0.000			0.008			0.005
AB Test AR(2)			0.757			0.089			0.951
Hansen Test-P values			0.321			0.947			0.961
No. instruments			149			109			109
Observations	1271	1271	1271	442	442	442	437	437	437

Notes: estimators employed are OLS and FE- within and System GMM. All models include year dummies,(coefficients not reported). We report *P*-values for all test statistics. Robust standard error in parentheses, ***, **, * indicate statistical significance at 1% , 5% and 10 % level respectively.

Table B2: Production function estimates – Sales deflated by firm-level prices

	Food and beverage			*Textile and Apparel*			*Leather and Tanning*		
Sales deflated by Firm price deflator	OLS Coeff (Se.)	FE Coeff (Se.)	GMM Coeff (Se.)	OLS Coeff (Se.)	FE Coeff (Se.)	GMM Coeff (Se.)	OLS Coeff (Se.)	FE Coeff (Se.)	GMM Coeff (Se.)
lnL_{it}	0.333***	0.179	0.669***	0.340*	0.453*	0.447**	0.105	0.143*	0.020
	(0.101)	(0.126)	(0.185)	(0.187)	(0.251)	(0.202)	(0.104)	(0.076)	(0.130)
lnK_{it}	0.132**	0.050	0.127**	0.006	0.075	0.029	0.147***	-0.044	0.377***
	(0.060)	(0.051)	(0.054)	(0.070)	(0.070)	(0.102)	(0.046)	(0.079)	(0.143)
lnM_{it}	0.243***	0.030***	0.200***	0.251***	0.176*	0.262**	0.186***	0.214***	0.240**
	(0.052)	(0.068)	(0.069)	(0.080)	(0.099)	(0.116)	(0.059)	(0.058)	(0.096)
Year dummies	*Included in all models*								
AB Test AR(1)			0.000			0.002			0.003
AB Test AR(2)			0.142			0.189			0.799
Hansen Test-P values			0.329			0.944			0.966
No. instruments			173			109			116
Observations	1255	1255	1255	435	435	435	437	437	437

Notes: estimators employed are OLS and FE- within and System GMM. All models include year dummies,(coefficients not reported). We report *P*-values for all test statistics. Robust standard error in parentheses, ***, **, * indicate statistical significance at 1% , 5% and 10 % level respectively.

Table B 3: Production function estimates-physical Physical output

	Food and beverage			*Textile and Apparel*			*Leather and Tanning*		
Physical output	OLS Coeff (Se.)	FE Coeff (Se.)	GMM Coeff (Se.)	OLS Coeff (Se.)	FE Coeff (Se.)	GMM Coeff (Se.)	OLS Coeff (Se.)	FE Coeff (Se.)	GMM Coeff (Se.)
lnL_{it}	0.455***	0.268**	0.477***	0.163**	0.108	0.333**	0.151(	0.183*	0.211*
	(0.094)	(0.105)	(0.145)	(0.069)	(0.219)	(0.160)	(0.089)	(0.102)	(0.123)
lnK_{it}	0.048**	0.097***	0.038	0.042	0.097	0.122	0.113***	0.028	0.183***
	(0.022)	(0.037)	(0.075)	(0.061)	(0.058)	(0.078)	(0.042)	(0.086)	(0.069)
lnM_{it}	0.213***	0.169**	0.208**	0.186***	0.198***	0.194**	0.194***	0.242***	0.164*
	(0.049)	(0.074)	(0.094)	(0.064)	(0.068)	(0.077)	(0.054)	(0.060)	(0.091)
Year dummies	*Included in all models*								
AB Test AR(1)			0.000			0.001			0.001
AB Test AR(2)			0.843			0.576			0.890
Hansen Test-P values			0.146			0.968			0.985
No. instruments			200			109			114
Observations	1266	1266	1266	437	437	437	435	435	435

Notes: estimators employed are OLS and FE- within and System GMM. All models include year dummies,(coefficients not reported). We report *P*-values for all test statistics. Robust standard error in parentheses, ***, **, * indicate statistical significance at 1% , 5% and 10 % level respectively.

Appendix C: Detail summary statistics of productivity and price

Table C1: The Percentiles distributions of TFP_IP

TFP_IP	*Exporters*			*Non-Exporters*		
	Percentile	Smallest	Largest	Percentile	Smallest	Largest
1%	703.42	284.45		338.01	27.37	
5%	2254.06	343.004		701.86	44.56	
10%	3525.60	634.58		1137.47	90.26	
25%	7167.65	635.76		2436.24	97.69	
50%	17391.06			5522.84		
75%	34437.53		171099.4	12470.63		116901
90%	51677.19		176556.3	24760.96		126994.6
95%	76325.3		207581.9	37345.28		146322.5
99%	164905.4		229834.7	66991.49		174708.3
Number of Observations	437			2546		
Skewness	15.203			3.667245		
Kurtosis	274.16			24.273		
Mean	25175.37			10359.26		
Std.Dev.	27205.21			14116.99		
Kolmogorov-Smirnov test for equality of distribution functions				P-values		
H_0:equality of distributions				0.000		
H_0: Exporters are more productive				1.000		
H_0: Non-exporters are more productive				0.000		

Table C2: The Percentiles distributions of TFP_FP

	Exporters			*Non-Exporters*		
TFP_FP	Percentile	Smallest	Largest	Percentile	Smallest	Largest
1%	29.79	1.37		61.48	0.206	
5%	340.34	3.36		290.28	1.94	
10%	1132.33	4.028		738.77	7.52	
25%	3578.44	15.49		2871.44	8.13	
50%	12934.14			11472.16		
75%	97129.82		5330723	63107.27		2.66e+07
90%	365475.1		5616862	350827.9		3.07e+07
95%	941897.3		5782755	979845.1		3.71e+07
99%	5013691		2.90e+07	5183925		4.24e+07
Number of Observations	438			2523		
Skewness	3.214			13.10866		
Kurtosis	19.182			208.6411		
Mean	267718.9			314590.1		
Std.Dev.	1546655			1969561		

Kolmogorov-Smirnov test for equality of distribution functions	P-values
H_0:equality of distributions	0.176
H_0: Exporters are more productive	0.927
H_0: Non-exporters are more productive	0.088

Table C 3: The Percentiles distributions of TFP_Q

TFP_Q	Exporters			Non-Exporters		
	Percentile	Smallest	Largest	Percentile	Smallest	Largest
1%	21.73	7.67		12.04	0.227	
5%	82.15	9.08		32.75	0.678	
10%	259.04	12.37		62.84	0.680	
25%	817.35	18.53		168.65	0.684	
50%	2592.32			575.71		
75%	11508.46		86410.48	2458.48		178733.3
90%	30260.96		96864.06	10973.47		179548.2
95%	43863.97		104342.5	24856.09		187083.2
99%	81099.92		136978	89667.18		1007917
Number of Observations	437			2538		
Skewness	3.164			23.81778		
Kurtosis	16.17			852.9283		
Mean	10003.91			5563.767		
Std.Dev.	16946.88			26209.01		
Kolmogorov-Smirnov test for equality of distribution functions				P-values		
H_0:equality of distributions				0.000		
H_0: Exporters are more productive				0.962		
H_0: Non-exporters are more productive				0.000		

Table C 4: The Percentiles distributions of price

	Exporters			***Non-Exporters***		
Firm price	Percentile	Smallest	Largest	Percentile	Smallest	Largest
1%	0.0149	0.0024		0.0017	0.00018	
5%	0.0316	0.0070		0.0080	0.00024	
10%	0.0681	0.0077		0.0226	0.00029	
25%	0.2162	0.0144		0.1094	0.000342	
50%	0.675			0.6154		
75%	1.143		913.928	1.1644	143.418	
90%	2.595		1825.759	2.4035	161.496	
95%	6.903		1861.072	4.046	669.791	
99%	166.808		3773.206	13.371	8713.553	
Number of Observations	437			2523		
Skewness	13.538			49.6997		
Kurtosis	204.285			2486.154		
Mean	21.651			5.1228		
Std.Dev.	223.252			174.047		
Kolmogorov-Smirnov test for equality of distribution functions					P-values	
H_0:equality of distributions					0.000	
H_0: Exporters charge higher prices					0.681	
H_0: Non-exporters are more productive					0.000	

Appendix D: Within and between summary statistics

Table D1: Overall, within and between standard deviations of main variables (from 2000 to 2009)

Variables	*Standard Deviation*			Number of observations	Number of firms
	Overall	Between	Within		
TFP_IP	1.238	1.131	0.564	2984	729
TFP_FP	2.430	2.176	1.300	2960	726
TFP_Q	2.033	1.820	0.965	2975	727
LP_IP	1.291	1.253	0.619	1984	729
LP_FP	2.391	1.984	1.333	2960	726
LP_Q	2.053	1.895	0.996	2975	727
Export status	0.353	0.286	0.164	2984	729
Employment	1.482	1.334	0.376	2984	729

Notes: all variables, except export status, are in logs. Export status is a dummy variable equals to one if a firm exports at time t and zero otherwise.

Appendix E : Quantile Regression

Table E1: Export premium

Dependent		*Quantile Regressions (Export premium)*								
		0.01	0.05	0.10	0.25	0.50	0.75	0.90	0.95	0.99
Variables	OLS	quant	quant	quant	quant	quant	quant	quant	quant	quant
TFP_IP	0. 91**	1.20*	0.82**	0.66**	0.69**	0.73 **	0.97**	0.89**	1.22**	1.33**
	(0.06)	(0.33)	(0.14)	(0.11)	(0.091)	(0.07)	(0.06)	(0.09)	(0.13)	(0.16)
TFP_FP	0.68**	-2.45	-0.083	0.726**	1.09**	1.07**	0.91**	0.25	0.20	-1.05
	(0.12)	(1.12)	(0.44)	(0.255)	(0.11)	(0.09)	(0.14)	(0.18)	(0.30)	(0.50)
TFP_Q	0.53**	-0.17	0.094	0.20	0.33	0.71**	0.50**	0.138	0.138	1.01*
	(0.10)	(0.45)	(0.23)	(0.18)	(0.18)	(0.13)	(0.09)	(0.11)	(0.84)	(0.34)
LP_IP	1.15**	1.66**	0.91**	1.36**	1.15**	1.01**	0.76**	0.99**	1.05**	1.15**
	(0.07)	(0.27)	(0.172)	(0.15)	(0.09)	(0.07)	(0.08)	(0.11)	(0.10)	(0.20)
LP_FP	0.58**	-1.36	0.02	0.64	1.05**	0.82**	0.50*	0.29	-0.138	-0.34
	(0.13)	(1.17)	(0.31)	(0.31)	(0.12)	(0.12)	(0.16)	(0.22)	(0.26)	(0.66)
LP_Q	0.53**	-0.051	0.23	0.17	0.47	0.61**	0.55**	0.072	0.18	1.48*
	(0.10)	(0.37)	(0.17)	(0.15)	(0.21)	(0.13)	(0.12)	(0.12)	(0.19)	(0.41)

Tests of coefficient equality across QR with different quantiles (P-values)

Null Hypothesis	TFP_IP	TFP_FP	TFP_Q	L P_IP	LP_FP	LP_Q
Joint equality of all quantiles	0.40	0.06	0.10	0.36	0.02	0.04
q01=q50	0.48	0.07	0.12	0.28	0.20	0.18
Q01=q75	0.73	0.09	0.20	0.13	0.27	0.21
Q01=q99	0.87	0.68	0.11	0.52	0.67	0.07
Q05=q50	0.74	0.06	0.06	0.78	0.05	0.18
Q05=q75	0.59	0.10	0.16	0.63	0.23	0.26
Q01=q99	0.26	0.32	0.12	0.64	0.64	0.11

Notes: The reported values are export premium computed as $exp(coefficient) - 1$. Asymptotic standard errors are in parentheses and are bootstrap standard errors based on 400 replications.* denotes statistical significance at 5%; ** denotes significance at 1%. All regressions controls for size, age, year and sector. The lower panel of the table reports the test for equality of coefficients across different quantiles. The null hypothesis is coefficients are equal. We provide P-values for joint equality tests and some selected quantiles equality tests for each regression.