# Doctoral Thesis

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# Essays on Productive Efficiency, Trade, and Market Power: Evidence from African Manufacturing Firms

A thesis submitted to the Doctoral School of Economics and Management in partial fulfilment of the requirements for the degree of Doctor of Philosophy (Ph.D.) in Economics and Management

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# Chapter 1

# Introduction

## 1.1 Overview

The transfer of production resources from low to high productive uses is a key driver of economic growth in less developed countries. This process of structural change and transformation plays a central role in the transition from low-income country to high-income country. The performance of most African countries towards a process of structural change has been dismal compared to other developing regions. Several authors have offered various explanations on the causes of low economic growth in Africa. Some of these explanations include but not limited to; lack of openness to trade, low-level of social capital, poor infrastructure, low capacity utilisation, low productivity, and institutions (Collier and Gunning, 1999; Devarajan et al., 2003; Fosu, 2013).

Undoubtedly, the manufacturing sector must play a pivotal role in the transformation process of any structural change. It is for this reason it became a "darling" for policy makers in developing countries (Tybout, 2000). However, the African manufacturing sector has not lived up to expectations to contribute to poverty reduction. For example, annual growth rate in value added for the manufacturing sector has been in declining state since the 1960's. According to African Development Indicators compiled by the World Bank, over the period 1966 to 1970, average value added in the manufacturing sector grew by 7.21%. The average growth rate declined to 5.13%, during the decade 1971 - 1980. The declining state of growth rate in value added for the manufacturing sector reduced to 2.15% during the decade 1981-1990, then reached its lowest point over the period 1991-2000 at 1.83% on average.

Two common explanations conjectured as the cause of the declining state of the manufacturing sector are Import Substitution Industrialisation (ISI) protection policies adopted in the 1970s and productive efficiency of the sector (Tybout, 2000; Söderbom and Teal, 2004). To avert the rigidities and the declining state of the economy, series of economic reforms and trade liberalization policies were implemented through the Structural Adjustment Programme (SAPs) devised by the World Bank and the International Monetary Fund in the 1980s.

Parallel to the Structural Adjustment Programme, the World Bank launched the Regional Program on Enterprise Development (RPED) in eight African countries with the aim of collecting firm-level data on a large scale to provide the basis of a comparative study of the manufacturing sector in Africa. RPED surveys were carried out in Burundi, Cameroon, Côte d'Ivoire, Ghana, Kenya, Tanzania, Zambia, and Zimbabwe between 1992 and 1995. Until then most studies on African manufacturing were based on individual researchers survey with different sampling techniques, making it difficult to derive solid and general empirical conclusions.

While some gains have been made, core issues surrounding structural change as well as questions regarding the possibility of the industrialisation continues to persist (Page, 2012). Specifically, some of these issues include: productive efficiency of manufacturing firms (Tybout, 2000; Söderbom and Teal, 2004); low internationalisation of manufacturing firms (Bigsten and Söderbom, 2006); market imperfections characterised by the presence of unproductive firms (Bloom et al., 2014). These three issues forms the core of this thesis to analyse their overall effect on manufacturing firms.

This thesis examines three main themes. These are: firms productive efficiency, internationalisation of African firms, and effect of liberalisation policies on market power and market imperfections. The thesis combines two main strands in economics literature in accessing the three main themes of the papers. The first strand regards methodological approaches to estimate a production function from which productive efficiency can be computed. Consistent estimation of productive efficiency is a necessary condition to analyse firm behaviour and their response to policy. The thesis critically examines methodologies to estimate productive efficiency. The big picture of the methodological issue is briefly introduced in next subsection.

The second strand, international trade and industrial development, analyse firms behaviour in foreign market as well as firms responses to trade liberalisation policies and their overall impact on structural change. The two strands of literature examined in this thesis resulted in three independent papers, each of which addresses specific issues along the spectrum of productive efficiency estimation, internationalisation, and market power. Subsection 1.3, provides a summary of each essay and research questions addressed in each paper.

## 1.2 Empirics of production function estimation

Productivity, the efficiency with which firms converts inputs into outputs, has played a dominant role in research agendas in various areas of economic research. Likewise, productivity has been central in the diagnostics of the ailments of African economies. Policies recommendations are formulated based on these diagnostics with the aim of accelerating development through the manufacturing sector. Therefore, an appropriate measurement of productive efficiency is necessary to derive policies prescriptions, which will enhance the role of the manufacturing sector in poverty reduction.

While there is no ambiguity in the theoretical definition of productive efficiency, the same cannot be said on empirical methods used to estimate productive efficiency from production data. De Loecker and Goldberg (2014) argued that with the term “productivity”, researchers often present a measure of “profitability” as a measure of “productive efficiency”. The issue of productive efficiency estimation is central in all the three essays of this dissertation. In this section, I summarise the main issue that cuts across all the three essays.

To estimate productive efficiency, one links firm-level output to its input through a production function. For instance, a Cobb-Douglas production function takes the form

$$Y_{it} = A_{it} K_{it}^{\beta k} L_{it}^{\beta l} M_{it}^{\beta m},$$

where $Y_{it}$ is the output of firm $i$ at time $t$, $K_{it}$, $L_{it}$, and $M_{it}$ indicate capital, labour, and material inputs respectively. Lastly, $A_{it}$ is Hicks-additive efficiency level of the firm.

Taking the natural logs of the production function gives,

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \varepsilon_{it},$$

where the log of the Hicksian neutral efficiency of a firm is made up of two components, that is, $ln(A_{it}) = \beta_0 + \varepsilon_{it}$, where $\beta_0$ is mean efficiency level across firms and $\varepsilon_{it}$ is firm-specific deviation from the mean. Furthermore, $\varepsilon_{it}$ can be decomposed into $u_{it}$ and $v_{it}$. The estimation equation can be written as

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + u_{it} + v_{it},$$

where firm-level productivity is defined as $\omega_{it} = \beta_0 + u_{it}$; with $v_{it}$ being $i.i.d$, representing deviations from the mean due to measurement errors or external conditions. The usual setup to estimate the production function and solve for firm-level productivity result in

$$\hat{\omega}_{it} = \hat{\beta}_0 + \hat{u}_{it} = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it}.$$

Greene (2005a) observed that, this general setup to estimate productive efficiency fails to distinguish between cross individual heterogeneity and efficiency. As such, failure to distinguish between the two may lead to estimated productive efficiency picking undesirable elements. Other scholars in the production function estimation literature have pointed out heterogeneity biases in the estimation of total factor productivity in the form demands shock, firm prices among others (Foster et al., 2008; De Loecker, 2011).

Furthermore, De Loecker and Goldberg (2014) demonstrated that when one uses revenue or sales as the output variable and expenditure on inputs as the input variable, the computed residual is a measure of profitability and not productive efficiency. These argumentations underline the necessity to reconsider methodologies used to recover the residual of the production function as a measure of productive efficiency.

Against this background, the methodological part of this thesis addresses heterogeneity bias in the estimation of productive efficiency. Where possible, I compare results to an estimation methodology that used a conventional approach and discusses policy implications of the approaches. The paragraph below outlines and summarises each essay.

## 1.3 Summary and outline of essays

The first paper – Reconsidering Heterogeneity and Efficiency in African Manufacturing – discusses in detail three methodologies to estimate productive efficiency in the stochastic frontier analysis framework. The first two models are conventional models due to Schmidt and Sickles (1984) and Cornwell et al. (1990), where the former assumes inefficiency is time-invariant while the latter allows inefficiency to vary over time. In these two models, firm-specific unobserved heterogeneity and inefficiency are treated as a single component, hence the term conventional models.

The third model builds on Greene's 2005a proposal to separate unobserved heterogeneity from inefficiency. Greene originally suggested to estimate the production function using maximum likelihood dummy variable estimator. However, the maximum likelihood dummy variable estimator suffers from incidental parameter problem making it an inconsistent estimator of the production function. Belotti and Ilardi (2015) proposed a solution using the pairwise difference estimator which avoid the incidental parameter problem.

Productive efficiency obtained from each of the methodology is then applied to the analyse the probability of export participation. The main research question is to examine whether productive efficiency determines export participation. Results show that the established relationship of productive efficiency being a significant determinant of export participation hinges on unobserved heterogeneity. For conventional models 1 and 2, the result is positive and significant. For model 3, which separate inefficiency and heterogeneity, the result show that productive efficiency does not determine export participation.

Two forms of robustness checks were applied to check the validity of the results. First, I applied Wooldridge (2005) to correct for heterogeneity *ex-post*. Second, given the weakness of the three models above to deal with endogeneity and simultaneity issues, I applied SYS-GMM approach to estimate the production function. Productive efficiency obtained from the SYS-GMM approach is then applied to analyse the probability of export participation as described above. Results showed that productive efficiency does not determine export participation.

The second paper – Trade-Productivity Nexus: Learning and Knowledge Spillovers – first examines productivity feedback from three modes of trade participation, export, import, and two-way trade taking into consideration the necessity to separate heterogeneity from efficiency. Results showed import had the highest likelihood to improve productive efficiency of trading firms. Most importantly, trade experience, measured by number of years engaged in a trading activity, is more significant for productivity feedback than trade mode. This suggest remaining on the international market improve firms productive efficiency rather than a one-time trade participation.

The second part of the paper analyses the possibility of knowledge spillovers from trading firms to non-trading firms. I analysed the effect of agglomeration of trading firms to non-trading firms in a given city, technological distance and absorptive capacity between trading firms and non-trading firms on two main spillovers channels. The main spillover channels is firms decision to trade. Results showed agglomeration had a weak effect on the two channels of knowledge spillovers. On the other hand, an increase in the technological distance between trading and non-trading firms negatively affect knowledge spillover whilst absorptive capacity had a positive impact.

The third paper – Markups, Market Imperfections, and Trade Openness – examines the impact of trade liberalisation on domestic market competition. I distinguish between market power in the product market, measured by markups on materials, and market power in the labour market, measured by degree of monopsony power. To infer markups from production data based on price-cost margins involves an estimation of a production function (De Loecker et al., 2016).

To draw casual inference on the impact of trade liberalisation on market power, Ghana's membership to the World Trade Organisation is used as an identification strategy to perform a difference-in-difference analysis. Results showed market power in the product market reduced in the aftermath of trade liberalisation for all sector, while results for market power in labour market were mixed. Furthermore, results suggested firms offsetting loss of market power in the product market by compressing wages given their monopsony power.

# Chapter 2

# Reconsidering Heterogeneity and Efficiency in African Manufacturing: Evidence from Ghana


## Abstract

This paper examines different methodologies to estimate productive efficiency and explores its implications for export and productivity nexus. Conventional models used to measure efficiency levels provide no mechanism to disentangle firm-specific unobserved heterogeneity from inefficiency, treating the two as a single component. Efficiency measures obtained under such approach can potentially lead to misleading results in economic applications. Therefore, the paper reconsiders efficiency estimation by applying two conventional models and a third one that separates unobserved heterogeneity from inefficiency, using data on a long panel of Ghana manufacturing firms from 1991-2002. Predicted firm-level efficiencies obtained from the three models are then used to study the export-productivity nexus. Results show that once firm-specific unobserved heterogeneity is separated from efficiency, export participation is not explained by productive efficiency. Results also enables to set a framework to uncover factors that impede African firm's export participation.



***Keywords :*** African manufacturing, Efficiency, Heterogeneity, Pairwise differencing
***JEL Classification :*** O14, D24, C23

## 2.1 Introduction

The manufacturing sector has long been recognised to play a pivotal role in the structural transformation of developing countries and to be a source of positive spillovers (Tybout, 2000). Yet, the manufacturing sector in Africa has not lived up to its potential of accelerating job creation and poverty reduction. A series of papers in the late 1990's and early 2000's based on the World Bank's Regional Programme on Enterprise Development (RPED) in Africa established stylised facts about manufacturing firms in the region. One of these findings was that, most African firms operate in their respective domestic markets, with few firms participating in exports either within Africa or outside the continent (Bigsten and Söderbom, 2006).

Policy recommendations based on the RPED findings were outlined with the aim to reverse Africa's economic poor performance (see Bigsten and Söderbom (2006) for full list). Nevertheless, neither the core of the issues have changed (Bloom et al., 2014) nor have questions about Africa's industrialisation (Page, 2012). Africa's growth turnaround between 1995-2005 and subsequent recovery from 2008-09 global crisis was mainly driven by rising commodity prices and discoveries of new natural resources without significant improvements in investment and trade (Arbache and Page, 2010).

One of the key issues and its policy recommendation forms the basis of this paper. Building on new-new trade theory, RPED studies attributed low export participation to low efficiency. Based on this, it was recommended to policy-makers to create incentives for African firms to strive to participate in foreign markets (Bigsten and Söderbom, 2006). In general, the export participation and efficiency link, is derived by estimating the probability of export on a measure of productive efficiency while controlling for various firm level covariates. Mostly, there is less scrutiny on the estimation of the production function and as a corollary, the derived measure of productive efficiency.

Methodologies usually used to estimate productive efficiency often fail to distinguish between inefficiency and firm-specific unobserved heterogeneity treating the two as a single component. Greene (2005a) observed that when the two components are treated as a single entity, efficiency scores will be biased as they may measure something else in addition to or instead of inefficiency. Hence, in the presence of this shortcoming, associated policy actions may not yield expected results.

This paper explores three methodologies on the treatment of the inefficiency component and firm-specific unobserved heterogeneity in the production function estimation using a panel of Ghanaian manufacturing firms. The first model is a conventional methodology that does not separate inefficiency from unobserved heterogeneity and assumes inefficiency to be constant over time. The second model improves upon the first by allowing inefficiency to vary over time while treating unobserved heterogeneity and inefficiency as a single component. The third model separates unobserved heterogeneity from inefficiency while treating inefficiency as time-varying.

Productive efficiency obtained from the three models are then applied to export participation estimation. The purpose of this exercise is to ascertain how different assumptions on inefficiency and unobserved heterogeneity affect the prediction of self-selection into export market. It is worth emphasizing this paper is not a comparison of various modes of estimating the production function as in Van Biesebroeck (2007). As illustrated in Van Beveren (2012), standard procedures in the estimation of total factor productivity, provide no explicit treatment of firm-specific unobserved heterogeneity. Beginning with the work of Foster et al. (2008), the standard approach of estimating total factor productivity has come under increasing scrutiny on the omission of firm-specific factors from the estimation framework.

The objective of this paper as well as its main research question, is to investigate the assumptions underlying the treatment of firm-specific unobserved heterogeneity and its impact on economic and policy applications. The paper also shows how the link between export participation and efficiency changes according to the treatment of unobserved heterogeneity in the production function estimation. The rest of the paper is organised as follows.

A brief discussion on technical efficiency is presented in the next section to highlight how inefficiency can be measured from the production function. Section 2.3 describes the source and features of the dataset. A short review of related studies using the dataset as well as some of the drawbacks in their methodologies is also discussed briefly. Section 2.4 presents each model and results obtained for each one. Section 2.5 explores the implication for export participation, while section 2.6 concludes.

## 2.2 Technical Efficiency

The origin of efficiency analysis can be traced to Koopmans (1951) and Debreu (1951); the former discussed production activity as efficient combination of inputs into outputs using the available technology while the latter proposed a coefficient measure of resource utilization. Farrell's (1957) seminal paper provided the foundation of the modern measurement of efficiency, with the most innovative aspect of his theory being the use of frontier function. Farrell acknowledged the difficulty involved in constructing a hypothetical production frontier against which to measure the efficiency of each firm in a given industry. He therefore suggested to construct an observed frontier based on input-output mix of producers. Hence, (in)efficiency can be measured as deviations from the best frontier.

It ought to be underlined that, efficiency measurement using the production frontier approach is relative to the set of firms in the sample in a given industry/economy. Thus, a firm may be efficient in a sector X of country A but not by world's standards.[1] In short, the deterministic production frontier model can be expressed as:

$$y_{it} = f(\mathbf{x}_{it}; \boldsymbol{\beta}) \cdot TE_{it}, \tag{2.1}$$

where $y_{it}$ is the output of firm $i$, $i = 1, \dots, I$ at time $t$, $t = 1, \dots, T$; $\mathbf{x}_{it}$ is a vector of N

[1]Supposing that production technology is "freely" available in more global world, Farrell's framework could be generalized to measure efficiency of firms in homogeneous sector across heterogeneous countries. Such development remains a possibility.

inputs used by firm $i$; $f(\mathbf{x}_{it};\boldsymbol{\beta})$ is the production frontier while $\boldsymbol{\beta}$ is a vector of technology parameters to be estimated. From equation (2.1), we can derive technical efficiency of firm $i$ as:

$$TE_{it} = \frac{y_{it}}{f(\mathbf{x}_{it};\boldsymbol{\beta})}, \tag{2.2}$$

thus, technical efficiency is the ratio of observed output to optimal feasible output. The (in)efficiency score of each firm will lie in the [0,1] interval.

Various parametric and non-parametric methods have been developed to measure the production frontier and its related efficiency score. Data envelopment analysis (DEA) based on mathematical programming and stochastic frontier analysis (SFA) based on econometric methods are the two dominant methodologies in efficiency analysis (Greene, 2008). In extreme synthesis, the DEA method constructs a piecewise linear frontier over the data without requiring any parametric assumptions on the production function. While this procedure has some attractive features, the deterministic nature of the method makes it very sensitive to measurement errors. All measurement errors are compounded into the inefficiency score. Hence, when measurement errors are non-negligible, parametric methods are more robust than non-parametric ones (Van Biesebroeck, 2007).

Aigner et al. (1977) and Meeusen and Broeck (1977) independently observed that the deterministic nature of the production function in equation (2.1) is not a true representation of the production process. There are numerous random shocks beyond the control of producer and may affect either positively or negatively the output of a firm. Hence, in order to compute the true (in)efficiency of a firm, the exogenous shock needs to be separated from firm output. The two papers simultaneously proposed the stochastic production frontier which incorporates firm-specific random shocks into equation (2.1). The original model in its cross-sectional framework can be expressed as

$$y_i = f(\mathbf{x}_i;\boldsymbol{\beta}) \cdot exp\{\nu_i\} \cdot TE_i, \tag{2.3}$$

where $[f(\mathbf{x}_i;\boldsymbol{\beta})) \cdot exp\{\nu_i\}]$ is the stochastic production frontier which incorporates both the deterministic part $f(\mathbf{x}_i;\boldsymbol{\beta})$ and firm-specific random part $exp\{\nu_i\}$. From equation (2.3) the technical efficiency definition exhibited in equation (2.2) is modified as

$$TE_i = \frac{y_i}{f(\mathbf{x}_i;\boldsymbol{\beta}) \cdot exp\{\nu_i\}}, \tag{2.4}$$

that is, the ratio of observed output to optimum feasible output characterized by random shocks.

Unlike non-parametric models, the stochastic production frontier is based on econometric analysis making it straightforward to conduct inference. This requires an explicit functional form to represent $f(\mathbf{x}_{it};\boldsymbol{\beta})$ which approximates production technology used to transform inputs into outputs. There exist several functional forms specification in production economics literature.[2] In general, economic theory does not provide a clear-cut guidance with respect

[2]For a brief discussion on production functions used for efficiency analysis, see Coelli et al. (2005) and

to the choice of functional form to represent technology.

Lau (1978, 1986) formulated a set of criteria to evaluate production and cost functional forms. These are: theoretical consistency, domain of applicability, flexibility, computational facility, and factual conformity. Sauer et al. (2006) presented a detail discussion of each criterion and its relation to technical efficiency estimation using stochastic frontier. Lau's *incompatibility theorem* derived from his criteria states that it is impossible to find a functional form that satisfies all the five criteria simultaneously (Lau, 1978). Sauer et al. (2006) proposed the magic triangle of functional choice which consist of: theoretical consistency, domain of applicability and flexibility. Moreover, Sauer et al. (2006) pointed out that there is a considerable trade-off between flexibility and theoretical consistency.

Two functional specifications, the Cobb-Douglas and the second-order transcendental logarithmic ('translog') dominate empirical applications in the stochastic frontier literature. The Cobb-Douglas production function is generally represented as

$$lnY_{it} = \alpha_0 + \sum_{j=1}^{J} \beta_j lnX_{jit}, \tag{2.5}$$

where $X_j$ denotes the list of factor inputs and $\beta$ are technology parameters to be estimated. While the translog production function introduced by Christensen et al. (1973), is represented as

$$lnY_{it} = \alpha_0 + \sum_{j=1}^{J} \beta_j lnX_{jit} + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J} \beta_{jk} lnX_{jit} lnX_{kit}. \tag{2.6}$$

One key advantage of the Cobb-Douglas specification is its simplicity which makes estimation and interpretation of results straightforward. For instance, the elasticity of $j:th$ input is given by $\beta_j$. However, the simplicity of the Cobb-Douglas function come at a cost of strong assumptions. It assumes all firms have the same production elasticities with elasticity of substitution between inputs set to 1. On the other hand, the flexibility of the translog production function allows elasticity of substitutions to vary with the level of inputs and across firms. Hence, technology is not imposed to be either homogeneous or homothetic as in the case of the Cobb-Douglas specification. However, the flexibility of the translog specification produces some side effects. The model is more difficult to interpret since estimated coefficients do not represent the elasticities of inputs. Only if inputs are measured relative to their means before estimation, can the coefficients be interpreted as elasticities. In addition, the translog specification may suffer from curvature violations, given that the model is not globally convex as compared to Cobb-Douglas.

It can be deduced that both the Cobb-Douglas and the translog production functions have properties that satisfies elements of Lau's criteria, but unable to satisfy all simultaneously. The Cobb-Douglas function is globally consistent but fails the flexibility test while the translog function is flexible but fails global theoretical consistency. In the presence of such trade-off, Lau (1986) proposed that one can choose a function that satisfies global theoretical

Kumbhakar and Lovell (2000).

consistency, in this case there is the need to check for flexibility or can opt for a flexible function and test for theoretical consistency.

From the above discussion, the empirical analysis herein will use both the Cobb-Douglas and the translog functional specifications. Notice that equation (2.5) is reduced form of equation (2.6). Given that equation (2.6) reduces to equation (2.5) if,

$$\frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J}\beta_{jk}lnX_{jit}lnX_{kit} = 0,$$

a likelihood ratio tests can be used to check for the specification the best describe the production technology in our context without imposing it a priori.

## 2.3 Data

The data for the empirical analysis is an annual panel survey of Ghanaian manufacturing firms from 1991 to 2002 made available by the Centre for the Study of African Economies (CSAE), University of Oxford. The first three rounds of the survey were collected under the World Bank's Regional Programme on Enterprise Development (RPED), while the remaining rounds were collected by joint effort of CSAE, University of Oxford, University of Ghana and Ghana Statistical Service under Ghana manufacturing enterprise survey (GMES).

The first sample included 200 firms operating in food and bakery, wood and furniture, textiles and garments, metal and machinery sectors that were drawn from the 1987 Manufacturing census. No sample attrition was recorded between the first two rounds, while the third round recorded the biggest attrition rate of approximately 30%. New random sample of firms were added to the survey to maintain similar sample size throughout the survey.

From the definition of technical efficiency in equations (2.2) and (2.4), aggregating all variables in the dataset would lead to biased estimates of efficiency since technology requirements differ from sector to sector. This study therefore follows previous studies on efficiency measurement on African manufacturing firms, for example, Chapelle and Plane (2005); Lundvall and Battese (2000), to disaggregate the sectors into the following: food processing, textiles, wood processing, and metals.

The dataset contains information on all the variables needed to estimate a production function. The dependent variable is real aggregate output for each firm. The following inputs variables are defined in the production function $f(\mathbf{x}_{it};\boldsymbol{\beta})$: physical capital, $K$, measured as replacement value of plant and machinery; labour, $L$, measured as total number of workers currently employed; raw materials, $M$, is annual total cost of raw materials. All monetary variables, gross output, physical capital and raw materials, have been deflated using firm-level price index provided in the dataset. Table (2.1) presents summary statistics of the variables used in the analysis.

With respect to previous studies which have used the dataset to estimate efficiency, this paper does not assume inefficiency to be time-invariant, as do Söderbom and Teal (2004). The

Table 2.1: Summary Statistics

| | Food Processing | | Textiles | | Wood Processing | | Metals | | All Sectors | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | S.D | Mean | S.D | Mean | S.D | Mean | S.D | Mean | S.D |
| Exports (dummy) | 0.28 | 0.45 | 0.25 | 0.43 | 0.45 | 0.50 | 0.31 | 0.46 | 0.33 | 0.47 |
| *Production function variables* | | | | | | | | | | |
| Log (Output) | 17.89 | 2.16 | 15.89 | 2.07 | 17.47 | 2.06 | 17.67 | 2.03 | 17.27 | 2.21 |
| Log (Capital) | 16.74 | 3.24 | 14.49 | 2.99 | 16.77 | 3.02 | 16.45 | 2.73 | 16.17 | 3.14 |
| Log (Employment) | 3.11 | 1.49 | 2.59 | 1.32 | 3.69 | 1.41 | 3.22 | 1.28 | 3.18 | 1.43 |
| Log (Raw Materials) | 17.24 | 2.09 | 15.05 | 2.20 | 16.50 | 1.95 | 16.93 | 2.05 | 16.46 | 2.22 |
| *Inefficiency determinants variables* ∗ | | | | | | | | | | |
| Worker's Age | 35.29 | 8.00 | 28.03 | 8.55 | 32.81 | 9.11 | 32.38 | 8.50 | 32.30 | 8.92 |
| Tenure | 8.12 | 5.48 | 5.26 | 4.98 | 6.22 | 4.98 | 7.09 | 5.39 | 6.71 | 5.31 |
| Firm Age, years | 19.90 | 13.91 | 17.82 | 10.75 | 18.96 | 13.14 | 17.21 | 11.33 | 18.51 | 12.45 |
| Fraction of Foreign Ownership | 0.09 | 0.22 | 0.09 | 0.22 | 0.13 | 0.28 | 0.17 | 0.29 | 0.12 | 0.26 |
| Number of Firms | 69 | | 65 | | 77 | | 63 | | 274 | |
| Number of Observations | 828 | | 780 | | 924 | | 756 | | 3288 | |

∗ Data on worker's age and tenure refers to firm-level average.

paper adopts a fixed-effects framework – which permits correlation between the inefficiency term and the production inputs – that differs from the random effects framework adopted by Roudaut (2006). Determinants of inefficiency are computed using a one-step approach rather than a two-step approach followed by Faruq et al. (2013). Inference from a two-step approach may be invalid due to complex and serial correlation among efficiency estimates (Simar and Wilson, 2007). Lastly, estimating separate production technology parameters and inefficiency determinants for each sectors provides the basis to draw appropriate policy implications instead of pursuing a "one-size-fits-all" solution.

## 2.4 Estimates and Results

There are numerous panel data models that one can choose to measure (in)efficiency of a firm.[3] As noted by Kumbhakar et al. (2014) efficiency measures are heavily dependent on the model chosen. However, there is no clear-cut theory in the choice of a particular model over others (Kumbhakar et al., 2014). In this empirical analysis, we will restrict ourselves to three types of models, in order to permit comparison of efficiency estimates using different models. The selected models are: the conventional time-invariant model due to Schmidt and Sickles (1984), a time-varying version due to Cornwell et al. (1990) and a model that permits to separate heterogeneity from inefficiency while allowing inefficiency to be time-varying due to Belotti and Ilardi (2015). In particular, the latter model avoids the incidental parameter

[3]For an overview of efficiency estimation models, see, Kumbhakar and Lovell (2000); Coelli et al. (2005). A comprehensive review of recent developments and applications are presented in Greene (2008) and Parmeter and Kumbhakar (2014).

problem which is present in the 'true fixed-effects' model proposed by Greene (2005a).[4]

There exist another class of models in the random effects framework built on the assumption of independence between the inefficiency term and firm covariates. Notable examples are: Kumbhakar (1990); Battese and Coelli (1992, 1995). However, estimates of the production function technology parameters in the random effects framework will be biased in the presence of correlation between inputs and inefficiency term (Tybout, 1992).

### 2.4.1 Model 1: Time-invariant model

The first generation of efficiency models which extended the cross-section framework to panel data considered inefficiency to be constant over time (Pitt and Lee, 1981; Schmidt and Sickles, 1984; Kumbhakar, 1987; Battese and Coelli, 1988). The basic feature underlying these time-invariant models puts strong emphasis on firms unobserved heterogeneity and relaxes distributional assumptions that were necessary in the cross-section framework. Hence, extending the notions of stochastic frontier into classical panel data methods, efficiency could be estimated using either least squares or maximum likelihood methods. For the purpose of this analysis, we choose the Schmidt and Sickles (1984) approach due to its distribution-free feature (Kumbhakar and Lovell, 2000). The model is represented as

$$y_{it} = \alpha + f(\mathbf{x}_{it};\boldsymbol{\beta}) + \nu_{it} - u_i, \tag{2.7}$$

where $y_{it}$ is the natural log of output; $\alpha$ is a common intercept; $f(\mathbf{x}_{it};\boldsymbol{\beta})$ represents the production technology discussed above; $\mathbf{x}_{it}$ is natural log of vector inputs; $\nu_{it}$ represents exogenous production shocks; and $u_i \geq 0$ is a non-negative time-invariant technical inefficiency for firm $i$.

Equation (2.7) can be estimated under either the fixed effects or the random effects framework. Under the fixed effects framework the model can be written as

$$\begin{aligned} y_{it} =& \beta_0 + \mathbf{x}'_{it}\boldsymbol{\beta} + \nu_{it} - u_i \\ y_{it} =& (\beta_0 - u_i) + \mathbf{x}'_{it}\boldsymbol{\beta} + \nu_{it} \\ y_{it} =& \alpha_i + \mathbf{x}'_{it}\boldsymbol{\beta} + \nu_{it} \end{aligned} \tag{2.8}$$

where $\alpha_i \equiv \beta_0 - u_i$. It ought to be recalled that, under fixed effects framework it is the assumed that $u_i$ can be correlated with $\mathbf{x}_{it}$. Schmidt and Sickles (1984) suggested to interpret $\alpha_i$ as firm specific inefficiency term. Inefficiency scores can then be computed by comparing the firm with the highest intercept to the rest of the sample firms. This is given as

$$\hat{u}_i = max_i\{\hat{\alpha}_i\} - \hat{\alpha}_i \geq 0, \qquad i = 1, \ldots, N. \tag{2.9}$$

The definition of inefficiency exhibited by equation (2.9) implicitly assumes that the most

[4]The incidental parameter problem demonstrated by Neyman and Scott (1948) arises when the number of parameters to be estimated increases with the cross-sectional units while T is fixed.

efficient firm is 100% efficient. Firm-specific efficiency can be obtained from equation (2.9) using Jondrow et al. (1982) approach by computing $\widehat{TE_i} = exp(-\hat{u}_i)$.

Alternatively, a random effects framework can be used to estimate equation (2.8) by imposing that $\alpha_i$ is random and uncorrelated with $\mathbf{x}_{it}$. If the assumption is truly correct then the random effects framework provides more efficient estimates of firm inefficiency than the fixed effects framework (Parmeter and Kumbhakar, 2014). One advantage of the random effects model is that time-invariant variables can be included in the regression without leading to collinearity like the previous case. Using the generalized least squares (GLS) estimator of the random effects framework, suppose the inefficiency term $u_i$ is a random variable. Let $E(u_i) = \mu$ and $u_i^* = u_i - \mu$, subtracting the inefficiency term $u_i$ from the intercept the GLS model can be written as

$$y_{it} = \alpha^* + \mathbf{x'}_{it}\boldsymbol{\beta} + \nu_{it} - u_i^*, \tag{2.10}$$

where $\alpha^* \equiv \alpha - \mu$. As noted by Parmeter and Kumbhakar (2014), defining $\hat{\varepsilon}_{it} = y_{it} - \mathbf{x'}_{it}\hat{\boldsymbol{\beta}}$, then $\alpha^* \equiv \alpha - \mu$ can be derived from the time average of $\hat{\varepsilon}_{it}$ for each cross-section,

$$\hat{\alpha}_i = \frac{1}{T}\sum_t(\hat{\varepsilon}_{it} - \hat{\alpha^*}), \qquad i = 1, \ldots, N. \tag{2.11}$$

Equation (2.11) can then be in-putted into equation (2.9) to derive firm-specific inefficiency level and its subsequent efficiency rate using Jondrow et al. (1982) approach.

**Results**

For each sector in our sample we present estimates results using both the fixed effects and the random effects frameworks. As hinted above, we will estimate equations (2.8) and (2.10) using both Cobb-Douglas and translog specification for the production technology. Tables (2.2) – (2.5) present estimates for food and bakery, textile and garments, wood and furniture and metal sectors respectively. For each sector, fixed effects estimates are reported under columns (1) and (2) while random effects estimates are reported under columns (3) and (4) for Cobb-Douglas and translog specifications respectively.

Marginal effects and elasticities of all the factor inputs are significant at 1% level under the random effects framework whereas capital is not significant under the fixed effects framework for food processing and metals. With the exception of the labour coefficient under FE for the metal sector, all the other inputs have the expected sign and magnitude under the Cobb-Douglas specification. Figure 2.1 presents the kernel density distribution of technical efficiency estimates – using translog function specification – for all the sectors. With the exception of the textile and garment sector which showed identical efficiency distribution for both fixed effects and random effects, there was great disparity of efficiency estimates between FE and RE.

In order to establish whether inefficiency is correlated to firm covariates or no, we carry out a Hausman specification test to determine the significance of the differences between the two frameworks. In addition to standard Hausman test, a robust version was carried out using

Table 2.2: Time-invariant model: Food Processing

| VARIABLES | (1) Cobb-Douglas FE | (2) Translog FE | (3) Cobb-Douglas RE | (4) Translog RE |
|---|---|---|---|---|
| Log (Capital) | 0.0766 | -1.928*** | 0.0493*** | -0.996*** |
| | (0.0826) | (0.587) | (0.0188) | (0.120) |
| Log (Labour) | 0.146*** | 2.001*** | 0.290*** | 3.007*** |
| | (0.0449) | (0.453) | (0.0377) | (0.291) |
| Log (Raw Materials) | 0.733*** | -0.207 | 0.743*** | -0.279 |
| | (0.0247) | (0.278) | (0.0220) | (0.242) |
| Log (Cap x Cap) | | 0.0307* | | 0.00967** |
| | | (0.0170) | | (0.00408) |
| Log (Lab x Lab) | | 0.0605* | | 0.137*** |
| | | (0.0352) | | (0.0229) |
| Log (R. Mat x R. Mat) | | 0.0114 | | 0.0120 |
| | | (0.0110) | | (0.00962) |
| Log (Cap x Lab) | | -0.0204 | | -0.0922*** |
| | | (0.0271) | | (0.0147) |
| Log (Cap x R. Mat) | | 0.0558*** | | 0.0632*** |
| | | (0.00908) | | (0.00778) |
| Log (Lab x R. Mat) | | -0.113*** | | -0.128*** |
| | | (0.0237) | | (0.0218) |
| Constant | 3.444** | 25.50*** | 3.331*** | 15.73*** |
| | (1.365) | (4.915) | (0.357) | (1.719) |
| Observations | 466 | 466 | 466 | 466 |
| $\bar{R}$-Squared | 0.980 | 0.983 | | |
| Number of firm | 59 | 59 | 59 | 59 |
| Firm FE | YES | YES | NO | NO |
| Year FE | YES | YES | YES | YES |

Sources: Author's computation based on data compiled by CSAE.
Robust standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

bootstrapping procedure. Results in Table 2.6 under the standard Hausman specification shows that, the notion of independence between inefficiency and firm covariates are rejected for all sectors. Under the robust Hausman specification, test using Cobb-Douglas production function confirms the results of the standard Hausman. However, the translog production function rejects the null hypothesis for food processing and textiles sectors.

The likelihood ratio test in table 2.7 seek to show which of the two production functions best suit production technology for each sector. Results in columns (1) and (2) clearly reject Cobb-Douglas function as best representation of production technology for all the four sectors. Although the likelihood test rejects the Cobb-Douglas production function for all sectors, it will be maintained in the next two models and test its significance accordingly. Columns (3) and (4) perform test on the significance of time fixed effects in the estimation function. Results clearly shows time fixed effects are to be maintained in all functions.

There are two major issues with the time-invariant models that calls for a cautious interpretation of the results. First, as the name implies, the model in equation (2.8) treats firm inefficiency as constant across time. This assumes that there is no learning-by-doing effect

Table 2.3: Time-invariant model: Textiles

| VARIABLES | (1)<br>Cobb-Douglas FE | (2)<br>Translog FE | (3)<br>Cobb-Douglas RE | (4)<br>Translog RE |
|---|---|---|---|---|
| Log (Capital) | 0.0643* | 0.599** | 0.126*** | 0.623*** |
| | (0.0333) | (0.281) | (0.0207) | (0.159) |
| Log (Labour) | 0.251*** | 0.461* | 0.286*** | 0.313 |
| | (0.0422) | (0.259) | (0.0363) | (0.237) |
| Log (Raw Materials) | 0.603*** | 0.0606 | 0.616*** | -0.0106 |
| | (0.0183) | (0.128) | (0.0172) | (0.114) |
| Log (Cap x Cap) | | 0.00674 | | 0.00843 |
| | | (0.00964) | | (0.00626) |
| Log (Lab x Lab) | | 0.0254 | | 0.0316 |
| | | (0.0254) | | (0.0211) |
| Log (R. Mat x R. Mat) | | 0.0512*** | | 0.0554*** |
| | | (0.00539) | | (0.00494) |
| Log (Cap x Lab) | | 0.0367** | | 0.0401*** |
| | | (0.0167) | | (0.0154) |
| Log (Cap x R. Mat) | | -0.0542*** | | -0.0576*** |
| | | (0.00821) | | (0.00765) |
| Log (Lab x R. Mat) | | -0.0593*** | | -0.0539*** |
| | | (0.0209) | | (0.0197) |
| Constant | 5.107*** | 4.510** | 4.051*** | 4.701*** |
| | (0.533) | (2.283) | (0.307) | (1.247) |
| Observations | 433 | 433 | 433 | 433 |
| R-squared | 0.793 | 0.842 | | |
| Number of firm | 58 | 58 | 58 | 58 |
| Firm FE | YES | YES | NO | NO |
| Year FE | YES | YES | YES | YES |

Sources: Author's computation.
Robust standard errors in parentheses $^{***}p < 0.01, ^{**} p < 0.05, ^{*} p < 0.1$

in the production process. In addition, this is unlikely to be true in a longer panel where exogenous shocks are likely to be higher. A Wald test on the significance of the year variables in Table (2.7) shows that time effects are significant for all the sectors in our data.

Secondly, the time-invariant model in equations (2.7), (2.8) and (2.10) assumes that the two-sided error terms $\nu_{it}$ and $u_i$ are homoscedastic. This is unlikely to be true and thus may lead to bias estimates of the frontier parameters. Kumbhakar and Lovell (2000) presented a detail discussion on the impact of ignoring heteroskedasticity in the error term. To overcome these two shortcomings, the next section will consider time-varying models which incorporate heteroskedasticity in the error term.

### 2.4.2 Model 2: Time-varying model

Cornwell et al. (1990) and Kumbhakar (1990) proposed a panel stochastic frontier model to account for time-varying technical inefficiency. For continuity with model 1, this sub-section follows Cornwell et al. (1990) approach. Recall the time-invariant Schmidt and Sickles (1984)

Table 2.4: Time-invariant model: Wood Processing

| VARIABLES | (1) Cobb-Douglas FE | (2) Translog FE | (3) Cobb-Douglas RE | (4) Translog RE |
|---|---|---|---|---|
| Log (Capital) | 0.0379 | 0.526* | 0.126*** | 0.206 |
| | (0.0590) | (0.286) | (0.0179) | (0.182) |
| Log (Labour) | 0.121*** | 0.391 | 0.215*** | 0.741* |
| | (0.0466) | (0.452) | (0.0361) | (0.406) |
| Log (Raw Materials) | 0.678*** | 0.459 | 0.713*** | 0.480* |
| | (0.0214) | (0.285) | (0.0196) | (0.269) |
| Log (Cap x Cap) | | -0.00200 | | 0.00864 |
| | | (0.0110) | | (0.00642) |
| Log (Lab x Lab) | | 0.0212 | | 0.0560* |
| | | (0.0318) | | (0.0289) |
| Log (R. Mat x R. Mat) | | 0.0420*** | | 0.0357*** |
| | | (0.0122) | | (0.0113) |
| Log (Cap x Lab) | | 0.0791** | | 0.0486** |
| | | (0.0328) | | (0.0247) |
| Log (Cap x R. Mat) | | -0.0467*** | | -0.0337*** |
| | | (0.0132) | | (0.0110) |
| Log (Lab x R. Mat) | | -0.103*** | | -0.104*** |
| | | (0.0297) | | (0.0277) |
| Constant | 5.083*** | 2.654 | 2.649*** | 2.858 |
| | (1.002) | (2.850) | (0.295) | (2.030) |
| Observations | 538 | 538 | 538 | 538 |
| R-squared | 0.729 | 0.765 | | |
| Number of firms | 72 | 72 | 72 | 72 |
| Firm FE | YES | YES | NO | NO |
| Year FE | YES | YES | YES | YES |

Sources: Author's computation.
Robust standard errors in parentheses $^{***}p < 0.01, ^{**} p < 0.05, ^{*} p < 0.1$

fixed effects model in equation (2.8):

$$y_{it} = \alpha_i + \mathbf{x'}_{it}\boldsymbol{\beta} + \nu_{it}, \tag{2.12}$$

where $\alpha_i \equiv \beta_0 - u_i$. Notice that the inefficiency term is confounded in the intercept. To allow inefficiency to be time-varying, Cornwell et al. (1990) suggested to replace $\alpha_i$ by $\alpha_{it}$, where

$$\alpha_{it} = \alpha_{0i} + \alpha_{1i}t + \alpha_{2i}t^2, \tag{2.13}$$

where the intercepts $(\alpha_{0i}, \alpha_{1i}, \alpha_{2i})$ are firm-specific and $t$ denote the time trend. Incorporating (2.13) into (2.12), the model can be generalised as

$$y_{it} = \alpha_{0i} + \mathbf{x'}_{it}\boldsymbol{\beta} + \varepsilon_{it}; \quad \varepsilon_{it} \equiv \nu_{it} + \alpha_{1i}t + \alpha_{2i}t^2. \tag{2.14}$$

Given that equation (2.14) is familiar to standard panel data model, the within estimator can then be applied to obtain estimates of the technology parameters as described in Schmidt

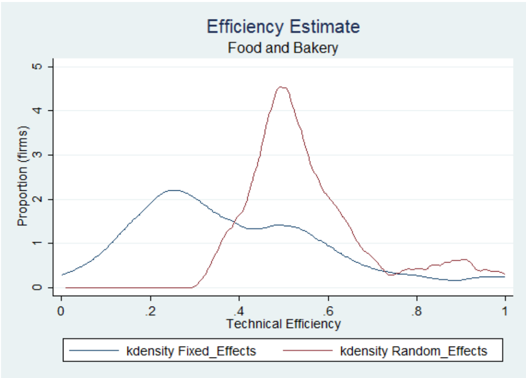
Table 2.5: Time-invariant model: Metals

| VARIABLES | (1) Cobb-Douglas FE | (2) Translog FE | (3) Cobb-Douglas RE | (4) Translog RE |
|---|---|---|---|---|
| Log (Capital) | 0.00399 | -0.268 | 0.126*** | 0.0364 |
| | (0.0494) | (0.272) | (0.0176) | (0.207) |
| Log (Labour) | -0.00760 | -0.445 | 0.0958** | -0.345 |
| | (0.0527) | (0.592) | (0.0394) | (0.506) |
| Log (Raw Materials) | 0.736*** | 1.679*** | 0.764*** | 1.443*** |
| | (0.0193) | (0.231) | (0.0171) | (0.216) |
| Log (Cap x Cap) | | 0.0357*** | | 0.0286*** |
| | | (0.00801) | | (0.00626) |
| Log (Lab x Lab) | | 0.0128 | | 0.0211 |
| | | (0.0434) | | (0.0379) |
| Log (R. Mat x R. Mat) | | -0.0123 | | -0.00362 |
| | | (0.00804) | | (0.00764) |
| Log (Cap x Lab) | | -0.0449 | | -0.0358 |
| | | (0.0330) | | (0.0265) |
| Log (Cap x R. Mat) | | -0.0453*** | | -0.0439*** |
| | | (0.0102) | | (0.00925) |
| Log (Lab x R. Mat) | | 0.0658** | | 0.0543* |
| | | (0.0309) | | (0.0284) |
| Constant | 4.943*** | -0.146 | 2.194*** | -2.266 |
| | (0.880) | (2.751) | (0.313) | (2.136) |
| Observations | 452 | 452 | 452 | 452 |
| R-squared | 0.827 | 0.853 | | |
| Number of firm | 59 | 59 | 59 | 59 |
| Firm FE | YES | YES | NO | NO |
| Year FE | YES | YES | YES | YES |

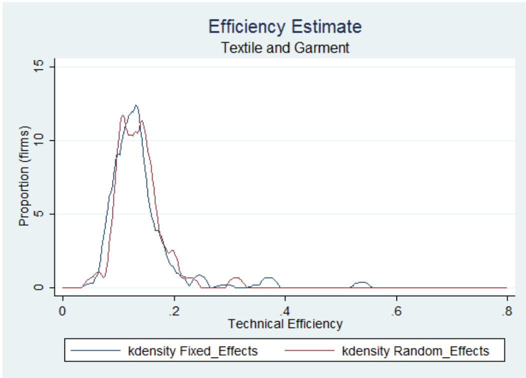
Sources: Author's computation.
Standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table 2.6: Hausman Specification Test for Fixed Effects and Random Effects

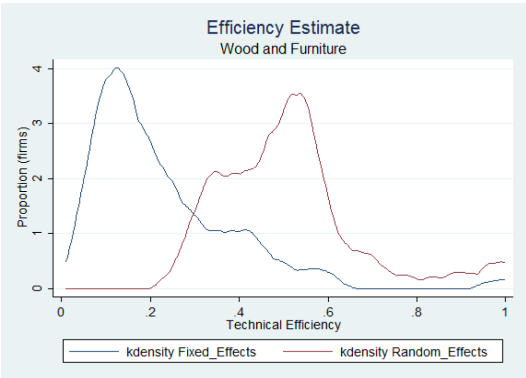
| Sector | Model | Standard Hausman $\chi^2 - statistic$ | Standard Hausman p-value | Robust Hausman $\chi^2 - statistic$ | Robust Hausman p-value |
|---|---|---|---|---|---|
| Ho: Difference in coefficients not systematic | | | | | |
| Food Processing: | | | | | |
| | Cobb-Douglas | 59.99 | 0.0000 | 16.08 | 0.0029 |
| | Translog | 34.80 | 0.0148 | 14.82 | 0.1389 |
| Textiles: | | | | | |
| | Cobb-Douglas | 24.22 | 0.0291 | 14.31 | 0.0064 |
| | Translog | 31.86 | 0.0324 | 10.13 | 0.4294 |
| Wood Processing: | | | | | |
| | Cobb-Douglas | 32.04 | 0.0008 | 21.69 | 0.0002 |
| | Translog | 41.09 | 0.0009 | 25.37 | 0.0047 |
| Metals | | | | | |
| | Cobb-Douglas | 29.13 | 0.0038 | 20.58 | 0.0004 |
| | Translog | 57.58 | 0.0000 | 29.05 | 0.0012 |



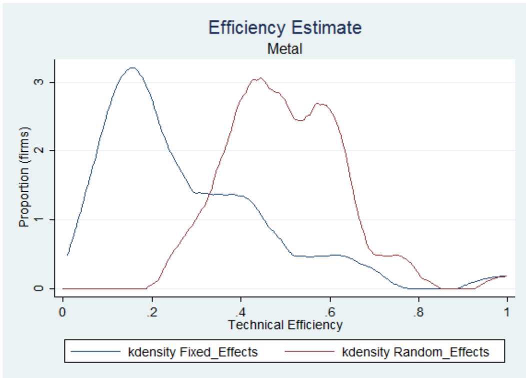

(a) Food Processing




(b) Textiles




(c) Wood




(d) Metals

Figure 2.1: Comparisons of Time-Invariant Efficiency Estimates Using Results from Translog Specification

Table 2.7: Test for Production Function specification and Year Fixed Effects

| | Likelihood Ratio Test | | Test for Time Fixed Effects | |
|---|---|---|---|---|
| | $\chi^2 - statistic$ | p-value | $F - statistic$ | p-value |
| | (1) | (2) | (3) | (4) |
| Food Processing: | 82.19 | 0.0000 | 3.78 | 0.0000 |
| Textiles: | 117.35 | 0.0000 | 2.88 | 0.0012 |
| Wood Processing: | 75.42 | 0.0000 | 3.4 | 0.0002 |
| Metal | 73.48 | 0.0000 | 12.34 | 0.0000 |
| All sectors | 200.35 | 0.0000 | 77.72 | 0.0000 |

The likelihood ratio test, performs the hypothesis that $\frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J}\beta_{jk}lnX_{jit}lnX_{kit} = 0$.
Test for time fixed effects, performs a test on the significance of time dummies.

and Sickles (1984). Firm-specific inefficiency for each period can be obtained from

$$\hat{u}_{it} = \hat{\alpha}_t - \hat{\alpha}_{it} \quad and \quad \hat{\alpha}_t = max_j(\hat{\alpha}_{jt}). \tag{2.15}$$

The main difference between inefficiency computed using equation (2.15) and its time-invariant counterpart in equation (2.9) lies with the choice of the best efficient firm. Given that $\hat{\alpha}_{jt}$ is likely to change on year-to-year basis, the same firm may not be efficient in every year. This makes it possible to choose the best efficient firm in a given year, unlike the time-invariant model whereby one firm is considered efficient throughout the years.

**Results**

Tables 2.8 and 2.9 show estimates of the parameters of the production function for food processing, textiles, wood, and metals sectors respectively. Keeping in line with the discussion on the structure of the production technology we presents estimates using both the Cobb-Douglas and the Translog specifications. The tables also report a joint hypothesis test that the frontier parameters, $\beta_{jk}$, in equation (2.6) reduces to the Cobb-Douglas form.

Table 2.8: Time Varying Estimates of Production Function Parameters

| | Food Processing | | Textiles | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| VARIABLES | Cobb-Douglas | Translog | Cobb-Douglas | Translog |
| Log Capital | 0.0525 | 0.497 | 0.116 | 1.173*** |
| | (0.0631) | (0.972) | (0.112) | (0.415) |
| Log Labour | 0.110* | 1.231 | 0.181*** | 0.448 |
| | (0.0592) | (1.059) | (0.0424) | (0.390) |
| Log Raw Materials | 0.678*** | -0.427 | 0.614*** | 0.0685 |
| | (0.0609) | (0.661) | (0.0352) | (0.293) |
| Log (Cap x Cap) | | -0.0166 | | -0.0143 |
| | | (0.0585) | | (0.0249) |
| Log (Lab x Lab) | | 0.0366 | | 0.0891 |
| | | (0.111) | | (0.0705) |
| Log (R. Mat x R. Mat) | | 0.0908** | | 0.103*** |
| | | (0.0426) | | (0.0225) |
| Log (Cap x Lab) | | 0.00969 | | 0.0132 |
| | | (0.0419) | | (0.0180) |
| Log (Cap x R.Mat) | | -0.0114 | | -0.0596*** |
| | | (0.0283) | | (0.0127) |
| Log (Lab x R. Mat) | | -0.0819 | | -0.0456 |
| | | (0.0672) | | (0.0353) |
| **DIAGNOSTICS AND TESTS** | | | | |
| Cobb-Douglas ($\chi^2$) | | 5.60 | | 40.73 |
| P-value | | 0.4689 | | 0.0000 |
| Scale Elasticity | | 0.84 | | 0.93 |
| P-value | | 0.0000 | | 0.0000 |
| Mean Efficiency | 0.29 | 0.23 | 0.36 | 0.26 |
| SD | [0.228] | [0.210] | [0.201] | [0 .252] |
| Observations | 463 | 463 | 429 | 429 |
| Number of firms | 56 | 56 | 54 | 54 |

Robust standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

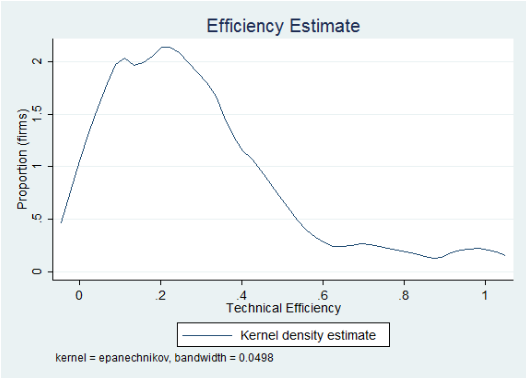
Table 2.9: Time Varying Estimates of Production Function Parameters

| | Wood and Furniture | | Metals | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| VARIABLES | Cobb-Douglas | Translog | Cobb-Douglas | Translog |
| Log Capital | 0.0831 | 1.141** | -0.122 | -0.00346 |
| | (0.120) | (0.515) | (0.0991) | (0.353) |
| Log Labour | 0.131** | 1.154** | -0.0207 | 0.399 |
| | (0.0607) | (0.457) | (0.0669) | (0.948) |
| Log Raw Materials | 0.618*** | 0.0215 | 0.685*** | 1.545*** |
| | (0.0521) | (0.371) | (0.0770) | (0.478) |
| Log (Cap x Cap) | | -0.0437 | | 0.0881** |
| | | (0.0410) | | (0.0406) |
| Log (Lab x Lab) | | -0.0753 | | 0.00802 |
| | | (0.0857) | | (0.116) |
| Log (R. Mat x R. Mat) | | 0.119*** | | 0.0256 |
| | | (0.0274) | | (0.0388) |
| Log (Cap x Lab) | | 0.109* | | -0.0277 |
| | | (0.0622) | | (0.0312) |
| Log (Cap x R.Mat) | | -0.0481*** | | -0.0794*** |
| | | (0.0141) | | (0.0281) |
| Log (Lab x R. Mat) | | -0.158*** | | -0.00510 |
| | | (0.0496) | | (0.0612) |
| **DIAGNOSTICS AND TESTS** | | | | |
| Cobb-Douglas ($\chi^2$) | | 55.42 | | 25.21 |
| p-value | | 0.0000 | | 0.0003 |
| Scale Elasticity | | 0.72 | | 0.55 |
| p-value | | 0.0000 | | 0.0000 |
| Mean Efficiency | 0.30 | 0.15 | 0.18 | 0.12 |
| | (0.213) | (0.197) | (0.205) | (0.191) |
| Observations | 533 | 533 | 448 | 448 |
| Number of firms | 67 | 67 | 55 | 55 |

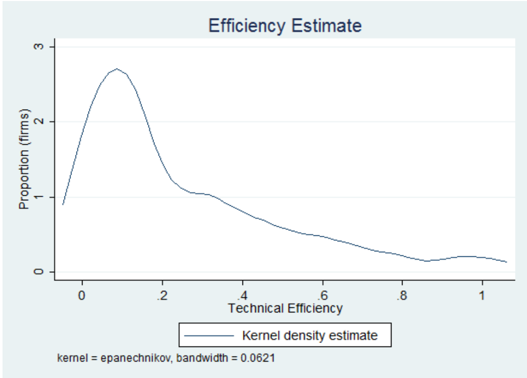
Standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Results of the test in Tables 2.8 and 2.9 shows that with exception of the food processing sector all the remaining sectors are best represented by a translog production technology. This is further reinforced by the fact that sector-level average efficiency scores computed from both specifications are very close.

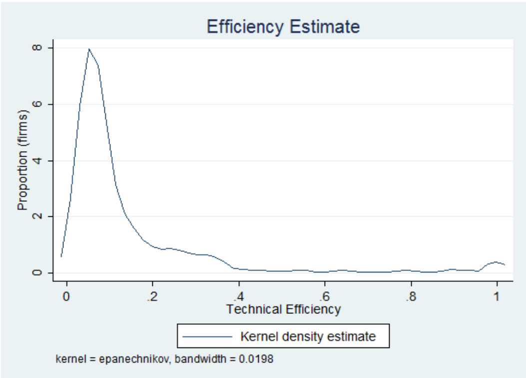
Two issues are worth mentioning. First, average efficiency scores from the time-varying model are generally low with respect to average efficiency scores of the time-invariant model. Second, Kernel density distribution in Figure 2.2 shows a low efficiency dispersion for wood, metals, and textiles sectors. A comparison of the efficiency distribution in Figures 2.1 and 2.2 underlines how results differs between time-invariant model and time-varying model.



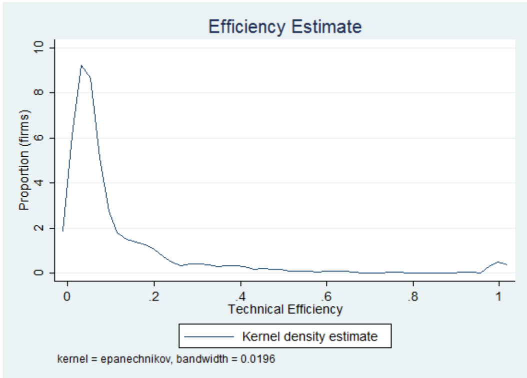

(a) Food Processing




(b) Textiles




(c) Wood




(d) Metals

Figure 2.2: Comparisons of Time-Varying Efficiency Estimates Using Results from Translog Specification

A minor downside of the Cornwell et al. (1990) model regards its treatment of technical change. Given that time trend is incorporated in the inefficiency parameter, it cannot be entered as a variable in the production function to capture technical change (Kumbhakar and Lovell, 2000). Additionally, time invariant variables cannot be included into the model due to multicollinearity issues as in all fixed effects framework. Parmeter and Kumbhakar (2014) showed that when N is large and T is small, the Cornwell et al. (1990) model could be over-parametrized in the specification of inefficiency.

To resolve this problem, Lee and Schmidt (1993) proposed an alternative formulation of the inefficiency function, which is specified as $u_{it} = u_i\lambda_t$, where $\lambda_t, t = 1, \ldots T$, are time specific effects (Parmeter and Kumbhakar, 2014). A major drawback of Lee and Schmidt (1993) model is that, temporal pattern of inefficiency is exactly the same for all firms, making it undesirable to impose such assumption in a developing country context. Kumbhakar and Lovell (2000) noted that the model is suitable for data with short panels, since it requires estimation of $T - 1$ parameters.

### 2.4.3 Model 3: Separating Unobserved Heterogeneity from Inefficiency

By observing the same production unit over time, longitudinal data offers an important advantage over cross-sectional data to observe and model time invariant cross unit heterogeneity in the production function. There exist firm-specific effects which are not directly related to the production process but nevertheless affect production outcome.[5] Greene (2005a) based on an earlier study [Greene (2004)] observed that conventional panel data stochastic frontier models do not address cross unit heterogeneity appropriately but force it into the inefficiency term. Treating the two components as unity fails to take into consideration unobserved factors that are not directly involved in the production process but perhaps affect output and general firm's performance.[6]

#### Greene Proposal and Incidental Parameter Problem

To conceptualise Greene's argument, consider the following stochastic frontier model

$$
\begin{aligned}
y_{it} =& f(\mathbf{x_{it}}, \mathbf{z_i}) = \mathbf{x}_{it}\boldsymbol{\beta} + \boldsymbol{\mu'}\mathbf{z}_i + \nu_{it} - u_{it}, && (2.16)\\
\nu_{it} \sim& \mathbb{N}(0, \sigma_v^2), && (2.17)\\
u_{it} =& |U_{it}| \quad \text{where} \quad U_{it} \sim \mathbb{N}(0, \sigma_u^2), \qquad i = 1, \dots, n, \quad t = 1, \dots, T, && (2.18)
\end{aligned}
$$

where the function $f(\cdot)$ has a time-varying component and a time-invariant component. Greene (2005a) argued that the time-varying component, $\mathbf{x}_{it}\boldsymbol{\beta}$, contains input quantities of the production function, and possibly functions of a time trend to account for technical change. The time-invariant component, $\boldsymbol{\mu'}\mathbf{z}_i$ are firm specific effects, which are not related to the production structure. Given that Model 1 and Model 2, do not account for, $\boldsymbol{\mu'}\mathbf{z}_i$, the term is passed unto the residual, hence, treated as part of (in)efficiency.

Notice that if the nature of, $\boldsymbol{\mu'}\mathbf{z}_i$, is clearly certain, a simple solution is to treat it as omitted variable bias. In that case, gathering additional data will be enough to solve the problem. The main question is, what exactly goes into the vector $\boldsymbol{\mu'}\mathbf{z}_i$? In other words, what are factors other than production inputs that determine efficiency (Syverson, 2011)? In view of this, Greene (2005a,b) proposed the "true" fixed-effects and random-effects (TFE & TRE) models which separates unobserved heterogeneity from inefficiency.[7]

Under the fixed effects framework, Greene argued that to separate firm-specific heterogeneity from the production structure, "...one can replace the overall constant term with a complete set of firm dummy variables, and estimate it by the now conventional means"

[5] On the original study on healthcare delivery, William Greene mentioned cultural differences or different forms of government across countries. Specific examples for firms ranges from management and organisation, location, and market power.

[6] For example, sales and firm efficiency are both measures of firm performance but different in nature. While firm efficiency are technically related to the production process, there exits factors and firm strategies such as discount sales which can increase volume of sales but are not related to the production process.

[7] This study adopts the fixed-effects framework, given that the assumption of zero correlation between the inefficiency term and the production inputs factors can potentially lead to technology heterogeneity bias.

(Greene, 2005a). Specifically, the resulting density function can be estimated by maximum likelihood dummy variables estimator (MLDVE).[8] However, this approach can potentially lead to the incidental parameter problem when T is fixed.[9] [10]

### Solution to Incidental Parameter Problem

Belotti and Ilardi (2012, 2015) proposed two alternative estimators that relies on first-difference data transformation to get rid of the nuisance parameters avoiding the incidental parameters problem entirely. Given the following stochastic production frontier model[11]

$$\begin{aligned} y_{it} = &\quad \alpha_i + \mathbf{x}_{it}\boldsymbol{\beta} + \varepsilon_{it}, && (2.19)\\ \varepsilon_{it} = &\quad \nu_{it} - u_{it}, && (2.20)\\ \nu_{it} \sim &\quad IID \quad \mathcal{N}(0, \psi^2), && (2.21)\\ u_{it} \sim &\quad IID \quad \mathcal{F}_u(\sigma), \qquad i = 1, \ldots, n, \quad t = 1, \ldots, T, && (2.22) \end{aligned}$$

where the composite error term $\varepsilon_{it}$ represents the difference between the idiosyncratic error term $\nu_{it}$ and the inefficiency term $u_{it}$. The other variables in equation (2.19) have their usual interpretation illustrated for models 1 and 2 above. In addition, it is assumed that the inefficiency $u_{it}$ is distributed according to $\mathcal{F}_u$ defined over $\mathbb{R}^+$ with scale parameter $\sigma$. The relative contribution of $u_{it}$ and $\nu_{it}$ to the variability of $\varepsilon_{it}$, termed as signal-to-noise ratio is defined as $\sigma/\psi$. The first-difference transformation applied on model (2.19) - (2.22) to get rid of the nuisance parameters can be derived as

$$\begin{aligned} &\Delta\mathbf{y}_i = \Delta X_i\boldsymbol{\beta} + \Delta\varepsilon_i, && (2.23)\\ &\Delta\boldsymbol{\varepsilon}_i = \Delta\nu_i - \Delta u_i, && (2.24)\\ &\Delta\boldsymbol{\nu}_i \sim IID \quad \mathcal{N}_{T-1}(0, \Psi), && (2.25)\\ &\Delta\mathbf{u}_i \sim IID \quad \mathcal{F}_{\Delta u}(\sigma), \qquad i = 1, \ldots, n \quad t = 1, \ldots, T, && (2.26) \end{aligned}$$

where $\Delta\mathbf{y}_i = (\Delta_{i2}, \ldots, \Delta y_{iT})$ with $\Delta y_{it} = y_{it} - y_{it-1}$ and $\Delta X_i$ is a $T - 1 \times k$ matrix of time-varying covariates whereby each $t - th$ row is denoted by $\Delta x_{it} = (\Delta x_{it1}, \ldots, \Delta x_{itk}), \forall t = 2, \ldots, T$.

Given the marginal likelihood contribution of $\Delta\nu_i$ and $\Delta u_i$ the authors noted that, the transformed model can either be estimated by marginal maximum simulated likelihood estimator (MMSLE) or pairwise difference estimator (PDE) (Belotti and Ilardi, 2012, 2015). For the purpose of this application, the pairwise difference estimator is preferred to the marginal maximum simulated likelihood estimator due to its restrictions free feature imposed

[8]The interested reader is referred to Greene (2005a) for complete exposition of the likelihood function.

[9]Notice that, the within estimator used in standard panel avoids the incidental parameter problem by wiping out $\alpha$ from the estimating equation.

[10]Results for the application of Greene's approach is reported in Appendix A.

[11]The reader is referred to Belotti and Ilardi (2015) for detail exposition of the two estimation procedures.

on the inefficiency term.[12] In principle, in other to introduce heteroskedasticity in $u$, only time invariant $z$ are allowed in its scale parameter, thus, $\sigma_i = g(Z_i\delta)$. On the contrary, heteroskedasticity in the pairwise difference estimator allows exogenous variables in the scale parameter to be time-varying, thus $\sigma_{it} = exp(z_{it}\gamma)$.

Finally, (in)efficiency scores can be computed from the mean of the conditional distribution of $u_{it}$ given $\varepsilon_{it}$. That is, $E(u_{it}|\hat{\varepsilon}_{it})$, where $\hat{\varepsilon}_{it} = y_{it} - \hat{\alpha}_i - \boldsymbol{x}_{it}\hat{\boldsymbol{\beta}}$. Notice that $\alpha_i$ was wiped out of the transformed model, hence, the fixed-effects estimation is undertaken at the second stage. This is given by

$$\hat{\alpha}_i = \frac{1}{T}\sum_{t=1}^{T}(y_{it} - \boldsymbol{x}_{it}\hat{\boldsymbol{\beta}} + \hat{c}_{it}) \qquad i = 1, \ldots, n, \tag{2.27}$$

where $\hat{\boldsymbol{\beta}}$ and $\hat{c}_{it} = E(u_{it}\backslash\hat{\boldsymbol{\beta}}, \hat{\sigma_{it}})$ are consistent estimates.

Continuing with the previous outline, the PDE estimator is applied using both Cobb-Douglas and translog production technology specifications. From equations (2.5) and (2.6), we can derive the following estimating equations for Cobb-Douglas and translog production functions respectively

$$lnY_{it} = \alpha_i + \sum_{j=1}^{3}\beta_j lnX_{jit} + \sum_{t=1992}^{2002} d_t + \nu_{it} - u_{it}, \tag{2.28}$$

$$lnY_{it} = \alpha_i + \sum_{j=1}^{3}\beta_j lnX_{jit} + \frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3}\beta_{jk} lnX_{jit} lnX_{kit} + \sum_{t=1992}^{2002} d_t + \nu_{it} - u_{it}. \tag{2.29}$$

In addition, inefficiency is assumed to be heteroskedastic and exponentially distributed. Thus, the scale parameter is $\sigma_{it} = \exp(z_{it}\gamma)$, where $z_{it}$ includes the following covariates: average work-force age, average workers' tenure, firm age, and fraction of foreign ownership. Workers' age and tenure simultaneously also captures information on work-force potential experience enabling to analyse the effect of human capital on the production process. Firm age also enables to determine whether there is learning-by-doing process where efficiency improves with firm age. It also enables to establish whether there is inertia whereby older firms grow to be obsolete or simply if firm age has no effect on efficiency. Fraction of foreign ownership captures information on whether foreign ownership brings about technical know-how in the production process.

### Results

Tables 2.10 and 2.11 reports estimated results for the food processing, textiles, wood processing, and metals sectors. Estimated marginal effects of the production inputs in Columns (1) and (2) from Cobb-Douglas and translog specifications do not vary much. Both specifications show that capital is not significant and surprisingly negative for the Cobb-Douglas specification. A Wald test in Column (2) rejects the translog specification in favour of the

[12] Belotti and Ilardi (2015) presents Monte Carlo experiments on the performance of the two estimators.

Table 2.10: Production Function Estimates and Determinants of Inefficiency

| | Food Processing | | Textiles | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| VARIABLES | Cobb-Douglas | Translog | Cobb-Douglas | Translog |
| ***Marginal Effects*** ① | | | | |
| Log Capital | -0.0168 | 0.0057 | 0.0523 | 0.0408 |
| | (0.0371) | (0.0326) | (0.0396) | (0.0568) |
| Log Labour | 0.0943*** | 0.099*** | 0.210*** | 0.188*** |
| | (0.0310) | (0.0245) | (0.0394) | (0.0462) |
| Log Raw Materials | 0.882*** | 0.870*** | 0.654*** | 0.684*** |
| | (0.0148) | (0.0179) | (0.0207) | (0.0236) |
| ***Determinants of Inefficiency*** ② | | | | |
| Workers' Age | 0.0359*** | 0.0350*** | -0.0138 | -0.0180 |
| | (0.00728) | (0.00736) | (0.0112) | (0.0165) |
| Tenure | -0.0615*** | -0.0594*** | -0.0142 | -0.0117 |
| | (0.0141) | (0.0134) | (0.0144) | (0.0257) |
| Firm Age, years | -0.00375 | -0.00453 | 0.0206*** | 0.0105 |
| | (0.00592) | (0.00593) | (0.00619) | (0.00760) |
| Fraction of Foreign Ownership | 0.496 | 0.471 | 0.128 | -2.758 |
| | (0.440) | (0.448) | (0.337) | (3.514) |
| Constant | -2.336*** | -2.307*** | -1.113*** | -0.905*** |
| | (0.280) | (0.288) | (0.302) | (0.318) |
| ***Estimated technical efficiencies*** | | | | |
| Mean | 0.807 | 0.808 | 0.748 | 0.788 |
| SD | 0.141 | 0.141 | 0.160 | 0.162 |
| Min | 0.086 | 0.086 | 0.053 | 0.176 |
| Max | 0.999 | 0.999 | 0.996 | 0.987 |
| **Diagnostics and Tests** | | | | |
| Scale Elasticity | 0.96 | 0.97 | 0.92 | 0.91 |
| P-value | 0.000 | 0.000 | 0.000 | 0.000 |
| Cobb-Douglas ($\chi^2$) | | 2.88 | | 325.51 |
| P-value | | 0.824 | | 0.000 |
| Wald Test - Z variables ($\chi^2$) | 41.70 | 43.96 | 13.83 | 8.81 |
| P-value | 0.000 | 0.000 | 0.008 | 0.066 |
| Observations | 377 | 377 | 364 | 364 |
| Number of firms | 49 | 49 | 48 | 48 |
| Year Dummies | YES | YES | YES | YES |

Robust standard errors in parentheses $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

① Marginal effects for the translog specification are evaluated at the sample mean of the inputs, while the marginal effects for the Cobb-Douglas specification are equal to their estimated coefficients.

② A negative sign indicates the variable reduces inefficiency thus making it a positive determinant of efficiency.

Cobb-Douglas. Determinants of inefficiency reported in Column (1) of Table 2.10 shows contrasting effect of human capital on inefficiency. While an increase in workers' tenure leads to a reduction in inefficiency, an increase in average workforce age increases inefficiency. A further

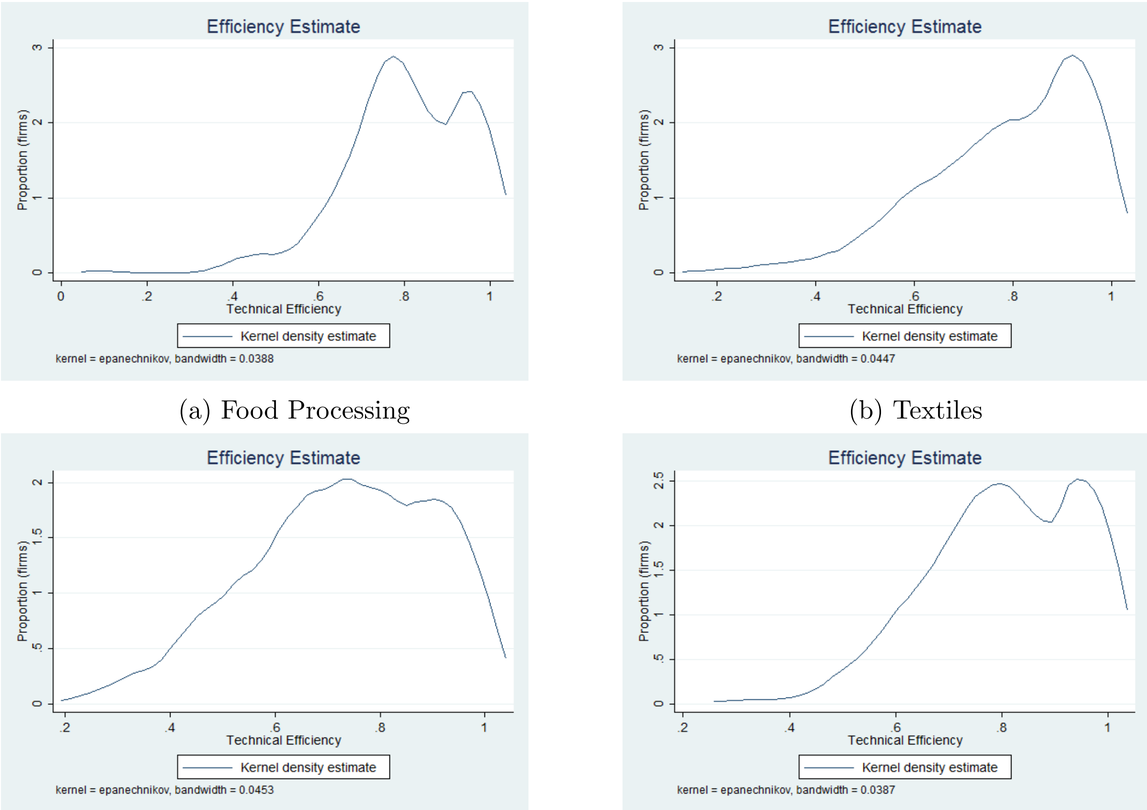
Table 2.11: Production Function Estimates and Determinants of Inefficiency

| | Wood Processing | | Metals | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| VARIABLES | Cobb-Douglas | Translog | Cobb-Douglas | Translog |
| ***Marginal Effects*** ① | | | | |
| Log Capital | 0.000127 | 0.0149 | -0.0440 | 0.0092 |
| | (0.0656) | (0.0710) | (0.0491) | (0.0378) |
| Log Labour | 0.111* | 0.098* | -0.0188 | -0.0116 |
| | (0.0603) | (0.0565) | (0.0461) | (0.0459) |
| Log Raw Materials | 0.708*** | 0.721*** | 0.787*** | 0.778*** |
| | (0.0240) | (0.0240) | (0.0207) | (0.0170) |
| ***Determinants of Inefficiency*** ② | | | | |
| Workers' Age | 0.0248** | 0.0250*** | -0.205 | -0.115 |
| | (0.0102) | (0.00967) | (0.463) | (0.477) |
| Tenure | -0.0370* | -0.0217 | 0.0863 | 0.119 |
| | (0.0192) | (0.0214) | (0.135) | (0.131) |
| Firm Age, years | 0.00523 | 0.00255 | -0.240** | -0.278** |
| | (0.00750) | (0.00716) | (0.121) | (0.130) |
| Fraction of Foreign Ownership | -0.485** | -0.479** | -0.400 | -0.476 |
| | (0.217) | (0.233) | (0.394) | (0.420) |
| Constant | -1.751*** | -1.850*** | -0.179 | -0.503 |
| | (0.300) | (0.290) | (1.521) | (1.566) |
| ***Estimated technical efficiencies*** | | | | |
| Mean | 0.724 | 0.727 | 0.791 | 0.806 |
| SD | 0.170 | 0.173 | 0.149 | 0.143 |
| Min | 0.213 | 0.238 | 0.262 | 0.296 |
| Max | 0.994 | 0.995 | 0.999 | 0.999 |
| ***Diagnostics and Tests*** | | | | |
| Scale Elasticity | 0.82 | 0.83 | 0.72 | 0.78 |
| P-value | 0.000 | 0.0000 | 0.000 | 0.000 |
| Cobb-Douglas ($\chi^2$) | | 71.78 | | 41.33 |
| P-value | | 0.000 | | 0.000 |
| Wald Test - Z variables ($\chi^2$) | 14.11 | 12.67 | 4.18 | 4.66 |
| P-value | 0.007 | 0.013 | 0.382 | 0.324 |
| Observations | 483 | 438 | 409 | 409 |
| Number of firms | 63 | 63 | 51 | 51 |
| Year Dummies | YES | YES | YES | YES |

Robust standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$
① Marginal effects for the translog specification are evaluated at the sample mean of the inputs, while the marginal effects for the Cobb-Douglas specification are equal to their estimated coefficients.
② A negative sign indicates the variable reduces inefficiency thus making it a positive determinant of efficiency.

probe on interaction between workers' age and tenure is needed before drawing conclusions for the food sector.

For the textiles sector, only labour and raw materials were significant to outputs as was




(a) Food Processing

(b) Textiles

(c) Woods

(d) Metal

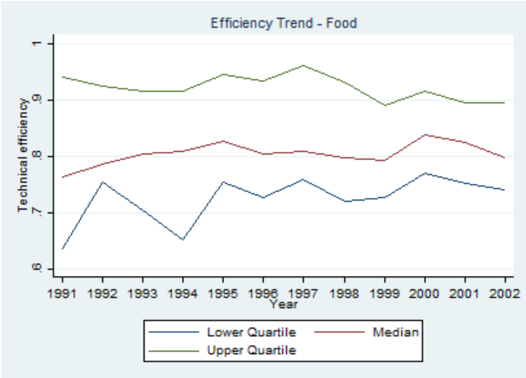
Figure 2.3: Comparisons of Time-Varying Efficiency Estimates

the case for the food sector. A test on the specification form of the production technology rejects the Cobb-Douglas specification in favour of the more flexible translog. Worker's age, tenure and fraction of foreign ownership had the expected sign but none was significant. A joint test on the validity of the covariates is only significant at 10%.

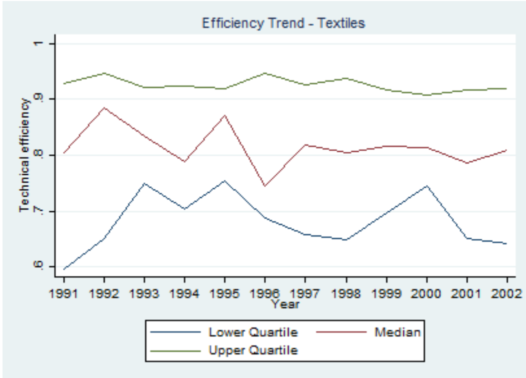
Results in Columns (2) and (4) in Table 2.11 show that the translog production function is best suited for both wood processing and metals sectors. Capital has neither a significant effect on output for wood processing nor metals. This leads to conclude that the effect of capital on output for the four sectors is none. Column (2) shows that labour input is only 10% significant for wood while it has a negative effect on output though not significant for metals in column (4). Observing the marginal effect of the three production inputs on output, one could ask if this is low value is added to final outputs in the transformation phase of the production process.

Column (2) of Table 2.11 also shows that an increase in average workforce age reduces efficiency while tenure contributes positively to efficiency though insignificant. Foreign ownership is a significant reduction of inefficiency for wood sector while insignificant for the metal sector. Firm age reduces inefficiency for the metal sector. A test on the joint significance of all the four variables is rejected.

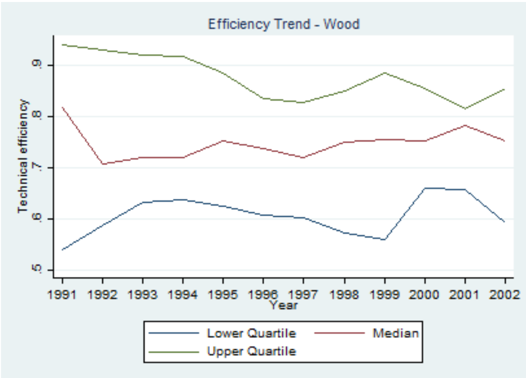
Figure 2.3 compares the kernel density distribution of productive efficiency obtained under the pairwise difference estimator for all sectors. In sharp contrast to Figures 2.1 and 2.2, the



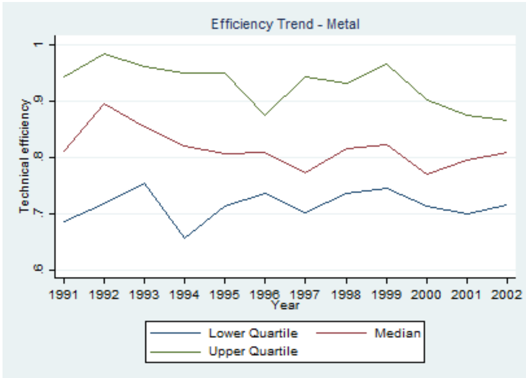

(a) Food Processing




(b) Textiles




(c) Wood Processing




(d) Metals

Figure 2.4: Comparisons of Efficiency Trend Over Time

density function is skewed towards the right suggesting high values in predicted productive efficiency in comparison with the two previous model. The food and textile sectors a flatter left tail of the density function.

Figure 2.4 compares trend in efficiency for firms in upper, median, and lower quartiles for all sectors from 1991 to 2002. For the food sector in panel (a), had a stable trend for the first part of the period before dropping slightly. Firms in the lower quartile, had a cyclical movements between 1991 and 1994 before consistently increasing for the remaining part of the period. For the food sector, firms in the lower quartile saw an improvement in their average efficiency level compared those in the median and upper quartile. For the textile sector in panel (b), firms in the upper quartile had a stable trend, whilst cyclical movement for lower quartile saw an erosion of gains made in the previous years.

Lastly, for the wood sector in panel (c), firms in the upper quartile registered a decrease in their average technical efficiency while the median and lower quartiles made small gains in efficiency levels. The metals sector in panel (d) presents a case of convergence of average efficiency over the decade.

## 2.5 Implication for Export Participation

This section explores economic implications of the three models presented above by investigating firms export participation. The sections seeks to show that the efficiency and export participation relationship established in new-new trade theory and advocated in policy recommendations hinges on the treatment of firm-specific unobserved heterogeneity in the estimation of productive efficiency.

The first question the section seeks to answer is whether exporters and non-exporters differs in efficiency levels, thereby making it a necessity to draw policy actions to increase efficiency levels of non-exporting firms. I use productive efficiency computed from Model 2 (which does not separate unobserved heterogeneity from efficiency) and Model 3 (which separate unobserved heterogeneity from efficiency) to compare efficiency levels of exporters and non-exporters.

Figure (2.5) compares the efficiency cumulative distribution functions for exporters and non-exporters.[13] In Model 2, shown in the left panel, there is a first-order stochastic dominance for exporters over non-exporters suggesting that exporters have higher productive efficiency compared to non-exporters. With regards to Model 3, shown in the right panel of Figure 2.5, there is no first-order stochastic dominance of exporters to non-exporters.

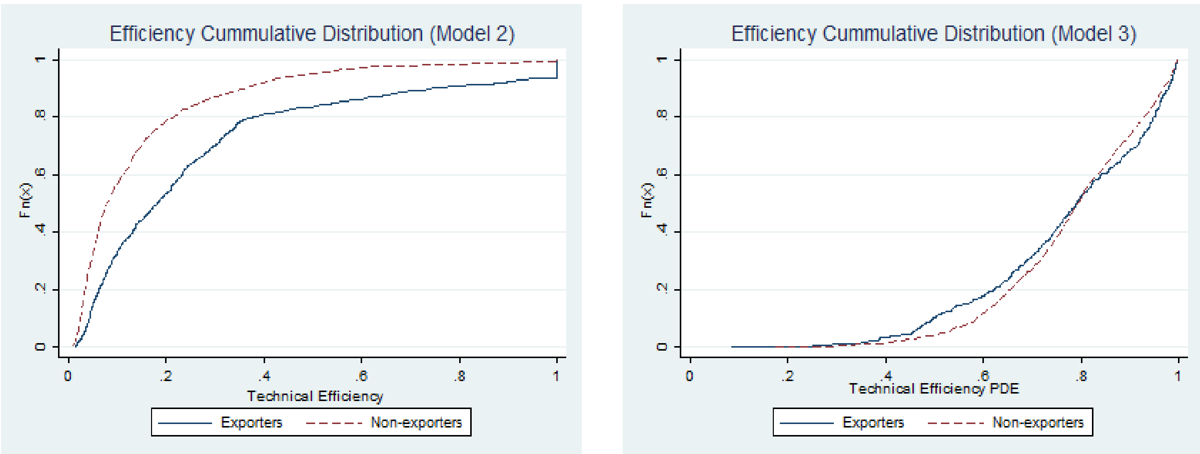



Figure 2.5: Comparisons of Cumulative Efficiency Distributions by Export Status

The cumulative distribution graphs for Model 2 and Model 3 clearly shows that, when one separate unobserved heterogeneity from efficiency, the productivity differences between exporters and non-exporters disappears. Most importantly, the left and right panels of Figure 2.5 offers different policy recommendation on actions to be taken to increase export participation of firms. One can raise concerns that the graphical analysis presented above is incomplete to warrant the conclusions stated above. To address such potential concerns, I use a econometric analysis to answer the main question posted above.

The empirical literature on export participation identifies two key factors that determine firm's export participation. These are entry barrier in the form of fixed sunk cost and

[13] Model 1 and Model 2 reports the same pattern and hence only one of them is reported here.

productive efficiency of the potential exporter (Bernard and Jensen, 1999*b*; Roberts and Tybout, 1997; Clerides et al., 1998).

Following Roberts and Tybout (1997), a firm decides to export if its expected revenue is greater than current cost and sunk cost of entry. Sunk cost significant export entry deterrent to enter the foreign market. Once a firm has paid up its sunk cost, it may continue to export at time $t$ even though export may not be profitable at time $t$. As a general practice, previous export participation is used to capture entry sunk cost. Large firms are more likely to export because they have lower marginal cost as well as pay higher wages than medium and small firms (Bernard and Jensen, 2004). To control for firm size effects, which can be a proxy for various firm characteristics, I introduce the log of number of employees as a measure of firm size and the ratio of wage bill to total employment. Due to uncertainty in the direction of causality between export participation and efficiency, the general praxis in the literature is to estimate the probability of exporting at time $t$ on characteristics of a firm at time $t-1$.

The reduced-form econometric specification adopted in the paper is given by:

$$EXP_{it} = \alpha + \gamma_1 Size_{i,t-1} + \gamma_2 Wage_{i,t-1} + \gamma_3 Eff^m_{i,t-1} + \theta EXP_{it-1} + \delta_s + \delta_t + e_{it}, \quad (2.30)$$

where the dependent variable, $(EXP_{it})$, is current export status; $EXP_{it-1}$ denotes previous year export status; $Size$ is the log of total number of workers; $Wage$ is the log of total wage bill (including allowances) to total number of workers; $Eff$ represents the predicted productive efficiency from the three models, where the superscript $m$ denotes the model used. Sector and time dummies are represented by $\delta_s$ and $\delta_t$ respectively, while $e_{it}$ denotes white noise.

Given that the predicted efficiency obtained under Model 1 is time-invariant, the lag value coincides with the current value. As such, results obtained for the time-invariant model ought to be interpreted with caution. For the purpose of comparing the treatment of heterogeneity in the estimation of the production function in export participation estimation, preferences is accorded to compare Model 2 and Model 3.

As postulated above, once a firm pays up entry sunk cost, it may continue to export even though its productive efficiency is currently low. Hence, productive efficiency may be a deterrent factor for first-time exporters than continuing exporters. A natural solution to this problem, is to estimate equation (2.30) only for export starters. Given the limited size of the dataset, an alternative solution is to interact sunk entry cost (previous export participation) and productive efficiency.[14] Equation (2.30) is therefore augmented as follows:

$$EXP_{it} = \alpha + \gamma_1 Size_{i,t-1} + \gamma_2 Wage_{i,t-1} + \gamma_3 Eff^m_{i,t-1} + \theta EXP_{it-1} + \lambda(EXP_{it-1} \times Eff^m_{it}) + \delta_s + \delta_t + e_{it}, \quad (2.31)$$

where all variables carries the same meaning as in equation (2.30).

[14] Thanks to one of the examiners for the suggestion.

Three different specifications in a binary-choice framework were used to estimate firms' decision to export exhibited in equations (2.30) and (2.31). These are: pooled probit, random effects probit, and dynamic probit. I report results for equations (2.30) and (2.31) under each specification. For each model presented in subsection 2.4.1 – 2.4.3, results for export decision estimates are reported in Tables 2.12 –2.14 respectively.

Few results are common to all specifications and models, which need commenting proceeding to highlight differences between models. First, for all specifications in Tables 2.12 – 2.14, the coefficient for lag export is positive and significant signalling the presence of sunk cost in export participation. Secondly, the wood sector is consistently positive and significant across all specifications and models, which may signal Ghana's comparative advantage in the wood sector.

The pooled and random effects probit results under columns (1) – (4) in Table 2.12 show a positive and significant result for firm size and wage variables. However, the coefficient for productive efficiency variable is positive but not significant. In Table 2.13, the coefficient for productive efficiency under columns (1) – (4) is positive and significant, confirming the relationship between export participation and productive efficiency in conventional models. However, the unstable results obtained for firm size under columns (1) – (4) in Table 2.13 raised suspicion on possible correlation between firm size and efficiency.

Given that productive efficiency obtained from Models 1 and 2 do not separate firms effects from efficiency, the main concern here is whether the residuals pick up size effects or not. To ascertain such possibility, Table 2.19 in Appendix C, presents correlation matrix between firm size and productive efficiency from all models under consideration. There is a positive correlation between firm size and efficiency for Models 1 and 2, though Model 1 presents a higher correlation.

Results for pooled probit and random effects probit under columns (1) – (4) in Table 2.14 show that the coefficient for efficiency computed using pairwise difference estimator (PDE) is not significant. Similar result was obtained for the coefficient of efficiency computed using Greene's true fixed effects (TFE) approach (Table 2.16 in Appendix A). On the other hand, firm size and wage are positive and significant in Tables 2.14 and 2.16. Likewise, the correlations between efficiency from TFE & PDE and firm size are slightly less than zero, signalling that, in the event of exclusion of firm size from the estimation equation, the significance of the coefficient of efficiency will not change even though the impact will be on the magnitude if the coefficient.

The pooled probit and random effects probit specifications confirm the hypothesis that established relationship between export participation and productive efficiency hinges on the treatment of unobserved heterogeneity. Specifically, production function estimation models that do not separate the two components give a positive and significant relationship (Model 2, Table 2.13). However, when the production function estimation separates the two – as in Model 3 – the relationship between export and productivity is not significant.

As further robustness check on the results, a third specification is added using Wooldridge (2005) approach for non-linear dynamic models. The Wooldridge specification under columns

Table 2.12: Export Participation (Model 1)

| | Pooled Probit | | Random Effects Probit | | Dynamic Probit | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $logSize_{t-1}$ | 0.130*** | 0.130*** | 0.192*** | 0.192*** | 0.178*** | 0.178*** |
| | (0.0459) | (0.0460) | (0.0647) | (0.0647) | (0.0671) | (0.0673) |
| $log(Wage/Employment)_{t-1}$ | 0.120*** | 0.121*** | 0.155** | 0.155** | 0.150** | 0.152** |
| | (0.0368) | (0.0369) | (0.0698) | (0.0707) | (0.0710) | (0.0721) |
| Efficiency (Model 1) | 0.438 | 0.506 | 0.288 | 0.292 | 0.385 | 0.338 |
| | (0.306) | (0.428) | (0.423) | (0.518) | (0.442) | (0.542) |
| $Export_{t-1}$ | 2.335*** | 2.369*** | 2.473*** | 2.475*** | 2.518*** | 2.488*** |
| | (0.110) | (0.181) | (0.172) | (0.257) | (0.177) | (0.264) |
| $(Export_{t-1} \times Efficiency)$ | | -0.114 | | -0.00753 | | 0.0887 |
| | | (0.422) | | (0.565) | | (0.582) |
| Textiles | 0.170 | 0.172 | 0.222 | 0.222 | 0.254 | 0.252 |
| | (0.160) | (0.162) | (0.225) | (0.225) | (0.233) | (0.234) |
| Wood | 0.289* | 0.292* | 0.368* | 0.368* | 0.432** | 0.431** |
| | (0.149) | (0.150) | (0.200) | (0.201) | (0.209) | (0.210) |
| Metals | 0.0900 | 0.0921 | 0.145 | 0.145 | 0.195 | 0.192 |
| | (0.135) | (0.135) | (0.177) | (0.178) | (0.185) | (0.186) |
| Initial Export Status | | | | | 0.674** | 0.678** |
| | | | | | (0.263) | (0.265) |
| Constant | -4.069*** | -4.095*** | -4.972*** | -4.971*** | -4.955*** | -4.967*** |
| | (0.461) | (0.492) | (1.032) | (1.034) | (1.053) | (1.058) |
| Observations | 1,460 | 1,460 | 1,322 | 1,322 | 1,322 | 1,322 |
| Number of firms | 225 | 225 | 213 | 213 | 213 | 213 |
| R-squared | 0.494 | 0.494 | | | | |
| Log-Likelihood | -444.384 | -444.356 | -294.95 | -294.95 | -291.62 | -291.609 |
| Time Dummies | No | No | Yes | Yes | Yes | Yes |

Robust standard errors in parentheses clustered at firm level $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table 2.13: Export Participation (Model 2)

| | Pooled Probit | | Random Effects Probit | | Dynamic Probit | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $logSize_{t-1}$ | 0.0757 | 0.0900* | 0.151** | 0.149** | 0.108 | 0.103 |
| | (0.0512) | (0.0544) | (0.0671) | (0.0675) | (0.0741) | (0.0732) |
| $log(Wage/Employment)_{t-1}$ | 0.138*** | 0.139*** | 0.140** | 0.139* | 0.118 | 0.112 |
| | (0.0378) | (0.0388) | (0.0709) | (0.0713) | (0.0732) | (0.0736) |
| $Efficiency_{t-1}$ (Model 2) | 0.870*** | 1.641*** | 0.849** | 0.892** | -0.340 | -0.173 |
| | (0.261) | (0.460) | (0.346) | (0.453) | (0.541) | (0.643) |
| $Export_{t-1}$ | 2.236*** | 2.418*** | 2.410*** | 2.429*** | 2.397*** | 2.471*** |
| | (0.113) | (0.157) | (0.181) | (0.223) | (0.198) | (0.250) |
| $(Export_{t-1} \times Efficiency)$ | | -1.253*** | | -0.0761 | | -0.248 |
| | | (0.456) | | (0.514) | | (0.535) |
| Textiles | -0.0433 | 0.0201 | 0.0996 | 0.103 | -0.00555 | -0.00373 |
| | (0.164) | (0.164) | (0.218) | (0.218) | (0.235) | (0.230) |
| Wood | 0.345** | 0.358** | 0.478** | 0.479** | 0.534** | 0.529** |
| | (0.143) | (0.147) | (0.198) | (0.197) | (0.228) | (0.223) |
| Metals | 0.107 | 0.122 | 0.207 | 0.210 | 0.209 | 0.219 |
| | (0.150) | (0.148) | (0.186) | (0.186) | (0.204) | (0.201) |
| Time Average Efficiency | | | | | 1.607** | 1.574** |
| | | | | | (0.768) | (0.757) |
| Initial Export Status | | | | | 0.673** | 0.642** |
| | | | | | (0.283) | (0.285) |
| Constant | -4.122*** | -4.290*** | -4.649*** | -4.630*** | -4.279*** | -4.177*** |
| | (0.488) | (0.512) | (1.067) | (1.072) | (1.087) | (1.091) |
| Observations | 1,430 | 1,423 | 1,310 | 1,310 | 1,309 | 1,309 |
| Number of firms | 203 | 203 | 202 | 202 | 202 | 202 |
| R-squared | 0.489 | 0.500 | | | | |
| Log-Likelihood | -432.559 | -420.827 | -290.113 | -290.10206 | -291.947 | -291.842 |
| Time Dummies | No | No | Yes | Yes | Yes | Yes |

Robust standard errors in parentheses clustered at firm level $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

(5) – (6) is the preferred specification for results in Tables 2.12, 2.13, 2.14, 2.16 & 2.18. The Wooldridge's approach offers two advantages over the pooled probit and random effects probit. First, the presence of lag dependent variable in the export decision exhibited in equation (2.30) could lead to serial correlation in the error term, causing estimates under columns (1) – (4) to be biased. The estimation properties of Wooldridge (2005) overcomes the serial correlation issue. Second, and most importantly, the Wooldridge (2005) approach permits to control for initial export status and firm-specific persistent heterogeneity irrespective of whether this had been done at the production function estimation stage. The application of the approach adds two additional variables, time average of predicted productive efficiency and initial export status to the export participation equations in (2.30) and (2.31).

Table 2.14: Export Participation (Model 3)

| | Pooled Probit | | Random Effects Probit | | Dynamic Probit | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $logSize_{t-1}$ | 0.175*** | 0.173*** | 0.238*** | 0.236*** | 0.237*** | 0.225*** |
| | (0.0454) | (0.0453) | (0.0681) | (0.0673) | (0.0699) | (0.0689) |
| $log(Wage/Employment)_{t-1}$ | 0.150*** | 0.149*** | 0.176** | 0.174** | 0.177** | 0.153** |
| | (0.0403) | (0.0406) | (0.0745) | (0.0742) | (0.0752) | (0.0753) |
| $Efficiency_{t-1}$(Model 3) | -0.102 | 0.381 | -0.0282 | 0.325 | 0.0505 | 0.186 |
| | (0.308) | (0.611) | (0.427) | (0.638) | (0.472) | (0.496) |
| $Export_{t-1}$ | 2.324*** | 2.861*** | 2.453*** | 2.962*** | 2.461*** | 2.529*** |
| | (0.119) | (0.543) | (0.188) | (0.692) | (0.192) | (0.664) |
| $(Export_{t-1} \times Efficiency)$ | | -0.679 | | -0.639 | | -0.478 |
| | | (0.675) | | (0.840) | | (0.570) |
| Textiles | 0.132 | 0.128 | 0.292 | 0.287 | 0.302 | 0.236 |
| | (0.162) | (0.161) | (0.230) | (0.228) | (0.234) | (0.231) |
| Wood | 0.249* | 0.248* | 0.399* | 0.392* | 0.388* | 0.354* |
| | (0.137) | (0.137) | (0.210) | (0.208) | (0.218) | (0.212) |
| Metals | 0.143 | 0.142 | 0.234 | 0.231 | 0.247 | 0.192 |
| | (0.138) | (0.137) | (0.197) | (0.195) | (0.200) | (0.195) |
| Time Average Efficiency | | | | | -0.422 | 0.0907 |
| | | | | | (1.148) | (1.177) |
| Initial Export Status | | | | | 0.225 | 0.285 |
| | | | | | (0.311) | (0.310) |
| Constant | -4.439*** | -4.796*** | -5.420*** | -5.661*** | -5.160*** | -4.876*** |
| | (0.536) | (0.660) | (1.156) | (1.202) | (1.284) | (1.293) |
| Observations | 1,291 | 1,291 | 1,174 | 1,174 | 1,174 | 1,137 |
| Number of firms | 206 | 206 | 198 | 198 | 198 | 197 |
| R-squared | 0.489 | 0.49 | | | | |
| Log-Likelihood | -395.956 | -395.495 | -263.455 | -263.164 | -263.15 | -256.65 |
| Time Dummies | No | No | Yes | Yes | Yes | Yes |

Robust standard errors in parentheses clustered at firm level $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

With focus on Model 2, results under column (5) in Table 2.13 show that, once we apply the Wooldridge approach, the coefficient for efficiency is no longer significant. Under column (6), interacting past export experience with efficiency returns a non-significant result. Persistent heterogeneity in the form of time-average efficiency and initial export status are significant, emphasising the importance of unobserved heterogeneity and sunk cost respectively.

On the hand, results under column (5) in Table 2.14 show no changes to the significance of the efficiency coefficient as well as that of firm size and wages. Similar pattern is observed for the true fixed effects model in Table 2.16. This leads us to confirm the hypothesis significance of the relationship between export participation and productive depends on the treatment of unobserved efficiency. Therefore, when the estimation of productive efficiency does not separate unobserved efficiency, application on export participation can lead policy recommendation, which may ot to produce intended results.

### Endogeneity and Simultaneity Issues

Given the importance of unobserved heterogeneity in productive efficiency estimation, Model 3 is chosen over the remaining two models as our preferred estimator of the production function. However, one disadvantage of all the models regards their lack of solution to the so-called endogeneity and simultaneity issues. Indeed, this is a well known issue in the stochastic production frontier analysis. The endogeneity and simultaneity bias are likely to impact on the estimated coefficients of the production inputs but less likely to impact the treatment of unobserved heterogeneity, which is the main objective of the paper.

Nevertheless, I perform a robustness check using a production function that controls for endogeneity and simultaneity bias. The main question under this paragraph is whether the conclusion on relation between export participation and productive efficiency holds notwithstanding the endogeneity and simultaneity bias present in the three models. To this end, I apply a SYS-GMM to estimate the production function and then apply predicted total factor productivity to export participation estimation. Tables 2.17 and 2.18 in the Appendix B present results for the production function estimation and implication on export participation respectively.

The coefficient for total factor productivity was not statistically significant under all six columns of Table 2.18.[15] The non-significance of the TFP variable is most likely due to the presence of firm size variable in the estimation equation due to the correlation between firm size and productivity.

All in all, firm-specific time-invariant unobserved heterogeneity plays an important role in productive efficiency estimation. Economic and policy applications of productive efficiency estimates that includes unobserved heterogeneity can lead to misleading results and policy recommendations. In our application to export participation, the reason that most African firms do not participate in export market can be other factors other than productive efficiency. For example, financial constraints can be the main reason most firms do not participate in export market rather than productive efficiency (Bellone et al., 2010). In conclusion,

[15] Bellone et al. (2010) found similar result, where the coefficient for TFP was negative and not significant.

results suggest the need to separate unobserved heterogeneity from productive efficiency in the production function estimation to avoid inaccurate policy recommendation in economic applications.

## 2.6 Concluding Remarks

Production function estimation is a core issue in the analysis of the supply side of the economy. Productive efficiency estimates obtained from production function estimation are used in a wide range of economic and policy applications. Unfortunately, conventional models to estimate production function mostly treat productive efficiency and firm-specific unobserved heterogeneity as a single component. The pretext of such choice is that, productive efficiency and firm-specific unobserved heterogeneity are unobservable by the econometrician. However, treating efficiency and unobserved heterogeneity as a single component can lead to inaccurate and misleading results in economic applications. In this paper, export participation was used to argue the importance of separating unobserved heterogeneity from efficiency.

The paper has illustrated this argument by using different models, which makes different assumptions on inefficiency and heterogeneity to estimate a production function. The first model, assumes inefficiency to be constant over time. The second model improves upon the first by allowing inefficiency to vary over time. These two models provides no mechanism to deal with unobserved heterogeneity. The third model, separates firm-specific unobserved heterogeneity from inefficiency in the estimation of the production function.

One key disadvantage of the models used to estimate the production function regards their treatment of endogeneity and simultaneity. As robustness check, I estimated the production function using SYS-GMM, which controls for endogeneity but does not separate unobserved heterogeneity from firm productivity. Applying all the predicted productive efficiency obtained from all the models to export participation, we find no correlation between predicted efficiency and export decision when we disentangle unobserved heterogeneity from efficiency. For productive efficiency obtained from model 3, I find no correlation for all three specifications of export decision.

For models that do not separate unobserved heterogeneity from productive efficiency, correlations found between export decision and efficiency in linear probability model, pooled probit and random effects probit, disappears once we apply Wooldridge (2005) approach that controls for initial conditions and unobserved heterogeneity *ex-post*.

Certainly, further work is needed in the estimation of production functions. In particular, an estimation technique that separates firm-specific unobserved heterogeneity from efficiency while controlling for endogeneity and simultaneity. This provides scope for further research.

# Appendix A: Greene True Fixed Effects Estimates Results

Table 2.15: Production Function Estimates Using Greene (2005) Approach

| Variables | Food | Textiles | Wood | Metals |
|---|---|---|---|---|
| ***Frontier*** | | | | |
| Log Capital | 0.0277 | 0.0753** | -0.00513 | -0.0161 |
| | (0.0891) | (0.0365) | (0.102) | (0.104) |
| Log Labour | 0.115* | 0.247*** | 0.140* | -0.0568 |
| | (0.0605) | (0.0596) | (0.0760) | (0.0669) |
| Log Raw Materials | 0.788*** | 0.638*** | 0.679*** | 0.740*** |
| | (0.0523) | (0.0377) | (0.0441) | (0.0347) |
| ***Determinants of Inefficiency***① | | | | |
| Workers Age | 0.111 | -0.0646 | 0.146* | -0.00487 |
| | (0.245) | (0.121) | (0.0805) | (0.0722) |
| Tenure | 0.0520 | 0.0297 | -0.173 | 0.0494 |
| | (0.641) | (0.140) | (0.130) | (0.0850) |
| Firm Age, years | -2.235** | 0.197*** | 0.0271 | -0.196** |
| | (0.993) | (0.0743) | (0.0222) | (0.0999) |
| Fraction of Foreign Ownership | -44.43*** | -43.27*** | -8.780** | -0.846 |
| | (8.402) | (14.38) | (3.608) | (1.172) |
| Constant | -5.844 | -5.443** | -6.827** | -0.788 |
| | (6.732) | (2.124) | (3.111) | (1.847) |
| ***Estimated technical efficiencies*** | | | | |
| Mean | 0.998 | 0.869 | 0.847 | 0.862 |
| SD | 0.011 | 0.151 | 0.129 | 0.123 |
| Min | 0.872 | 0.013 | 0.183 | 0.341 |
| Max | 1.000 | 1.000 | 0.997 | 0.994 |
| ***Diagnostics and Tests*** | | | | |
| Scale Elasticity | 0.931 | 0.961 | 0.814 | 0.667 |
| P-value | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald Test - Z Variables | 123.760 | 45.510 | 11.860 | 6.160 |
| P-value | 0.000 | 0.000 | 0.018 | 0.188 |
| Observations | 377 | 364 | 483 | 411 |
| Number of Firms | 49 | 48 | 63 | 51 |
| Year Dummies | Yes | Yes | Yes | Yes |

Robust standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

① A negative sign indicates the variable reduces inefficiency thus making it a positive determinant of efficiency.

Table 2.16: Export Participation (Greene's True Fixed Effects)

| | Pooled Probit | | Random Effects Probit | | Dynamic Probit | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $logSize_{t-1}$ | 0.173*** | 0.168*** | 0.235*** | 0.228*** | 0.228*** | 0.223*** |
| | (0.0455) | (0.0450) | (0.0679) | (0.0668) | (0.0681) | (0.0672) |
| $log(Wage/Employment)_{t-1}$ | 0.149*** | 0.148*** | 0.176** | 0.170** | 0.175** | 0.170** |
| | (0.0398) | (0.0397) | (0.0740) | (0.0739) | (0.0740) | (0.0740) |
| $Efficiency_{t-1}$ (Model TFE) | 0.260 | 1.340 | 0.276 | 1.453 | -0.102 | 1.018 |
| | (0.390) | (0.898) | (0.539) | (0.993) | (0.974) | (1.319) |
| $Export_{t-1}$ | 2.326*** | 3.604*** | 2.460*** | 4.083*** | 2.481*** | 4.072*** |
| | (0.119) | (0.868) | (0.187) | (1.035) | (0.188) | (1.021) |
| $(Export_{t-1} \times Efficiency)$ | | -1.416 | | -1.794 | | -1.764 |
| | | (0.922) | | (1.128) | | (1.116) |
| Textiles | 0.165 | 0.179 | 0.326 | 0.348 | 0.343 | 0.364 |
| | (0.173) | (0.171) | (0.239) | (0.237) | (0.243) | (0.240) |
| Wood | 0.298** | 0.326** | 0.440** | 0.480** | 0.468** | 0.508** |
| | (0.147) | (0.150) | (0.221) | (0.221) | (0.228) | (0.228) |
| Metals | 0.174 | 0.189 | 0.264 | 0.299 | 0.294 | 0.329 |
| | (0.148) | (0.147) | (0.205) | (0.203) | (0.211) | (0.209) |
| Time Average Efficiency | | | | | 0.517 | 0.546 |
| | | | | | (1.142) | (1.171) |
| Initial Export Status | | | | | 0.209 | 0.197 |
| | | | | | (0.309) | (0.310) |
| Constant | -4.757*** | -5.726*** | -5.691*** | -6.670*** | -5.803*** | -6.766*** |
| | (0.653) | (1.041) | (1.239) | (1.442) | (1.302) | (1.482) |
| Observations | 1,292 | 1,292 | 1,175 | 1,175 | 1,175 | 1,175 |
| Number of firms | 206 | 206 | 198 | 198 | 198 | 198 |
| R-squared | 0.490 | 0.491 | | | | |
| Log-Likelihood | -395.836 | -394.708 | -263.332 | -261.92 | -263.001 | -261.607 |
| Time Dummies | No | No | Yes | Yes | Yes | Yes |

Robust standard errors in parentheses clustered at firm level $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

## Appendix B: Endogeneity and Simultaneity Issues

Table 2.17 report production function estimate using system GMM. I used a two-step GMM estimate, where standard errors were corrected using Windmeijer (2005). Given the sensitivity of SYS-GMM to sample size, I estimated the production function over the whole sample of firms while including sector dummies.

Table 2.17: System GMM Estimate of Production Function

| VARIABLES | All Sectors |
|---|---|
| Log Capital | 0.142** |
| | (0.0615) |
| Log Labour | 0.239** |
| | (0.0955) |
| Log Raw materials | 0.546*** |
| | (0.0825) |
| Worker's Age | -0.0110 |
| | (0.00932) |
| Tenure | 0.0150** |
| | (0.00725) |
| Firm Age, years | 0.000731 |
| | (0.00250) |
| Fraction of Foreign Ownership | -0.00133 |
| | (0.00202) |
| Constant | 2.075*** |
| | (0.701) |
| | |
| Observations | 1,442 |
| Number of firm | 213 |
| Scale Elasticity | 0.927 |
| Arellano-Bond test for AR(1) : P-value | 0.000 |
| Arellano-Bond test for AR(2) : P-value | 0.168 |
| Sargan - Hansen: P-value | 0.215 |
| Number of Instruments | 62 |
| Sector Dummies | Yes |

Corrected standard errors in parentheses $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$

Table 2.18 report results from export decision function exhibited in equation (2.30) in the main text. Main description and discussion of the results are reported in the main text.

Table 2.18: Export Participation: Estimates from SYS-GMM

| | Pooled Probit | | Random Effects Probit | | Dynamic Probit | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $logSize_{t-1}$ | 0.240*** | 0.248*** | 0.276*** | 0.294*** | 0.229*** | 0.253*** |
| | (0.0749) | (0.0766) | (0.0836) | (0.0876) | (0.0826) | (0.0853) |
| $log(Wage/Employment)_{t-1}$ | 0.308*** | 0.302*** | 0.147 | 0.134 | 0.112 | 0.0951 |
| | (0.0625) | (0.0633) | (0.0965) | (0.0995) | (0.0978) | (0.0994) |
| $TFP_{t-1}$ | -0.0140 | -0.0439 | 0.0857 | -0.00920 | -0.234 | -0.166 |
| | (0.189) | (0.185) | (0.189) | (0.248) | (0.246) | (0.263) |
| $Export_{t-1}$ | 1.916*** | 0.494 | 2.160*** | 1.821 | 2.179*** | 1.805 |
| | (0.152) | (1.336) | (0.217) | (1.474) | (0.224) | (1.470) |
| $(Export_{t-1} \times TFP)$ | | 0.218 | | 0.228 | | -0.0302 |
| | | (0.217) | | (0.260) | | (0.297) |
| Textiles | 0.354 | 0.360 | 0.262 | 0.318 | 0.350 | 0.376 |
| | (0.292) | (0.301) | (0.281) | (0.293) | (0.293) | (0.296) |
| Wood | 0.500** | 0.486** | 0.498** | 0.530** | 0.617** | 0.604** |
| | (0.233) | (0.246) | (0.250) | (0.265) | (0.271) | (0.274) |
| Metals | 0.240 | 0.275 | 0.207 | 0.246 | 0.225 | 0.262 |
| | (0.242) | (0.246) | (0.235) | (0.245) | (0.241) | (0.243) |
| Time Average Efficiency | | | | | 0.657** | 0.687* |
| | | | | | (0.332) | (0.383) |
| Initial Export Status | | | | | 0.446 | 0.470 |
| | | | | | (0.395) | (0.404) |
| Constant | -6.982*** | -6.489*** | -5.633*** | -5.925*** | -6.842*** | -6.645*** |
| | (0.994) | (1.374) | (1.310) | (1.554) | (1.630) | (1.752) |
| Observations | 1,121 | 1,079 | 1,121 | 1,079 | 1,121 | 1,079 |
| Number of firms | 193 | 193 | 193 | 190 | 193 | 190 |
| R-squared | 0.493 | 0.502 | | | | |
| Log-Likelihood | -287.15 | -274.944 | -250.34335 | -241.277 | -247.518 | -238.875 |
| Time Dummies | No | No | Yes | Yes | Yes | Yes |

Robust standard errors in parentheses clustered at firm level $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

## Appendix C: Correlation Test

Table 2.19: Correlation Matrix

| | Log Size | Efficiency (Model 1) | Efficiency (Model 2) | Efficiency (Model 3: PDE) | Efficiency (Greene TFE) | TFP (SYS-GMM) |
|---|---|---|---|---|---|---|
| Log Size | 1 | | | | | |
| Efficiency (Model 1) | 0.5863 | 1 | | | | |
| Efficiency (Model 2) | 0.4588 | 0.4634 | 1 | | | |
| Efficiency (Model 3: PDE) | -0.0055 | 0.0191 | 0.1551 | 1 | | |
| Efficiency (Greene TFE) | -0.0305 | 0.1302 | 0.0823 | 0.4678 | 1 | |
| TFP (SYS-GMM) | 0.4225 | 0.5414 | 0.4324 | 0.4559 | 0.1967 | 1 |

# Chapter 3

# Trade-Productivity Nexus: Learning and Knowledge Spillovers in African Manufacturing


## Abstract

This paper examines productive efficiency feedback from three modes of trade participation - export only, import only, and two-way - normalising the demand shock on the production frontier. Ignoring the demand shock on the production frontier can lead to biased estimates of the impact of trade on productivity, a common practice that has contributed its inconclusive evidence. The new estimation technique shows that import has a higher likelihood to improve productive efficiency. The paper also find a non-linear relationship between trade experience and productive efficiency with variations across industries and in the curvature of the relation. The second part of the paper analyses general knowledge spillovers from trading firms to non-trading firms bridging two strands of the literature on export-destination-specific spillovers and R&D spillovers. Three mechanisms are examined as potential channels: agglomeration, technology distance, and absorptive capacity. Agglomeration has a weak effect on decision to enter foreign market. Technology distance has a negative and significant effect on decision to trade, while absorptive capacity has a positive and significant effect.



***Keywords :*** Trade, Learning, Knowledge Spillovers, African Manufacturing
***JEL Classification :*** F14, F63, D22, O12

## 3.1 Introduction

The role of trade to enhance long-run economic growth and improve aggregate productivity is widely recognised consensus in economics. Trade facilitates transfer of knowledge and technology from advanced countries to less developed countries. This relationship has been proven theoretically (Grossman and Helpman, 1991; Feeney, 1999); as well as documented empirically (Giles and Williams, 2000a,b).

The prospects of technology transfer through trade remained a macro-level discussion until the first firm-level study on the U.S economy by Bernard and Jensen (1995). The export-productivity relationship established in their study significantly shaped the international trade literature. The direction of causality between export and productivity soon became a central focus of the literature. While many studies agreed on most efficient firms self-selecting into export markets in the event of trade liberalization, the possibility of productivity improvements feedback from trade remains mixed (Wagner, 2007, 2012).

Methodological issues mainly account for the disparities of the mixed findings on the learning-by-exporting hypothesis (Wagner, 2007; ISGEP, 2008; De Loecker, 2013). Furthermore, a growing body of research in the innovation literature has suggested that the positive export-productivity relationship is due to product innovation rather than expected process innovation casting further doubts on previous findings (Altomonte et al., 2013; Cassiman and Golovko, 2007, 2011) . This argument reinforces the need for further research on the productivity feedback from trade participation despite existing large literature. Likewise, the need to establish a conclusive evidence is also necessary for policy-makers of developing countries to draw up effective industrial and trade policies to enhance rapid poverty reduction.

In a related discussion on the role of trade to enhance economic growth, existing research has established the existence of destination-specific export spillovers (Koenig, 2009) as well as the likelihood of foreign direct investments (FDI) to improve productivity of domestic firms through technology transfer (Javorcik, 2004). However, there is a gap in the literature on possible knowledge spillovers between trading firms and non-trading in terms of productivity improvements or their general probability to trade which is not destination-specific. The basic rationale is that, in the presence of knowledge spillovers from trading firms to non-trading firms, the latter group might be able to improve their productive efficiency. Once non-trading firms have increased their productivity, they are likely to participate in trade irrespective of the trade destination of previous traders.

In view of the above, this paper contributes to the discussion on trade-productivity nexus in two ways. First, the paper proposes a new estimation technique to analyse productive efficiency improvements subject to firms' trade participation. In a nutshell, the Hicks-additive term in the standard total factor productivity (TFP) estimation methods encompasses both demand and supply shocks to generate a shift of the production frontier. Hence, if a firm exports to the foreign market as a result of product innovation, a positive coefficient for export generated in the production function overstates the effect of export on productivity. The optimal solution is to disintegrate demand and supply shocks and isolate the former.

The estimation technique proposed in this paper first establishes the optimal productive efficiency frontier and finds the actual position of the firm with respect to its frontier. In this manner, any productive efficiency improvements due to trade participation is detected by a movement of the firm towards its optimal frontier.

The second contribution of the paper fills a gap in the existing literature by examining knowledge spillovers from traders to non-traders by analysing firms propensity to trade. The second part also offers possible mechanisms through which knowledge spillovers can occur. This is done by considering agglomeration effect, technological distance between traders and non-traders as well as their absorptive capacity.

The following research questions are posed along the development of the various sections of the paper. Do firms improve their productive efficiency by exporting to foreign markets, importing intermediate inputs or by combining both activities? Does the number of years spent in trading activity have an impact on productive efficiency? Is the relationship between trade experience and productive efficiency (if present) linear or non-linear? Last, but not least, what channels of knowledge spillovers exist between trading firms and non-trading firms? As it can be noted from the research questions, the analysis is broadened to cover three main forms of trade participation: export of outputs, import of raw materials and combination of both activities.

The paper is outlined as follows. Section 3.2 briefly reviews theoretical and empirical literature on trade-productivity nexus with a subsection that presents selected papers on African countries. The large size of the literature requires this paper to narrow the review on aspects specific to the arguments herein. Section 3.3 presents the main body of the methodology to detect learning effects from trade participation. Section 3.4 presents the data and some descriptive statistics. Discussion of the results are presented in section 3.5 as well as robustness check and discussions on endogeneity issues. Section 3.6 presents the analysis on knowledge spillovers while section 3.7 concludes the paper.

## 3.2 Trade and Productivity Nexus

There exists a systematic consensus that trade generally leads to welfare improvements of participating countries. The specific channel of effect had been ongoing in economic and policy discussions for many years, predominantly at macro and industry levels. Bernard and Jensen (1995)'s seminal paper provided the first insight on the relationship between exports and productivity at firm level, shifting the focus of discussion to micro level. A wide range of empirical regularities that emerged following Bernard and Jensen's ground-breaking paper could not be explained by existing theories on international trade.[1]

Melitz (2003) addresses the theoretical shortcomings in a general equilibrium framework with focus on firm heterogeneity and productivity as in Jovanovic (1982) and Hopenhayn (1992). In extreme synthesis, given that firms differ in productivity levels, the presence of sunk costs implies that only few firms that can participate in trade. Trade liberalization

[1] For a detail overview, see Bernard et al. (2007).

increases competition for resources between firms and entry of new firms with productivity above the average threshold. Increased competition induces exit of low productive firms and reallocations of resources between surviving firms. The most productive of the surviving firms self-select into foreign markets while the remaining firms serve the domestic market.

A vast empirical literature confirms various aspects of the Melitz's model and has documented substantial differences between exporters and their domestic counterparts. Across a wide range of studies, exporting firms were found to be more productive, larger and to pay higher wages than non exporting firms (Bernard and Jensen, 1999*a*,*b*; Bernard et al., 2007). Two hypotheses emerged as explanations for productivity differentials between exporting firms and non-exporting firms: self-selection and productivity feedback from exporting (Wagner, 2007).

Self-selection of more productive firms into the exports market is the leading explanation in trade literature. This is due to extra costs such as transportation, distribution,and marketing, which firms must incur in order to sell outputs in foreign markets. These investments are irreversible once made. Hence, based on the assumption that high productive firms are also the most profitable, only the most productive firms can afford to pay such sunk costs without losing money and will therefore self-select into exporting.

The second hypothesis points to the fact that once firms are in foreign markets they are exposed to more competition and consumers with different taste relative to consumers in their home country. The likelihood of a firm to remain on the foreign market depends on its ability to learn new technological know-how from its competitors and consumers abroad. Hence, exporting is expected to make firms more productive.

Theoretical underpinnings of the relationship between technology adoption and firm productivity has been analysed in Melitz and Costantini (2007) and Atkeson and Burstein (2010). The mere anticipation of trade liberalization can induce firms to accelerate adoption of new technologies in preparation of export market entry (Melitz and Costantini, 2007). In Atkeson and Burstein (2010)'s dynamic heterogeneous model, firms can benefit from trade liberalization through product and process innovation. The authors postulate that trade liberalization has substantial indirect effect on a firm's exit, export, and process innovation decisions, yet, welfare gains induced by the reallocation mechanism could be offset by product innovation.

They showed that it is a result of the free-entry condition in steady-state equilibrium and profits associated with creating new products. A reduction in international trade cost raises expected profits for creating new products. Hence, an increase in real wage and aggregate output is necessary to offset the additional profits in equilibrium. In the absence of an increase in real wage and aggregate output, the welfare gains of trade is eroded by product innovation.

The endogenous growth literature has long asserted the possibility of trade to enhance growth through knowledge spillovers of trading partners (Grossman and Helpman, 1991). Subsequent trade literature that emerged at micro level, focused almost exclusively on technology transfer and potential knowledge spillovers from Foreign Direct Investments (FDI) to domestic firms (Javorcik, 2004). However, presuming firms from developing countries acquire new knowledge conditional to their participation in foreign market, there could be a potential transfer of knowledge from trading firms to non-trading firms. To the best of my knowledge, such possibility has not been investigated for developing countries.

This paper fills this gap by investigating whether there exist knowledge spillovers from trading firms to non-trading firms thereby increasing the aggregate productivity of the economy. The policy implications of filling this gap can help to shield further light on what kind of industrial policies developing countries ought to undertake in order to maximise their gains from trade.

### 3.2.1 Evidence from African Firms: Selected Review

Mengistae and Pattillo (2004) documented the existence of exporter premium for firms in Kenya, Ghana and Ethiopia. Dividing exporters into subgroup of direct exporters – without using domestic intermediaries – those who export outside the African region and other exporters. They found a premium of 17 percent in total factor productivity for exporters with respect to non-exporters across the three countries. In addition, direct exporters registered 22 percent premium over indirect exporters, while firms exporting outside the region had a relative premium of 20 percent as compared to those exporting within the region. The authors did not provide a specific direction of causality on whether the export premium originates from self-selection or learning-by-exporting.

Bigsten et al. (2004) did a follow-up study on Cameroon, Ghana, Kenya and Zimbabwe, which documented a positive relationship between lagged export status and productivity. However, their results were statistically significant only when they completely ignored firm-specific effects or when the latter is modelled to follow a discrete multinomial distribution (as proposed by Heckman and Singer (1984)). When they assumed that the random firm effect in both the production function and the export equation follows a bivariate normal distribution and thus integrates them out, – as proposed by Clerides et al. (1998) – results becomes insignificant. Robustness check with system GMM estimator, to correct for simultaneity, fails to find significant results on the positive relationship between exporting and productivity. In addition, the authors found no evidence of self-selection of productive firms into export market. Though the authors pointed out strong presence of unobserved heterogeneity, their assumption that firms operate with the same production technology in all sectors and in all countries may appears restrictive.

Addressing some of the issues stated above, Van Biesebroeck (2005) pointed out that the small sample size in the Bigsten et al. (2004) study was a concern. He therefore extended the number of countries to nine: Burundi, Cameroon Cote d'Ivoire, Ethiopia, Ghana, Kenya, Tanzania, Zambia and Zimbabwe. Four econometric methodologies were then used to estimate productivity gains from exporting. The benchmark random effects model yielded a positive productivity gain of 26% from exporting. Using GMM-SYS estimator of Blundell and Bond (1998), to account for simultaneity between input choices and unobserved productivity, export participation produced productivity gain of 28%. The third methodology, which consists of a joint estimate of the production function and export participation decision following Clerides et al. (1998) approach yielded a positive impact of 25%. Notice that the same methodology applied in Bigsten et al. (2004) produced insignificant result on the effect of export on productivity. Lastly, a semi-parametric methodology following Olley and Pakes (1996) yielded 25% impact of export on productivity.

Some factors ought to be underlined with respect to studies summarised above. First, while there is a general consensus on self-selection of most productive firms into export market, the same cannot be said on the learning-by-exporting hypothesis. In a two-series extensive survey, Wagner (2007, 2012) confirms the self-selection hypothesis almost for countries surveyed. However, post-entry productivity gains are not universal across all studies. In a related cross-country comparison by the ISGEP (2008), it was found that, on average, productivity gains from export tend to be higher for countries with low export participation, lower GDP, and more restrictive trade regimes.

### 3.2.2 What shifts the frontier?

The standard approach to estimate the effect of export activities on productivity models exporting as a shift of the production frontier in a Hicks-neutral fashion.[2] Such approach to estimate the productivity-export link ignores the effect of a demand shock on the production function (Foster et al., 2008). In the presence of demand shocks it is plausible to assume that firms engage in innovation activities to respond to demand variations.[3] Indeed, a growing body of empirical research has established a relationship between innovation and the export-productivity nexus (Cassiman and Golovko, 2007; Cassiman et al., 2010; Cassiman and Golovko, 2011; Becker and Egger, 2013; Altomonte et al., 2013).

Moreover, when innovative activities are decomposed into product and process innovation, empirical evidence suggests that product innovation drives export at firm level (Cassiman et al., 2010; Becker and Egger, 2013). However, evidence of a possible reverse causality (from export to innovation) is weak (Altomonte et al., 2013). Cassiman et al. (2010) argued that if such possibility exists, it is more likely to be the result of product rather than process innovation.

The theoretical model of Atkeson and Burstein (2010) and the empirical evidence on innovation-export-productivity suggest that if product innovation is the main element driving the positive relation between export and productivity, then failure to account for demand shocks will produce biased results. Given that the Hicks-addictive term in the production function encompasses both demand and supply shocks, there is the need to separate them in order to obtain the "true" effects of trade policy on productive efficiency.

When detailed data are available at product level, De Loecker (2011), proposed a solution that combines a demand system with the production function estimation. Using firm-product data on Belgium's textiles sector in application of his methodology, De Loecker found a lower

[2]A simplified production function usually estimated takes the form: $y_{it} = f(l_{it}, k_{it}) + w_{it} + \epsilon_{it}$ where $w_{it} = \alpha EXPORT + v_{it}$. See Van Biesebroeck (2005); Wagner (2007); De Loecker (2013) for detailed expositions.

[3]Recall similar line of reasoning in Atkeson and Burstein (2010) on firms engaging in product innovation as a result of trade liberalisation.

productivity gain once demand shocks are controlled. Yoko and Yoshihiko (2013) proposed an alternative solution which involves decomposition of total factor productivity (TFP) into supply and demand shocks using information on productive capacity collected during firm surveys.

## 3.3 Detecting Efficiency Gains from Trade

The construction of the optimal production frontier also takes into account the production levels of all firms in the same 2-digit industry level classification. By concentrating on the supply/productivity shocks that reduce technical inefficiencies, the approach permits to directly observe productivity gains from trade by observing changes in productive efficiency with respect to optimal frontier.

We examine the relationship between trade variables and productive efficiency using Stochastic Frontier (SF) approach. The SF framework developed independently by Aigner et al. (1977) and Meeusen and Broeck (1977) permits to estimate the effect of trade on efficiency through movement towards the optimal frontier. The class of models used under this section separates firm-specific unobserved heterogeneity from the technical efficiency component.

### 3.3.1 Model

Consider the following stochastic production frontier model

$$y_{it} = \alpha_i + \mathbf{x}_{it}\boldsymbol{\beta} + \varepsilon_{it}, \tag{3.1}$$

$$\varepsilon_{it} = \nu_{it} - u_{it}, \tag{3.2}$$

$$\nu_{it} \sim IID \quad \mathcal{N}(0, \psi^2), \tag{3.3}$$

$$u_{it} \sim IID \quad \mathcal{F}_u(\sigma), \qquad i = 1, \ldots, n, \quad t = 1, \ldots, T, \tag{3.4}$$

where $y_{it}$ is the natural log of output for firm $i$ at time $t$; $\alpha_i$ represents firm-specific (unobserved) effects; $\mathbf{x}_{it}$ is a vector of production inputs and $\boldsymbol{\beta}$ their associated production technology to be estimated. The composite error term $\varepsilon_{it}$ represents the difference between the idiosyncratic error term $\nu_{it}$ and the inefficiency component $u_{it}$.[4] The two error components are both assumed to be independent and identically distributed. In addition, the idiosyncratic error term has a normal distribution, while the inefficiency component is distributed according to generic "one-parameter" distribution defined over $\mathbb{R}^+$ and a scale parameter $\sigma$.

A wide range of methodologies have been proposed to estimate the stochastic frontier production function.[5] Greene (2005a) observed that conventional panel data models fail to separate inefficiency from time-invariant firm heterogeneity. By so doing, the computed inefficiency measure under this approach picks up heterogeneity or instead of inefficiency.

[4]Technical inefficiency is a constant feature of the production process and arises from various sources. Notice that, this component is completely ignored in the Solow type approach to measure productive efficiency.

[5]See Kumbhakar and Lovell (2000) for an overview of SF models and Parmeter and Kumbhakar (2014) for an update on recent developments.

The proposed solution to circumvent the problem unfortunately suffers from the incidental parameter problem (Greene, 2005b).

Belotti and Ilardi (2015) proposed a solution that relies on first-difference data transformation to eliminate nuisance parameters.[6] Applying the first-difference data transformation strategy, the model (3.1) - (3.4) can be rewritten as

$$\Delta \mathbf{y}_i = \Delta X_i \boldsymbol{\beta} + \Delta \varepsilon_i, \tag{3.5}$$

$$\Delta \boldsymbol{\varepsilon}_i = \Delta \nu_i - \Delta u_i, \tag{3.6}$$

$$\Delta \boldsymbol{\nu}_i \sim IID \quad \mathcal{N}_{T-1}(\mathbf{0}, \Psi), \tag{3.7}$$

$$\Delta \mathbf{u}_i \sim IID \quad \mathcal{F}_{\Delta u}(\sigma), \qquad i = 1, \ldots, n \quad t = 1, \ldots, T, \tag{3.8}$$

where $\Delta \mathbf{y}_i = (\Delta_{i2}, \ldots, \Delta y_{iT})$ with $\Delta y_{it} = y_{it} - y_{it-1}$ and $\Delta X_i$ is a $T - 1 \times k$ matrix of time-varying covariates whereby each $t - th$ row is denoted by $\Delta x_{it} = (\Delta x_{it1}, \ldots, \Delta x_{itk}), \forall t = 2, \ldots, T$.

The assumption underlying the idiosyncratic error, $\nu_{it}$, implies that $\Delta \boldsymbol{\nu}_i$ has a $T - 1$-variate normal distribution with covariance matrix $\Psi = \phi^2 \Lambda_{T-1}$, where $\Lambda_{T-1}$ is a symmetric tridiagonal $T - 1 \times T - 1$ matrix. Given the assumption of independence between $\Delta \boldsymbol{\nu}_i$ and $\Delta u_i$ a marginal likelihood contribution can be derived as

$$\begin{aligned} L_i^*(\theta) &= \int f(\Delta \boldsymbol{\nu}_i, \Delta \mathbf{u}_i \backslash \theta) d\Delta \mathbf{u}_i = \int f(\Delta \boldsymbol{\nu}_i \backslash \theta) f(\Delta \mathbf{u}_i \backslash \sigma) d\Delta \mathbf{u}_i \\ &= \int f(\Delta \mathbf{y}_i \backslash \boldsymbol{\beta}, \psi, \Delta \mathbf{X}_i, \Delta \mathbf{u}_i) f(\Delta \mathbf{u}_i \backslash \sigma) d\Delta \mathbf{u}_i \end{aligned} \tag{3.9}$$

where $\theta = (\boldsymbol{\beta}', \sigma, \psi)$. Belotti and Ilardi (2015) noted that the marginalization of $\Delta \mathbf{u}_i$ in equation (3.9) can be performed under two estimation strategies: marginal maximum simulated likelihood estimation (MMSLE) or pairwise difference estimation (PDE).

The pairwise difference estimator is preferred to the marginal maximum simulated likelihood estimator for the purpose of this analysis. The PDE imposes less restrictions on the model in order to derive a closed-form expression for equation (3.9). In addition, MMSLE allows only time invariant $z$ variables in the scale parameter, thus, $\sigma_i = g(Z_i \delta)$. The PDE, on the contrary, allows $z$ variables to be time-varying, thus, $\sigma_{it} = exp(z_{it}, \gamma)$.

[6] The reader is referred to Belotti and Ilardi (2015) for full exposition of the model.

### 3.3.2 Estimation

Applying the pairwise difference estimator, the following estimation model can be derived to represent the stochastic production frontier

$$y_{it} = \alpha_i + f(x_{it}; \beta) + \nu_{it} - u_{it}, \tag{3.10}$$
$$\nu_{it} \sim \mathcal{N}(0, \psi^2), \tag{3.11}$$
$$u_{it} \sim \mathcal{E}(\sigma_{it}), \tag{3.12}$$
$$\sigma_{it} = exp\left(\gamma_0 + \sum_i z_{it}\gamma_i\right), \qquad i = 1, \dots, n, \quad t = 1, \dots, T, \tag{3.13}$$

where inefficiency is assumed to be heteroskedastic and follow a normal-exponential distribution.[7] The production technology, $f(x_{it}; \beta)$ in (3.10) is represented by the Cobb-Douglas production function specification.[8] Hence, equation (3.10) is augmented as follows

$$lnY_{it} = \alpha_i + \sum_{j=1}^{3} \beta_j lnX_{jit} + \sum_{t=1992}^{2002} d_t + \nu_{it} - u_{it}, \tag{3.14}$$

where the vector of production inputs is represented by labour, capital and raw materials.

The main focus of estimation procedure is to determine the effect of trade variables on production efficiency. The scale parameter in equation (3.13) allows to achieve the estimation goal in one-stage regression. Following De Loecker (2013) we allow a dynamic effect of trade variables on productive efficiency by using one-lag period of trade variables. For example, the effect of export on productive efficiency is modelled as $\sigma_{it} = exp(\gamma_0 + export_{it-1})$ in the scale parameter.

Moreover, the scale parameter also permits to control for other factors the directly affect the production process. In particular, human capital variables, in the form of workers age and tenure are included in the scale parameter. Within the framework of trade and productivity nexus, export activities have particularly a dominant position with regards to other trade variables. However, firms can improve their productive efficiency through other trade channels such as imports of intermediaries materials and those who engage in two-way trading.[9]

Kenneth Arrow in his seminal paper on learning-by-doing stated that, "learning is the product of experience. Learning can only take place through the attempt to solve a problem and therefore only takes place during activity" (Arrow, 1962). The above statement sets a pre-condition that for learning to take place, the economic agent (firm or individual) must come into contact with new challenges and an attempt must be initiated to overcome them. That is to say an exposure to the international market must have taken place in the first instance.

[7]Inefficiency can also be modelled to follow a half-normal as well as well normal-truncated distributions. Technical details are available in Belotti and Ilardi (2015).

[8]The production technology is generally unknown, hence, it would have been appropriate to choose a flexible production function such as the translog. However, due to data restrictions the Cobb-Douglas is preferred.

[9]Two-way traders are defined as firms that import intermediaries and export outputs.

After the pre-condition has been met, the next step regards the frequency of engaging in the said activity. Various scenarios are likely to emerge in the performance-experience relationship. Firms exporting for the first time may encounter a learning curve before stabilising in equilibrium at either diminishing/increasing marginal returns or a linear decreasing/increasing returns. Hence, this paper defines trade experience as the total number of years a firm has effectively participated in the trading activity. For example, given a time trend of – $t_1, t_2, t_3$ – if a firm exports in $t_1$ and $t_3$ but not in $t_2$, the total number of export experience is two years.

In view of the above, the paper first estimate a productive efficiency without any trade variables which will permits to track changes in efficiency and scale economies once trade variables are added to the estimation equation.[10] The next step will estimate the effect of each trade variable singularly on productive efficiency in order to provide a comparative analysis between the trade variables. In addition to the lag status of trade participation a first and second order polynomial of trade experience is added to capture linear and non-linear relationships between experience and performance. Hence, equation (3.13) can be rewritten more explicitly as follows for each trade variable

$$\sigma_{it} = exp(\gamma_0 + \gamma_1 age_{it} + \gamma_2 tenure_{it} + \gamma_3 exports_{it-1} + \gamma_4 yrexpt_{it} + \gamma_5 yrexpt_{it}^2) \tag{3.15}$$

$$\sigma_{it} = exp(\gamma_0 + \gamma_1 age_{it} + \gamma_2 tenure_{it} + \gamma_3 imports_{it-1} + \gamma_4 yrimpt_{it} + \gamma_5 yrimpt_{it}^2) \tag{3.16}$$

$$\sigma_{it} = exp(\gamma_0 + \gamma_1 age_{it} + \gamma_2 tenure_{it} + \gamma_3 twoway_{it-1} + \gamma_4 yrtway_{it} + \gamma_5 yrtway_{it}^2). \tag{3.17}$$

Firm-level (in)efficiency scores can be predicted from each estimation equation following Jondrow et al. (1982). This can be computed by exploiting the mean of the conditional distribution of $u_{it}$ given $\hat{\varepsilon}_{it}$, evaluated at $\hat{\varepsilon}_{it} = y_{it} - \hat{\alpha}_i - \boldsymbol{x}_{it}\hat{\boldsymbol{\beta}}$. By conditions (3.11) and (3.12) we can derive the mean of the distribution as follows

$$\hat{u}_{it} = \mathbb{E}(u_{it} \backslash \varepsilon_{it}) = \psi \left[ \frac{\phi\left(\frac{\varepsilon_{it}}{\psi} + \frac{\psi}{\sigma_{it}}\right)}{1 - \Phi\left(\frac{\varepsilon_{it}}{\psi} + \frac{\psi}{\sigma_{it}}\right)} - \left(\frac{\varepsilon_{it}}{\psi} + \frac{\psi}{\sigma_{it}}\right) \right], \tag{3.18}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are pdf and cdf respectively. The (in)efficiency score derived by equation (3.18) will serve as a starting point to analyse potential knowledge spillovers from trading firms to non-trading firms.

Notice that the unobserved firm fixed effects was wiped out during the transformation stage. The unobserved heterogeneity can be obtained by maximising the log-likelihood of the untransformed model. This is given by

$$\hat{\alpha}_i = \frac{1}{T} \sum_{t=1}^{T} (y_{it} - \boldsymbol{x}_{it}\hat{\boldsymbol{\beta}} + \hat{c}_{it}) \qquad i = 1, \ldots, n, \tag{3.19}$$

where $\hat{\boldsymbol{\beta}}$ and $\hat{c}_{it} = E(u_{it} \backslash \hat{\boldsymbol{\beta}}, \hat{\sigma_{it}})$ are consistent estimates. By assuming inefficiency follows a

[10] This step will also be useful for robustness check when we apply a two-step estimation strategy to control for endogeneity issues.

normal-exponential distribution, $u_{it} \sim \mathcal{E}(\sigma_{it})$, then, $\hat{c}_{it} = \hat{\sigma}_{it}$.

## 3.4 Data and Descriptive Statistics

The data for the empirical analysis is an annual panel survey of Ghanaian manufacturing firms from 1991 to 2002 collected under the World Bank's Regional Programme on Enterprise Development (RPED) and Ghana Manufacturing Enterprise Survey (GMES). It is a twelve-year wave survey with the first three rounds collected under RPED programme while the remaining were collected under GMES with a joint effort of the University of Oxford, University of Ghana, and Ghana Statistical Service. The data was made freely available by the Centre for the Study of African Economies (CSAE), University of Oxford.

Table 3.1: Summary Statistics

| | Food | | Textiles | | Wood | | Metals | | All Sectors | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | S.D | Mean | S.D | Mean | S.D | Mean | S.D | Mean | S.D |
| *Production Function Variables* | | | | | | | | | | |
| Log (Output) | 17.78 | 2.569 | 15.64 | 2.851 | 17.38 | 2.427 | 17.67 | 2.027 | 17.15 | 2.615 |
| Log (Capital) | 16.62 | 3.191 | 14.46 | 2.965 | 16.79 | 3.017 | 16.40 | 2.711 | 16.12 | 3.116 |
| Log (Employment) | 3.094 | 1.475 | 2.571 | 1.317 | 3.706 | 1.399 | 3.218 | 1.282 | 3.177 | 1.431 |
| Log (Raw Materials) | 17.10 | 2.604 | 14.84 | 2.796 | 16.32 | 2.592 | 16.79 | 2.567 | 16.29 | 2.765 |
| *Human Capital Variables* | | | | | | | | | | |
| Worker's Age | 34.88 | 7.989 | 27.50 | 8.062 | 32.72 | 8.730 | 31.92 | 8.433 | 31.91 | 8.711 |
| Tenure | 8.054 | 5.609 | 5.067 | 4.898 | 6.120 | 4.879 | 6.793 | 5.175 | 6.528 | 5.241 |
| Number of Firms | 63 | | 60 | | 76 | | 63 | | 262 | |
| Number of Observations | 484 | | 447 | | 552 | | 472 | | 1,955 | |

The first sample included 200 firms operating in food and bakery, wood and furniture, textiles and garments, metal and machinery sectors that were drawn from the 1987 Manufacturing Census. No sample attrition was recorded between the first two rounds, while the third round recorded the biggest attrition rate of approximately 30%. New random sample of firms were added to the survey to maintain similar sample size throughout the survey.

The first three waves of the dataset is contained in the three major studies of export and productivity in Sub-Saharan African countries. Besides the methodology which is completely different with regards to previous studies, two features further distinguish this study from previous ones. First, this paper does not pool data from different countries but focuses only on Ghana. The choice of Ghana over other countries is due to the long time dimension which effectively permits to account for time-invariant unobserved firm-specific heterogeneity. Secondly, this paper accounts for sector heterogeneity by fitting separate optimal frontiers for each sector, rather than pooling all firms together and imposing a single frontier for all sectors.

Table 3.1 reports summary statistics of the estimation variables while Table 3.2 breaks down the compositions of firms for each sector based on their trade status. Table 3.2 shows

Table 3.2: Trade Status Composition in Percentages

| Sector | Obs. | Non-Traders | Importers-only | Exporters-only | Two-way | Total |
|---|---|---|---|---|---|---|
| Food | 453 | 56.73 | 32.01 | 5.30 | 5.96 | 100 |
| Textiles | 424 | 63.44 | 33.73 | 0.71 | 2.12 | 100 |
| Wood | 524 | 45.61 | 23.09 | 23.85 | 7.44 | 100 |
| Metals | 443 | 39.95 | 48.98 | 4.06 | 7.00 | 100 |
| All Sectors | 1,844 | 51.08 | 33.95 | 9.22 | 5.75 | 100 |

that the metal sector is the most traded sector with almost 65% of firms being traders. The Wood sector follows next with 58% being traders while the textile sector is the least traded. The food sector is 3 percentage points short for traded firms to achieve an equal split of traders and non-traders.

The wood sector also has the highest concentration of firms who only export with 25% of total firms. Another picture that emerges from Table 3.2 shows that the importers-only are the largest trading group, with the metal sector registering 50 percent of all firms importing intermediate inputs. The high internationalization level of the metal sector offers a suitable scenario to examine whether trade has any effect on productive efficiency even in the presence of the low number of observations.

Table 3.3: Conditional Relative Frequencies of Traders

| | Export Population | | Import Population | |
|---|---|---|---|---|
| | Export-only | Two-way | Import-only | Two-way |
| Food | 0.49 | 0.51 | 0.82 | 0.18 |
| Textiles | 0.38 | 0.62 | 0.85 | 0.15 |
| Wood | 0.77 | 0.23 | 0.76 | 0.24 |
| Metals | 0.37 | 0.63 | 0.85 | 0.15 |
| All Sectors | 0.60 | 0.40 | 0.82 | 0.18 |

Table 3.3 further breaks down the likelihood of being a two-way trader given that a firm is already a one-way trader. The big picture from the importers population shows that, importers are more likely to be one-way traders (82% on average) than two-way (18% on average). On the other hand, the export population of firms presents a heterogeneous picture among the sectors. The food sector appears evenly split between exporters and two-way traders while more than two-thirds of the export population for the wood sector is only engaged in export. The textiles and metals sectors register 62 percent and 63 percent respectively for exporters who are engaged in two-way trading.

Finally, we distinguish between traders and non-traders by firm performance following the initial approach proposed by Bernard and Jensen (1995). With respect to the baseline category of non-traders, I estimate a regression of the form:

$$ln(X)_{it} = \alpha + \beta_1 importeronly_{it} + \beta_2 exporteronly_{it} + \beta_3 twowaytrader_{it} + S_h + \delta_t + \mu_{it}, \quad (3.20)$$

where $X_{it}$ indicates firm characteristics variables, $importeronly_{it}$ is a dummy variable if a firm is an importer only, $exporteronly_{it}$ is a dummy variable if a firm is an exporter only, $twowaytrader_{it}$ is a dummy variable if a firm is a two-way trader, $S_h$ is a 2-digit ISIC sector codes to account for sector heterogeneity, $t$ are time dummies, and $\mu_i$ represents the error term.

Table 3.4: Traders Premium

| Variables | Output per Worker | Value Added per Worker | Size | Capital/Labour Ratio | Wage per worker | Productive Efficiency❖ |
|---|---|---|---|---|---|---|
| Importers Only | 0.607*** | 0.717*** | 0.931*** | 1.043*** | 0.624*** | -0.00216 |
| | (0.0556) | (0.0658) | (0.0637) | (0.107) | (0.0646) | (0.00877) |
| Exporters Only | 0.942*** | 0.793*** | 1.624*** | 2.133*** | 1.044*** | -0.00253 |
| | (0.0893) | (0.110) | (0.107) | (0.171) | (0.0841) | (0.0150) |
| Two-way Traders | 1.252*** | 1.449*** | 2.408*** | 2.511*** | 1.379*** | 0.0141 |
| | (0.121) | (0.124) | (0.138) | (0.179) | (0.107) | (0.0178) |
| Constant | 14.38*** | 12.95*** | 2.595*** | 13.07*** | 11.81*** | 0.738*** |
| | (0.0925) | (0.107) | (0.104) | (0.158) | (0.0890) | (0.0193) |
| Industry FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Observations | 1,834 | 1,736 | 1,840 | 1,804 | 1,637 | 1,490 |
| R-squared | 0.320 | 0.230 | 0.311 | 0.342 | 0.467 | 0.025 |

Robust standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

❖ The measure of productive efficiency is taken from estimates reported in Table 3.7.

Using six firm performances and characteristics variables, Table (3.4) shows that trading firms perform better with respect to their non-trading counterparts. In five out of six variables, the general picture that emerges from Table (3.4) shows that, two-way traders are the largest and perform better followed by exporters only and importers only. Though the exit minimal differences trade categories in productive efficiency, such differences are not statistically significant.

Table 3.5: Correlation Matrix Between Labour Prod and Prod Efficiency

| | Output per worker | Value Added per worker | Productive Efficiency |
|---|---|---|---|
| Output per worker | 1 | | |
| Value Added per worker | 0.8732*** | 1 | |
| Productive Efficiency | 0.2416*** | 0.3449*** | 1 |

P-Values indicated by stars $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table 3.5 presents correlation between two measures of labour productivity and productive efficiency. Although the correlation is positive, the coefficient between productive efficiency and labour productivity is not as strong as that between the two measures of labour productivity.

## 3.5 Results and Discussion

To verify the hypothesis of sector heterogeneity, which will require a separate production function for each sector, I first estimate a complex model.[11] Each production input and year dummies are interacted with sector dummies to form the production frontier. I then apply the chow test procedure to test equality production inputs across sectors. Results of the chow test in Table 3.6 indicate that, indeed the sectors have different slopes of optimal frontier based on their production inputs.

Table 3.6: Data Poolability and Chow Test

| Null Hypothesis on Inputs | No Technical Change | | Technical Change | |
|---|---|---|---|---|
| | $\chi^2$ | P-Value | $\chi^2$ | P-Value |
| Ho: $\beta K_{food} = \beta K_{textile} = \beta K_{wood} = \beta K_{metal}$ | 3.25 | 0.3543 | 278.24 | 0.0000 |
| Ho: $\beta L_{food} = \beta L_{textile} = \beta L_{wood} = \beta L_{metal}$ | 11.38 | 0.0098 | 320.88 | 0.0000 |
| Ho: $\beta M_{food} = \beta M_{textile} = \beta M_{wood} = \beta M_{metal}$ | 216.95 | 0.0000 | 1959.27 | 0.0000 |

Chow test procedure was implemented after estimates of a complex model allowing different slopes for each input by sector. Time dummies interacted with sector dummies were excluded under "No Technical Change", while they were added under "Technical Change."

### 3.5.1 No-Trade Variables

Table 3.7 shows results of productive efficiency estimation without trade variables. The first four columns show results for each sector while results for all sectors taken together is presented in the last column. Results from the scale parameter shows that an increase in the average workforce age has the tendency to increase inefficiency while a long working relationship reduces inefficiency. A Wald test on the joint significance of workforce age and tenure performs badly for textiles, wood and metal sectors while it is highly significant for food and the pooled data of all sectors. The different effects of workers age and tenure on each sector points out potential sectoral heterogeneity, which would have been missed by just considering the pooled data. The computed mean technical efficiency levels are similar across the sectors, however, a close inspection shows that the textile sector had the lowest minimum efficiency level.

### 3.5.2 Exports

Table 3.8 presents results of the effect export activities on productive efficiency. The negative sign for the coefficient of lag export status for textiles, wood and metals indicate that export participation has the potentiality to reduce inefficiencies at firm-level. However, for the textiles sector, the reduction in inefficiency due to export participation is statistically significant at 5%.

[11] See Appendix A for results.

Table 3.7: No-Trade Production Frontier and Efficiency Estimates

| Variables | Food | Textiles | Wood | Metals | All Sectors |
|---|---|---|---|---|---|
| ***Marginal Effects (Frontier)*** | | | | | |
| Log Capital | -0.0168 | 0.0519 | 0.0192 | -0.0466 | 0.0272 |
| | (0.0297) | (0.0362) | (0.0622) | (0.0470) | (0.0311) |
| Log Labour | 0.100*** | 0.227*** | 0.117** | -0.0168 | 0.167*** |
| | (0.0294) | (0.0429) | (0.0519) | (0.0472) | (0.0250) |
| Log Raw Materials | 0.884*** | 0.642*** | 0.710*** | 0.792*** | 0.720*** |
| | (0.0134) | (0.0212) | (0.0222) | (0.0194) | (0.0114) |
| ***Determinants of Inefficiency ①*** | | | | | |
| Workers' Age | 0.0350*** | -0.287 | 0.0197** | 0.00885 | 0.0134*** |
| | (0.00758) | (0.268) | (0.00974) | (0.0141) | (0.00474) |
| Tenure | -0.0520*** | 0.0226 | -0.0247 | -0.0376* | -0.0281*** |
| | (0.0120) | (0.0673) | (0.0174) | (0.0215) | (0.00709) |
| Constant | -2.331*** | -0.242 | -1.590*** | -1.387*** | -1.442*** |
| | (0.282) | (0.861) | (0.280) | (0.363) | (0.136) |
| ***Estimated Technical Efficiency*** | | | | | |
| Mean | 0.763 | 0.737 | 0.712 | 0.744 | 0.742 |
| SD | 0.130 | 0.159 | 0.175 | 0.129 | 0.162 |
| Min | 0.085 | 0.059 | 0.239 | 0.263 | 0.050 |
| Max | 1.000 | 0.997 | 0.999 | 0.998 | 0.997 |
| ***Diagnostics and Tests*** | | | | | |
| Scale Elasticity | 0.97 | 0.92 | 0.85 | 0.73 | 0.91 |
| P-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald Test - Z variables ($\chi^2$) | 30.74 | 1.44 | 4.12 | 3.63 | 15.85 |
| P-value | 0.000 | 0.486 | 0.128 | 0.163 | 0.000 |
| Criterion Function | -284.223 | -860.073 | -1208.600 | -609.383 | -3664.302 |
| Observations | 408 | 365 | 498 | 429 | 1,701 |
| Number of firms | 54 | 49 | 65 | 55 | 223 |
| Year Dummies | YES | YES | YES | YES | YES |

Standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

① A negative sign indicates the variable reduces inefficiency thus making it a positive determinant of efficiency.

Table 3.8: Effect of Export Activities on Productive Efficiency

| Variables | Food | Textiles | Wood | Metals | All Sectors |
|---|---|---|---|---|---|
| ***Marginal Effects (Frontier)*** | | | | | |
| Log Capital | -0.0248 | 0.0156 | 0.0730 | -0.171*** | -0.000597 |
| | (0.0306) | (0.0397) | (0.0734) | (0.0556) | (0.0323) |
| Log Labour | 0.0725** | 0.0889** | 0.105** | -0.0421 | 0.0981*** |
| | (0.0303) | (0.0452) | (0.0429) | (0.0262) | (0.0273) |
| Log Raw Materials | 0.939*** | 0.685*** | 0.701*** | 0.783*** | 0.731*** |
| | (0.0119) | (0.0238) | (0.0198) | (0.0146) | (0.0130) |
| ***Determinants of Inefficiency*** ① | | | | | |
| Workers' Age | 0.0385*** | 0.0238 | 0.750* | 0.440 | 0.0216*** |
| | (0.00721) | (0.499) | (0.406) | (0.446) | (0.00679) |
| Tenure | -0.0504*** | -0.0136 | -0.178 | 0.0401 | -0.0305*** |
| | (0.0104) | (0.111) | (0.121) | (0.141) | (0.00969) |
| Lag Export Status | 0.00650 | -0.225** | -0.0257 | -0.108 | -0.0470 |
| | (0.175) | (0.108) | (0.193) | (0.236) | (0.0912) |
| Years in Export | 0.393*** | 0.126 | 0.0337 | 0.248 | -0.0242 |
| | (0.0818) | (0.201) | (0.125) | (0.224) | (0.0566) |
| Years in Export Squared | -0.0471*** | -0.00500 | 0.00148 | -0.0635** | 0.00454 |
| | (0.0102) | (0.0188) | (0.0125) | (0.0305) | (0.00617) |
| Constant | -2.758*** | -1.327 | -3.768*** | -2.867** | -1.818*** |
| | (0.265) | (1.541) | (1.245) | (1.380) | (0.178) |
| ***Estimated Technical Efficiency*** | | | | | |
| Mean | 0.808 | 0.686 | 0.759 | 0.764 | 0.776 |
| SD | 0.127 | 0.132 | 0.174 | 0.129 | 0.158 |
| Min | 0.085 | 0.245 | 0.265 | 0.280 | 0.127 |
| Max | 0.998 | 0.981 | 0.999 | 0.994 | 0.999 |
| ***Diagnostics and Tests*** | | | | | |
| Scale Elasticity | 0.99 | 0.79 | 0.88 | 0.57 | 0.83 |
| P-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald Test - Z variables ($\chi^2$) | 69.60 | 13.25 | 12.1 | 63.73 | 14.81 |
| P-value | 0.000 | 0.021 | 0.034 | 0.000 | 0.011 |
| Criterion Function | 41.455 | -378.590 | -426.897 | -92.287 | -1422.534 |
| Observations | 298 | 253 | 352 | 290 | 1,198 |
| Number of firms | 49 | 40 | 56 | 45 | 190 |
| Year Dummies | YES | YES | YES | YES | YES |

Standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

① A negative sign indicates the variable reduces inefficiency thus making it a positive determinant of efficiency.

Experience in export market has a remarkable non-linear effect in reducing inefficiency. Plotting efficiency level on a vertical axis and years of export experience on a horizontal axis, the general picture that emerges is a U-shaped relationship between efficiency and export experience. The results show that within the first years of exposure in the international market, African firms witness a sharp decrease in productive efficiency levels before reversal of effects whereby export participation leads to an increase in efficiency levels. This seems to suggest within the first years of export participation, firms struggle to be competitive in the export market.

Therefore, an increase in the years of experience on the international market is needed before firms actually start to reduce productive inefficiencies. The lengthy process of learning might seem that firms learn-to-export rather than learn-from-export in the first years of export participation. Similar results has been found for Morocco and Ethiopia respectively (Fafchamps et al., 2002; Siba and Gebreeyesus, 2017). Another caveat from the results suggest that firms which are impatient to go through the lengthy learning process may choose to exit the export market once they are faced with high requirements of the foreign market. Unsurprisingly, the average number of years in export market are 0.66, 1.18, 1.32 and 2.87 for textiles, food, metals, and wood respectively.

### 3.5.3 Imports

Table 3.9 presents results of the effect of import participation on firm-level productive efficiency. The textiles and metal sectors reported a negative sign for the coefficient of lag import status while food and wood reported the opposite sign. However only wood and metals had a statistical significance results at 1% and 5% respectively.

With regards to experience in participation in import only, the general picture that emerges shows that experience had no significant results across all four sectors. Given that experience played a significant role in export as reported under subsection 3.5.2, the data was probed further by undertaking two experiments to check whether the presence of second polynomial could be creating problems given the sample size of the dataset.[12] The two experiments consisted of removing the second polynomial order ($\gamma_5$) for import experience in the first instance and complete removal of import experience ($\gamma_5, \&, \gamma_4$).

In the first experiment, only the wood sector reported a decrease of inefficiency for the coefficient of years in import while results for the other sectors remained unchanged. It is worth to mention that no significant changes were observed for the other variables in the scale parameter. In the second experimentation, the food and metal sectors reported a decrease in productive inefficiency for the coefficient of lag of import status. Hence, the results for the effect of import participation on productive efficiency could suggest that, the subsequent increase in current efficiency levels following past import status can be interpreted as access to quality intermediaries.

[12]Results were not reported here, but available on request.

Table 3.9: Effect of Import Activities on Productive Efficiency

| Variables | Food | Textiles | Wood | Metals | All Sectors |
|---|---|---|---|---|---|
| ***Marginal Effects (Frontier)*** | | | | | |
| Log Capital | 0.0172 | 0.0424 | -0.180*** | -0.0907 | -0.0122 |
| | (0.0387) | (0.0332) | (0.0642) | (0.0657) | (0.0340) |
| Log Labour | 0.115*** | 0.261*** | 0.103** | -0.00294 | 0.176*** |
| | (0.0330) | (0.0394) | (0.0503) | (0.0574) | (0.0256) |
| Log Raw Materials | 0.857*** | 0.625*** | 0.729*** | 0.776*** | 0.716*** |
| | (0.0166) | (0.0168) | (0.0204) | (0.0198) | (0.0118) |
| ***Determinants of Inefficiency*** ① | | | | | |
| Workers' Age | 0.0275*** | -0.127 | 0.933*** | 0.321 | 0.0185*** |
| | (0.00965) | (0.322) | (0.341) | (0.461) | (0.00584) |
| Tenure | -0.0644*** | -0.0108 | -0.218* | -0.0485 | -0.0322*** |
| | (0.0173) | (0.0935) | (0.121) | (0.128) | (0.00939) |
| Lag Import Status | 0.0977 | -0.113 | 0.244*** | -0.205** | -0.0788 |
| | (0.135) | (0.119) | (0.0840) | (0.0871) | (0.0615) |
| Years in Import | 0.00629 | -0.0387 | -0.0394 | 0.105 | -0.00404 |
| | (0.0830) | (0.0662) | (0.0901) | (0.105) | (0.0388) |
| Years in Import Squared | 0.00451 | 0.00412 | -0.00241 | -0.00863 | 0.000410 |
| | (0.00927) | (0.00506) | (0.0112) | (0.00747) | (0.00348) |
| Constant | -2.320*** | -0.651 | -3.967*** | -2.489* | -1.573*** |
| | (0.254) | (0.984) | (1.113) | (1.488) | (0.176) |
| ***Estimated Technical Efficiency*** | | | | | |
| Mean | 0.824 | 0.738 | 0.732 | 0.786 | 0.751 |
| SD | 0.128 | 0.161 | 0.175 | 0.146 | 0.159 |
| Min | 0.390 | 0.276 | 0.230 | 0.264 | 0.251 |
| Max | 0.997 | 0.997 | 0.998 | 1.000 | 0.998 |
| ***Diagnostics and Tests*** | | | | | |
| Scale Elasticity | 0.99 | 0.93 | 0.65 | 0.68 | 0.88 |
| P-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald Test - Z variables ($\chi^2$) | 22.99 | 2.76 | 15.14 | 7.55 | 15.7 |
| P-value | 0.000 | 0.737 | 0.010 | 0.183 | 0.008 |
| Criterion Function | -90.392 | -579.514 | -801.758 | -420.394 | -2464.392 |
| Observations | 335 | 305 | 425 | 349 | 1,418 |
| Number of firms | 50 | 46 | 61 | 50 | 207 |
| Year Dummies | YES | YES | YES | YES | YES |

Standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

① A negative sign indicates the variable reduces inefficiency thus making it a positive determinant of efficiency.

### 3.5.4 Two-way

Table 3.10 presents results for two-way trading activities on productive efficiency. The positive sign of the coefficient of lag two-way status in three sectors - though statistically significant for metal sector only - might give the impression that two-way participation decreases efficiency. This may seem quite puzzling, as two-way traders are very active on the international market with respect to only one-way traders. Indeed, a look at the coefficients of years in two-way trading reveals more information on two-way trading and productive efficiency.

The food and textiles sectors report a U-shaped relationship between productive efficiency and experience in two-way trading. For these two sectors, firms encounter difficulties in their first years of two-way trading. The mechanism in this scenario is very similar to the export participation case in which the learning process is lengthy.

On the other hand, the wood and metal sectors present inverted-U shaped relationship between efficiency and two-way trading experience. In this case, there is a sharp increase in efficiency levels following international market exposure. The bell shaped relationship also implies that after two-way trading experience has reached a maximum point, any additional year to experience is likely to translate into marginal diminishing returns.

Having analysed all trading experiences separately, the paper proceeds to analyse all trading under subsection 3.5.5 to provide a complete overview of the results.

### 3.5.5 All Trade Variables

Table 3.11 presents results for all trading activities for each sector and pool data of all sectors. While results under subsections 3.5.2 and 3.5.3 included all populations of exporters and importers respectively, under this subsection, we distinguish one-way traders from two-way traders to avoid double counting.

With regards to the lag of exporters only status, the textile sector shows a significant reduction of inefficiency following past export exposure. The sector based results for lag export only status are in line with the results presented in subsection 3.5.2. In addition, Column (5) reports significant results for the pooled data unlike in Table 3.8 where results for the pooled data were not statistically significant.

Likewise, results for lag of imports only status were similar to that of Table 3.9. The textiles and metal sectors reported a negative sign indicating a reduction in inefficiency even though none was significant. In similar fashion, the food and wood sectors reported a positive sign, however, only the food sector has a statistically significant result. The pooled data reported a reduction of inefficiency for the lag of import status at 5% significance level.

In the full specification for all trading activities, the coefficient for lag of two-way traders was not statistically significant for all sectors and the pooled data. It is however interesting to note that the patterns of the coefficient for two-way trading experience were exactly the same as those reported in Table 3.10.

The most significant changes occurred with regards to years of import experience. The food and textiles sectors reported no significance with regards to years of import experience.

Table 3.10: Effect of Two-way Activities on Productive Efficiency

| Variables | Food | Textiles | Wood | Metals | All Sectors |
|---|---|---|---|---|---|
| ***Marginal Effects (Frontier)*** | | | | | |
| Log Capital | -0.0199 | -0.0205 | 0.0539 | 0.0711 | -0.00323 |
| | (0.0366) | (0.0701) | (0.0898) | (0.0935) | (0.0370) |
| Log Labour | 0.0709** | 0.208*** | 0.0402 | -0.0593 | 0.118*** |
| | (0.0312) | (0.0503) | (0.0399) | (0.0510) | (0.0297) |
| Log Raw Materials | 0.922*** | 0.599*** | 0.724*** | 0.785*** | 0.724*** |
| | (0.0158) | (0.0225) | (0.0175) | (0.0161) | (0.0136) |
| ***Determinants of Inefficiency*** ① | | | | | |
| Workers' Age | 0.0482*** | 0.00234 | 1.081*** | 0.765 | 0.0234*** |
| | (0.00902) | (0.0177) | (0.324) | (0.596) | (0.00629) |
| Tenure | -0.0766*** | -0.00660 | -0.303** | 0.0104 | -0.0320*** |
| | (0.0216) | (0.0221) | (0.125) | (0.172) | (0.0101) |
| Lag Two-way Status | 0.0487 | 0.549 | -0.00939 | 0.509** | 0.192 |
| | (0.191) | (0.567) | (0.115) | (0.211) | (0.154) |
| Years in Two-way | 0.433** | 0.503* | -0.335*** | -1.140*** | -0.0340 |
| | (0.191) | (0.272) | (0.127) | (0.158) | (0.101) |
| Years in Two-way Squared | -0.0534* | -0.110* | 0.0927*** | 0.132*** | 0.00706 |
| | (0.0274) | (0.0619) | (0.0222) | (0.0237) | (0.0190) |
| Constant | -3.057*** | -1.437*** | -4.656*** | -3.894** | -1.896*** |
| | (0.265) | (0.426) | (1.012) | (1.821) | (0.167) |
| ***Estimated Technical Efficiency*** | | | | | |
| Mean | 0.883 | 0.766 | 0.772 | 0.769 | 0.781 |
| SD | 0.119 | 0.153 | 0.174 | 0.139 | 0.154 |
| Min | 0.430 | 0.298 | 0.177 | 0.266 | 0.258 |
| Max | 0.999 | 0.993 | 0.999 | 1.000 | 0.999 |
| ***Diagnostics and Tests*** | | | | | |
| Scale Elasticity | 0.97 | 0.79 | 0.82 | 0.80 | 0.84 |
| P-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald Test - Z variables ($\chi^2$) | 40.55 | 8.69 | 36.72 | 114.42 | 18.34 |
| P-value | 0.000 | 0.122 | 0.000 | 0.000 | 0.003 |
| Criterion Function | 114.301 | -305.323 | -298.808 | -140.258 | -1166.045 |
| Observations | 270 | 234 | 326 | 264 | 1,097 |
| Number of firms | 48 | 40 | 55 | 45 | 188 |
| Year Dummies | YES | YES | YES | YES | YES |

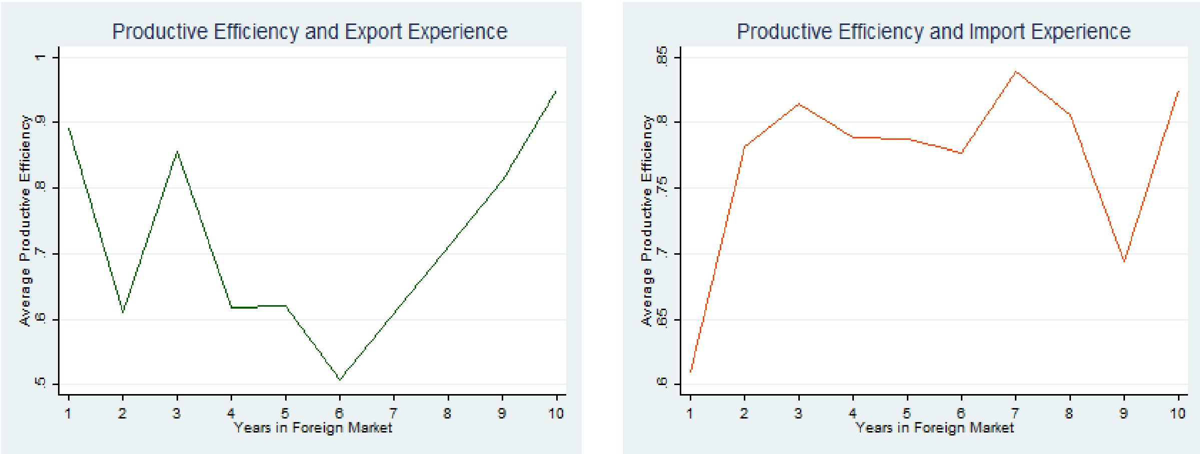
Standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$
① A negative sign indicates the variable reduces inefficiency thus making it a positive determinant of efficiency.

Table 3.11: Effect of Trading Activities on Productive Efficiency

| Variables | Food | Textiles | Wood | Metals | All Sectors |
|---|---|---|---|---|---|
| ***Marginal Effects (Frontier)*** | | | | | |
| Log Capital | -0.0201 | -0.000466 | 0.0513 | 0.128*** | -0.00247 |
| | (0.0362) | (0.0670) | (0.0882) | (1.07e-07) | (0.0354) |
| Log Labour | 0.0783** | 0.200*** | 0.0529 | 0.0999*** | 0.106*** |
| | (0.0316) | (0.0438) | (0.0444) | (2.40e-09) | (0.0292) |
| Log Raw Materials | 0.927*** | 0.614*** | 0.749*** | 0.759*** | 0.732*** |
| | (0.0159) | (0.0220) | (0.0217) | (1.19e-08) | (0.0139) |
| ***Determinants of Inefficiency*** | | | | | |
| Workers' Age | 0.0486*** | -0.0320 | 0.920** | 0.426 | 0.0266*** |
| | (0.0106) | (0.567) | (0.409) | (0.617) | (0.00686) |
| Tenure | -0.0751*** | -0.0622 | -0.400*** | 0.161 | -0.0345*** |
| | (0.0269) | (0.137) | (0.141) | (0.165) | (0.0108) |
| Lag Exporters Only | 0.0971 | -1.240** | -0.132 | 0.151 | -0.314* |
| | (0.499) | (0.594) | (0.228) | (0.144) | (0.173) |
| Years in Export Only | -0.0319 | -0.328 | 0.268* | 1.802*** | 0.213** |
| | (0.225) | (0.390) | (0.146) | (0.230) | (0.0835) |
| Years in Export Only Squared | 0.000573 | 0.141 | -0.0355** | -0.655*** | -0.0272*** |
| | (0.0237) | (0.102) | (0.0159) | (0.0471) | (0.00936) |
| Lag Import Only | 0.232** | -0.215 | 0.249 | -0.159 | -0.163** |
| | (0.111) | (0.144) | (0.153) | (0.119) | (0.0636) |
| Years in Import Only | 0.0543 | -0.0490 | -0.268** | 0.275* | -0.0407 |
| | (0.154) | (0.0874) | (0.117) | (0.153) | (0.0503) |
| Years in Import Only Squared | -0.0123 | 0.00989 | 0.0231 | -0.0258** | 0.00689 |
| | (0.0232) | (0.00971) | (0.0147) | (0.0128) | (0.00559) |
| Lag Two-way Traders | 0.254 | -0.0258 | 0.0213 | 0.173 | -0.0142 |
| | (0.226) | (0.258) | (0.225) | (0.257) | (0.141) |
| Years in Two-way | 0.351* | 0.907** | -0.409*** | -1.094*** | -0.0595 |
| | (0.211) | (0.358) | (0.149) | (0.223) | (0.101) |
| Years in Two-way Squared | -0.0454 | -0.230** | 0.0876*** | 0.133*** | 0.0103 |
| | (0.0294) | (0.103) | (0.0236) | (0.0320) | (0.0173) |
| Constant | -3.147*** | -1.198 | -3.765*** | -3.414* | -1.923*** |
| | (0.284) | (1.744) | (1.305) | (1.895) | (0.195) |
| ***Estimated Technical Efficiency*** | | | | | |
| Mean | 0.883 | 0.768 | 0.775 | 0.744 | 0.783 |
| SD | 0.119 | 0.158 | 0.184 | 0.155 | 0.156 |
| Min | 0.435 | 0.301 | 0.183 | 0.263 | 0.235 |
| Max | 0.999 | 0.993 | 0.996 | 0.995 | 0.999 |
| ***Diagnostics and Tests*** | | | | | |
| Scale Elasticity | 0.99 | 0.81 | 0.85 | 0.99 | 0.83 |
| P-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald Test - Z variables | 49.22 | 57.08 | 56.9 | 524.22 | 36.19 |
| P-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Criterion Function | 118.773 | -279.466 | -255.146 | 451.911 | -1116.990 |
| Observations | 270 | 233 | 326 | 264 | 1,097 |
| Number of firms | 48 | 40 | 55 | 45 | 188 |
| Year Dummies | YES | YES | YES | YES | YES |

Standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

The wood sector, however, reported a linear relationship between productive efficiency and years of import experience. The result showed that a cumulative years of experience leads to a decrease in inefficiency (hence increase in efficiency level) before levelling up to no significance in the second order polynomial.




(a) Export (b) Import

Figure 3.1: Productive Efficiency and Trade Experience

However, the U-shaped relationship between export experience and productive efficiency is confirmed. Figure 3.1 put into perspective the relationship between trade experience and productive efficiency. It can be observed that in the first year in foreign market, exporters had a higher productive efficiency than importers. In panel (b) of Figure 3.1, importers enjoy an immediate upward rise in efficiency level, with smaller variations afterwards, until a cyclical movement between the eight and tenth years.

In panel (a) of Figure 3.1, exporters are experienced a bumpy-ride in the first years in foreign market. An immediate decrease in efficiency level, followed by a quick rise and fall makes the impact of export on efficiency negative in the first years. The relationship tends positive on the sixth year in foreign market. This suggest that firms would have to endure a negative effect within the first six years, before the effect turns positive. The threshold of six years, may be too long for some firms to remain on the market.

In conclusion, the U-shaped relationship between export experience and productive efficiency, suggest that firms learn-to-export rather than learning from export. On the other hand, firms engaged in imports, rather learn from importing. This calls for policy actions in the case of exporting, at least to reduce the threshold year before export experience have positive impact on productive efficiency.

### 3.5.6 Endogeneity Issues and Robustness Check

The derivation of the model in Section 3.3 and its estimation leaves out a fundamental issue that needs discussion. The pairwise difference estimation does not provide any mechanism to deal with endogeneity issues in the estimation of the production function. Specifically, when endogeneity in the choice of the production inputs are not taken into account, the estimated production frontier is likely to be biased.

Though a central problem in the stochastic frontier models, Kutlu (2010) presented a two-step GMM solution via maximum likelihood estimation while Tran and Tsionas (2013) presented an improved one-step GMM solution. However, both methods relied on Battese and Coelli (1992) maximum likelihood framework which does not separate firm specific time-invariant heterogeneity from inefficiency.

Emvalomatis (2012) proposed a solution in the Bayesian estimation framework whereby unobserved heterogeneity is separated from the dynamic frontier. However, the specification of the model through Bayesian correlated random effects requires a parametric distribution for the firm-specific effects to be specified.[13]

### A Two-Step Estimation

In this paragraph, a two-step estimation strategy is adopted to control for endogeneity issues in the determinants of inefficiency. I am fully aware of consistence issues raised by Wang and Schmidt (2002) in the application of the two-step estimation strategy. The preferred estimates of the paper remains the one-step approach outlined above. However, the use of the two-step approach will enable a comparison with the estimates derived above and an assessment on whether endogeneity affects estimated coefficients. Using the inefficiency variable predicted according to equation (3.18), the following empirical equation s estimated,

$$\hat{u}_{it} = \theta_0 + \theta_1 Expt_{it-1} + \theta_2 Impt_{it-1} + \theta_3 Tway_{it-1} + \lambda' \mathbf{Z} + S_h + \delta_t + \xi_{it}, \tag{3.21}$$

where $Expt$, $Impt$ and $Tway$ represent the lag status of export only, import only and two-way trading activities; $\mathbf{Z}$ is a vector of number of years in trading activity in first and second order polynomial; $S_h$ represents 3-digit ISIC sector dummies;[14] $\delta_t$ captures time dummies; and, $\xi_{it}$ is the usual idiosyncratic error term. The dependent variable is predicted from results reported in Table 3.7, where no trading variables were added to the estimated equation. As such, average workers' age and tenure at firm level cannot be added to the two-step equation above.

The generalised method of moments (GMM) estimator is implemented to estimate equation (3.21). The lag status of trade participation (export only, import only and two-way) were instrumented. The following variables were used as instruments: second lag of trade participation, trade tariffs at 3-digit ISIC level, percentage of inputs imported, firm-specific inputs and outputs prices indexes.

[13]Belotti and Ilardi (2015) proposed an extension of the PDE estimator by allowing inefficiency to follow AR(1) whereby estimation is performed via MCMC likewise in the Bayesian framework. Simulation results showed that performance of the dynamic PDE is subject to the level of autocorrelation, the length of the time as well as the cross-sectional dimension. Several convergence issues were encountered in the application of the dynamic PDE.

[14]The purpose of estimating at 3-digit sector levels is to fully exploit data on tariffs, which are used as instruments.

Table 3.12: Effects of Trade on Technical Inefficiency (GMM Estimates)

| Dependent Variable: $\hat{u}_{it}$ | Food | Textiles | Wood | Metals | All Sectors |
|---|---|---|---|---|---|
| Lag Exporters Only | 0.0627 | -0.191 | 0.104 | -0.497 | 0.00460 |
| | (0.155) | (0.231) | (0.188) | (0.325) | (0.112) |
| Lag Import Only | 0.0426 | -0.315*** | 0.0149 | -0.183** | -0.125*** |
| | (0.0611) | (0.107) | (0.0862) | (0.0826) | (0.0397) |
| Lag Two-way Traders | 0.0787 | -0.476*** | 0.131 | 0.122 | 0.134 |
| | (0.141) | (0.165) | (0.199) | (0.248) | (0.0992) |
| Years in Export Only | 0.0297 | 0.110 | -0.00863 | 0.0675 | -0.00355 |
| | (0.0294) | (0.0853) | (0.0290) | (0.0597) | (0.0171) |
| Years in Export Only Sqd | -0.00510** | -0.0284* | -0.000733 | -0.00368 | -0.000896 |
| | (0.00207) | (0.0164) | (0.00220) | (0.00631) | (0.00152) |
| Years in Import Only | 0.0260* | 0.0203 | -0.0620*** | 0.0441** | 0.00901 |
| | (0.0156) | (0.0196) | (0.0229) | (0.0208) | (0.00999) |
| Years in Import Only Squared | -0.00413** | 0.000541 | 0.00690*** | -0.00318** | 0.000483 |
| | (0.00203) | (0.00201) | (0.00206) | (0.00146) | (0.00104) |
| Years in Two-way | -0.0238 | -0.0542 | -0.0400 | -0.0835 | -0.0294 |
| | (0.0479) | (0.0517) | (0.0403) | (0.0880) | (0.0254) |
| Years in Two-way Squared | -0.000136 | 0.0200** | 0.00597 | 0.00816 | 0.000387 |
| | (0.00561) | (0.0100) | (0.00812) | (0.00986) | (0.00306) |
| Constant | 0.243*** | 0.460*** | 0.447*** | 0.280*** | 0.332*** |
| | (0.0290) | (0.0642) | (0.103) | (0.0596) | (0.0272) |
| Observations | 200 | 175 | 270 | 181 | 902 |
| **Summary for First-Stage Regression Results** | | | | | |
| Lag Exporters Only (P-Value) | 0.3358 | 0.0007 | 0.0000 | 0.0222 | 0.0000 |
| Lag Import Only (P-Value) | 0.0000 | 0.0001 | 0.0000 | 0.0000 | 0.0000 |
| Lag Two-way Traders (P-Value) | 0.0940 | 0.0058 | 0.0000 | 0.3350 | 0.0000 |
| **IV Test Statistics Heteroskedasticity-robust** | | | | | |
| Hansen J statistic (P-value) | 0.5086 | 0.3408 | 0.1160 | 0.1082 | 0.2012 |
| *Underidentification test:* | | | | | |
| Kleibergen-Paap rk LM statistic (P-value) | 0.5590 | 0.0162 | 0.0048 | 0.0334 | 0.0000 |
| *Weak identification (1-stage):* | | | | | |
| Cragg-Donald Wald F statistic | 2.52 | 4.37 | 7.95 | 3.05 | 26.11 |
| Kleibergen-Paap Wald rk F statistic | 0.69 | 3.17 | 2.41 | 1.79 | 8.78 |
| *Weak-instrument-robust inference:* | | | | | |
| Anderson-Rubin Wald test (P-value) | 0.5470 | 0.0005 | 0.4931 | 0.0032 | 0.0021 |
| Stock-Wright LM S statistic (P-Value) | 0.7369 | 0.0067 | 0.5624 | 0.0337 | 0.0036 |

Robust standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Results are presented in Table 3.12, with each column representing each sector while the last column aggregates all sectors. The results suggest lag of import only reduces technical inefficiencies compared to other modes of trade participation. A surprising result is the coefficient of lag export only for the aggregated estimates. While coefficient signalled that export only reduces inefficiency at 10% significance level in Table 3.11, we find the opposite result here, but not significant. In addition, there are not many changes with regards to results obtained under this approach and the preferred one-stage estimates reported in Table 3.11.

In the bottom part of Table 3.12 various tests are reported as part of the implementation of the GMM procedure (see Baum et al. (2007) for full details). The Hansen J statistic test the overidentification of the instruments, failure to reject the test means overidentification restrictions are valid. From Table 3.12, the p-value of the Hansen J statistic for all estimation equations are greater than 10%, suggesting all the equations satisfy the over-identification conditions.

The Hansen J statistic is a necessary condition but not sufficient to draw final conclusion. The underidentification test examines whether or not the rank conditions of the matrix is satisfied or not. Rejection of the underidentification test means the matrix has full rank and identified while failure to reject implies rank-deficient and identification (Baum et al., 2007). The type of statistic used to perform the underidentification test depends on the assumption of the error term, i.e, homoscedastic or heteroskedastic. The Kleibergen-Paap rank statistic is robust to heteroskedasticity (Baum et al., 2007). With the exception of the food sector, the p-value of the Kleibergen-Paap rank statistic for all the other equations are less than 0.05% implying the equations are identified.

The Anderson-Rubin Wald test and the Stock-Wright LM S statistic both test the hypothesis that the instruments are weak against the alternative that they are not weak (Baum et al., 2007). For the textiles and metals sectors as well as the aggregated data, we reject the null hypothesis that the set of instruments are weak. On the contrary, we fail to reject the null hypothesis for the food and wood sectors. Such result is plausible given that I use the same sets of instruments for all sectors, which implies conditions underlying trading outcomes differs from sector to sector.

Though the estimates of the robustness check do not differentiate largely from the preferred one-stage estimates doubts can be raised about the handling of measurement error in the SFA technique. Van Biesebroeck (2007) demonstrated that in the presence of measurement error, the SFA technique performs badly in productivity estimation. It ought to be pointed out that Van Biesebroeck used Battese and Coelli (1992) approach developed under maximum likelihood estimation for his exercise, which is different from the pairwise difference estimation applied in this paper. To address those concerns, I repeat the robustness check using the standard procedure to estimate production function.

Table 3.13: Effects of Trade Activities on Total Factor Productivity (GMM Estimates)

| ***Dependent Variable:*** Log Output | Food | Textiles | Wood | Metals | All Sectors |
|---|---|---|---|---|---|
| Log Capital | 0.0989 | 0.200** | 0.131*** | 0.162*** | 0.163*** |
| | (0.0853) | (0.0801) | (0.00642) | (0.0498) | (0.0374) |
| Log Labour | 0.214** | 0.248*** | 0.212*** | 0.158*** | 0.232*** |
| | (0.0981) | (0.0190) | (0.0386) | (0.0343) | (0.0325) |
| Log Raw Materials | 0.688*** | 0.597*** | 0.655*** | 0.755*** | 0.679*** |
| | (0.0987) | (0.102) | (0.0196) | (0.0110) | (0.0264) |
| ***Dependent Variable:*** $ln(\widehat{\omega})_{it}$ | Food | Textiles | Wood | Metals | All Sectors |
| Workers' Age | -0.0399*** | -0.229*** | 0.0363*** | 0.00131 | 0.0208*** |
| | (0.00781) | (0.0312) | (0.00767) | (0.0134) | (0.00325) |
| Tenure | 0.0256** | 0.197*** | -0.00506 | 0.00243 | 0.000601 |
| | (0.0111) | (0.0438) | (0.00977) | (0.0279) | (0.00465) |
| Lag Exporters Only | -0.113 | 8.081* | 0.288 | 1.493 | 0.312 |
| | (0.944) | (4.709) | (0.319) | (1.218) | (0.227) |
| Lag Import Only | 0.292 | 0.182 | 0.0521 | 0.812*** | 0.346*** |
| | (0.280) | (0.564) | (0.164) | (0.297) | (0.0762) |
| Lag Two-way Traders | -0.0285 | 2.093 | 0.0309 | 0.750 | 0.145 |
| | (0.576) | (2.976) | (0.442) | (0.583) | (0.226) |
| Years in Export Only | -0.438*** | -3.849** | 0.0180 | 0.116 | 0.00983 |
| | (0.130) | (1.691) | (0.0496) | (0.200) | (0.0332) |
| Years in Export Only Sqd | 0.0338*** | 0.804*** | 0.000977 | 0.00790 | 0.000241 |
| | (0.00794) | (0.296) | (0.00374) | (0.0244) | (0.00257) |
| Years in Import Only | -0.158* | -0.0457 | 0.0882* | -0.542*** | 0.00112 |
| | (0.0850) | (0.114) | (0.0454) | (0.0898) | (0.0183) |
| Years in Import Only Squared | -0.000291 | -0.0274** | -0.0108*** | 0.0549*** | -0.00256 |
| | (0.0106) | (0.0112) | (0.00405) | (0.00728) | (0.00192) |
| Years in Two-way | -0.431** | -1.394* | 0.0806 | -0.699*** | 0.106* |
| | (0.186) | (0.751) | (0.0836) | (0.210) | (0.0556) |
| Years in Two-way Squared | 0.0488** | -0.0476 | 0.0244 | 0.137*** | -0.00316 |
| | (0.0193) | (0.136) | (0.0149) | (0.0253) | (0.00693) |
| Constant | 0.932*** | -3.326*** | 3.963*** | 8.931*** | 4.333*** |
| | (0.275) | (0.740) | (0.266) | (0.425) | (0.100) |
| Observations | 223 | 195 | 270 | 213 | 902 |
| **Summary for First-Stage Regression Results** | | | | | |
| Lag Exporters Only (P-Value) | 0.1748 | 0.0680 | 0.0000 | 0.1334 | 0.0000 |
| Lag Import Only (P-Value) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Lag Two-way Traders (P-Value) | 0.0269 | 0.0042 | 0.0000 | 0.1174 | 0.0000 |
| **IV Test Statistics Heteroskedasticity-robust** | | | | | |
| Hansen J statistic (P-value) | 0.1033 | 0.2015 | 0.7783 | 0.4521 | 0.3591 |
| *Underidentification test:* | | | | | |
| Kleibergen-Paap rk LM statistic (P-value) | 0.1461 | 0.0561 | 0.0046 | 0.0209 | 0.0000 |
| *Weak identification (1-stage):* | | | | | |
| Cragg-Donald Wald F statistic | 4.20 | 1.66 | 7.79 | 4.15 | 26.08 |
| *Weak-instrument-robust inference:* | | | | | |
| Anderson-Rubin Wald test (P-value) | 0.2700 | 0.0404 | 0.8470 | 0.0397 | 0.0002 |
| Stock-Wright LM S statistic (P-Value) | 0.3442 | 0.1040 | 0.8693 | 0.1295 | 0.0005 |

Standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

**Comparison with Standard Approach**

There are many estimation techniques to recover productive efficiency within the standard TFP approach each responding to one or various estimation biases (Van Beveren, 2012). The semi-parametric approach proposed by Levinsohn and Petrin (2003) is sufficient to address the simultaneity and endogeneity issues raised under this sub-section.[15] Using predicted TFP from Cobb-Douglas production function specification, the paper estimates the following

$$ln(\widehat{\omega})_{it} = \theta_0 + \theta_1 Expt_{it-1} + \theta_2 Impt_{it-1} + \theta_3 Tway_{it-1} + \lambda'\mathbf{Z} + S_j + \delta_t + \xi_{it}, \tag{3.22}$$

where explanatory variables are defined in (3.21). The only change made to equation (3.22) involves the control vector, $\mathbf{Z}$, where firm level average workers age and tenure are included.[16]

The upper part of Table 3.13 report the coefficients of the production function variables using the Levinsohn and Petrin approach. Clearly, the semi-parametric approach performs better than fixed effects approach used to estimate the production function in previous sections. Van Beveren (2012) explains in detail the differences between different frameworks to estimate the production function.

Interestingly, results in the lower part of Table 3.13 confirm that of Table 3.11. In Table 3.13 only the textile sector reported a favourable impact of lag export on productive efficiency same as Table[17] 3.11. In addition, majority of the impact of trade experiences variables on productive inefficiency are confirmed with what was obtained with the proposed approach. In particular, the u-shaped relationship is confirmed for food and textiles sectors. We can therefore be confident that results reported under Table 3.11 reflect the impact of trade on productive efficiency.

## 3.6 Trade and Knowledge Spillovers

This second part of the paper seeks to analyse possible transfer of knowledge between trading firms and non-trading firms. Supposing firms participating in trading activities either by export only, import only or two-way trading accumulates knowledge from foreign markets, how does this affect non-trading firms?

Parallel lines of literature have established firm level destination-specific export spillovers for France (Koenig, 2009; Koenig et al., 2010), Denmark (Choquette and Meinen, 2015), and many others. A common identification strategy in this case, is to regress the probability that a firm starts to export to a specific destination on the mass of firms within its agglomeration domain already exporting to that destination. Another stream of literature has also analysed spillover effects from multinational firms engaged in foreign direct investment (FDI) with domestic firms (Javorcik, 2004). Researchers usually regress productivity growth of domestic firms linked with FDI along the supply chain of the production process. This can be estimated

[15] A short overview of estimation techniques is offered by Van Beveren (2012).

[16] An appropriate one-stage TFP estimation that takes into account price heterogeneity and input allocation is on-going.

[17] Recall that a negative coefficient means a favourable impact in the SFA framework.

with transaction level information between FDIs and domestic firms through forward and backward linkages (see Newman et al. (2015) for recent application on Vietnam).

This section of the paper bridges and fills gaps in the current literature in two ways. First, the paper explores knowledge spillovers between trading and non-trading through their probability to trade. Second, the section opens up the black box on which mechanisms (dis)enhances spillovers between trading and non-trading firms. The section exploits information on productive efficiency of the firm computed in the first part, work-force skill composition, and value-added per worker to build technological distance and absorptive capacity between trading and non-trading firms.

The first spillover variable is constructed with an intent to capture agglomeration effect, a strategy commonly applied in literature. Given that exact distances are not available, we proxy by considering the number of firms engaged in any trading activity in a city at time $t$ divided by the number of firms in that city at time $t$. Thus,

$$\text{Ratio}_{it} = \frac{\sum_{i=1}^{T} Traders_{it} Area_{ct}}{\sum_{i=1}^{N} Firms_{it} Area_{ct}}.$$

The second variable aims to capture technological distance/proximity between trading firms and non-trading firms in a technological space. Although technological distance can vary based on firms' industry, data limitations do not allow to further differentiate intra-industry and inter-industry technological distances.

Given that technological distance/proximity is not directly observed, a common strategy used to study spillovers in R&D literature involves construction of proxy measures (Jaffe, 1986; Bloom et al., 2013). To this end, the paper constructed technological distance and absorptive capacity between trading firms and non-trading firms using the Mahanalobis distance. The distance score between a trading firm $f$ and a non-trading firm $d$ (limited to two variables) is given by:

$$\text{Dist Score}_{fd} = \sqrt{(n-g)\sum_{i=1}^{P}\sum_{j=1}^{P}\omega_{ij}(\bar{a}_{if}-\bar{a}_{id})(\bar{a}_{jf}-\bar{a}_{jd})}$$

where $n$ is the sample units; $g$ is the number of groups; $\omega_{ij}$ is the within group inverse covariance matrix; $\bar{a}_{if}$ and $\bar{a}_{jf}$ are the means of the $ith$ and $jth$ variables in each group – traders, $f$, and non-traders, $d$ – with $i \neq j$. The skill composition of a firm is a good reflection of its technology. For this purpose, the proportion of workforce which has completed - university education, secondary education, and primary education - are chosen as the base variables.

Therefore, to compute a proxy for technology distance between trading and non-trading firms using the Mahanalobis distance, the following variables were used: firm level skill composition and predicted productive efficiency level.[18] On the other hand, to compute a proxy for absorptive capacity between trading and non-trading firms, the following variables

[18] I chose estimated efficiency from Table 3.11.

were used: firm level skill composition and value-added per worker.

**Propensity to Trade**

To assess the spillover effect, the firm's decision to trade is modelled as

$$P(y_{it} = 1|x_{it}, \varepsilon_{it}) = \Lambda(\gamma_1 Ratio_{it} + \gamma_2 TechDist_{it} + \gamma_3 AbsCap_{it} + x'_{it}\beta + \delta_t + \delta_s + \varepsilon_{it}) \quad (3.23)$$

where $y_{it}$ is an indicator variable equal to 1 if a firm trade in year $t$ and 0 otherwise; $x_{it}$ contains firm level covariates such as the log of wage per employee, firm age, log of firm size, ownership status, and technical efficiency. $\Lambda$ is the logistic cumulative distribution function indicating we allow $\varepsilon_{it}$ to follow a logistic distribution in line with studies on export spillovers (Koenig, 2009; Choquette and Meinen, 2015). Time fixed effects as well as industry fixed effects are also controlled for in all estimations.

The coefficient $\gamma_1$ in the logistic function (3.23) captures agglomeration effect of trading firms on a firm decision to trade. The technological distance between trading and non-trading firms, captured by $\gamma_2$, is expected to negatively impact firms decision to trade. On the other hand, firm-level absorptive capacity, $\gamma_3$, is expected to have a positive effect on firms decision to trade.

Results of a pooled logit, random effect logit as well as dynamic specifications are reported in Table 3.14. Given that the dynamic logit specification in column (4) allows to control for trade sunk cost, it is hence stated as the preferred specification. In the baseline model, all three variables of interest are statistically significant at 1% and have the expected sign. The ratio of traders to all firms as well as absorptive capacity of the firm have a positive effect on the decision to trade while the technology distance has a negative effect. The results suggest that if firms are technically different in a given technological space, a further increase in this distance reduces any possible spillover gains. Given that the proxy measures of technological distance and absorptive capacity contains the same base variables, we test the null hypothesis that their coefficients are the same against the alternative that they are different. That is, $\gamma_2 = \gamma_3$. Results reported in the bottom part of the Table indicate they are statistically different.

A number of firm level covariates were added to the estimation equation to check the robustness of the results in Column (1). While changes occurred in the magnitude of the effects, the signs of the coefficients remain unchanged. With regards to the control variables, reported in column (2), wage per employee, foreign ownership, and technical efficiency are not statistically significant. The result on technical efficiency reflects arguments and results presented in Chapter 2. On the contrary, firm age is negative and significant at 10% significance level. Likewise, firm size is positive and significant indicating large firms have higher propensity to trade.

Columns (3) and (4), take the panel nature of the dataset into account by estimating a random effects as well as a dynamic logit specifications. Agglomeration loses its significance although the sign of the coefficient remains unchanged. In columns (3) and (4), an increase in

Table 3.14: Firms Propensity to Trade

| VARIABLES | Pooled Logit (1) | Pooled Logit (2) | RE Logit (3) | Dynamic Logit (4) |
|---|---|---|---|---|
| Ratio of Traders to all Firms (By city) | 3.778*** | 2.679** | 1.576 | 0.00164 |
| | (0.886) | (1.247) | (1.793) | (1.362) |
| Technology Distance | -0.942*** | -0.622*** | -0.491* | -0.477** |
| | (0.221) | (0.197) | (0.291) | (0.216) |
| Absorptive Capacity | 0.951*** | 0.546** | 0.861*** | 0.752*** |
| | (0.224) | (0.215) | (0.328) | (0.266) |
| ln(Wage per Employee) | | 0.119 | 0.232 | 0.0586 |
| | | (0.0869) | (0.147) | (0.108) |
| Firm age | | -0.0175* | -0.0252 | -0.0136 |
| | | (0.0104) | (0.0203) | (0.0103) |
| ln(Firm Size) | | 0.627*** | 1.291*** | 0.459*** |
| | | (0.143) | (0.219) | (0.130) |
| Any Foreign Ownership (Dummy) | | 0.226 | 0.668 | 0.208 |
| | | (0.357) | (0.641) | (0.312) |
| Technical Efficiency | | -0.754 | -0.240 | -1.023 |
| | | (0.609) | (0.731) | (0.628) |
| Lag Trade Status | | | | 3.271*** |
| | | | | (0.238) |
| Constant | -1.847*** | -4.042*** | -8.220*** | -2.782*** |
| | (0.549) | (1.279) | (2.388) | (0.866) |
| Observations | 1,110 | 994 | 884 | 884 |
| $PseudoR^2$ | 0.103 | 0.182 | | |
| Test: $\gamma_2 = \gamma_3$ (P-Value) | 0.000 | 0.004 | 0.023 | 0.008 |
| Industry FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |

Robust standard errors in parentheses clustered at firm-level $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

the technology distance between trading and non-trading firms reduces the likelihood for firms to trade. Absorptive capacity has a positive impact on propensity to trade and significant at 1% significance level under columns (3) and (4).

In summary, this section has shown that there is a potential, but no automatic spillover effect between trading firms and non-trading firms. In particular, agglomeration seems to be a weak spillover variable for firm's propensity to trade. Firms with higher absorptive capacity can take advantage of information flow from trading firms to either increase their propensity to trade. On the opposite, an increase in the technological distance decreases spillovers between trading and non-trading firms.

## 3.7 Conclusions

This paper has estimated the productivity feedback from trade participation using a methodology that separates firm-specific unobserved heterogeneity from productive efficiency. Ignoring firm-specific unobserved heterogeneity such as demand shock will lead to overestimation of the impact of trade on productivity and worse compounds product with process innovation. It is therefore imperative to understand the productivity feedback from trade participation both for economic theory and policy intervention.

In so doing, this paper has applied a new estimation technique to analyse productivity feedback from trade. Two additional robustness checks were undertaken to address concerns of endogeneity and simultaneity associated with the preferred technique. The general picture indicates trade participation either by export only or import only statistically improved productive efficiency. In addition, there are substantial differences across sectors. Most importantly, there is a non-linear relationship between trade experience and learning.

The second part of the paper has examined potential knowledge spillovers from trading firms to non-trading firms through their decision to trade. Firms' agglomeration, technology distance and firm's absorptive capacity were analysed as possible mechanisms of the spillover channels. Agglomeration, - measured by the ratio of trading firms to all firms in a location - has a weak effect on the probability to trade internationally.

An increase in the technological distance between trading and non-trading firms has a negative and significant effect on the decision to trade. As expected, the proxy measure of firms' absorptive capacity has a positive and significant effect on propensity to trade. Moreover, the null hypothesis that the two proxies are the same is rejected. Data limitations do not permit to further breakdown the analysis at intra-industry variation. The paper ends by calling for more data in this direction to aid appropriate evaluations of trade and industry policies in developing countries.

# Appendix A: A Complex Model of Production Function

Table 3.15: Complex Production Function to Perform Chow Test

| Variable | Frontier | Usigma |
|---|---|---|
| $Capital_{food}$ | -0.0325 | |
| | (0.0650) | |
| $Labour_{food}$ | 0.0745 | |
| | (0.0476) | |
| $Materials_{food}$ | 0.922*** | |
| | (0.0165) | |
| $Capital_{textile}$ | 0.0733** | |
| | (0.0335) | |
| $Labour_{textile}$ | 0.238*** | |
| | (0.0376) | |
| $Materials_{textile}$ | 0.617*** | |
| | (0.0156) | |
| $Capital_{wood}$ | 0.00685 | |
| | (0.0660) | |
| $Labour_{wood}$ | 0.124** | |
| | (0.0499) | |
| $Materials_{wood}$ | 0.630*** | |
| | (0.0186) | |
| $Capital_{metal}$ | -0.0195 | |
| | (0.0657) | |
| $Labour_{metal}$ | 0.0386 | |
| | (0.0637) | |
| $Materials_{metal}$ | 0.725*** | |
| | (0.0159) | |
| Workers' Age | | 0.0266*** |
| | | (0.00251) |
| Tenure | | -0.0559*** |
| | | (0.00351) |
| Constant | | -1.567*** |
| | | (0.0737) |
| Observations | 1,711 | 1,711 |
| Number of firms | 224 | 224 |

Standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$
Equation includes sector dummies interacted with year dummies.

## Appendix B: Application of Greene True Fixed Effects

This section applies Greene's true-fixed effects methodology to estimate the impact of trade on productive efficiency as explained under Section 3.3. This serves as robustness check to the pairwise difference estimator employed in the main text. For this purpose, I replicate Tables 3.10 and 3.11 into Tables 3.16 and 3.17 respectively.

The true-fixed effects model ought to be interpreted cautiously for two main reason. The first regards the presence of incidental parameter problems already explained in Chapter 2 of the thesis. Secondly, the maximum likelihood dummy variable (MLDV) estimation methodology utilised by the true-fixed effects requires an estimation of a separate for each unit of observation. This means, the presence of firm-specific intercepts makes estimation of the model quiet demanding. Hence, when the number of observations are few, adding additional variables makes it difficult to compute the Hessian matrix.

With just 234 observations and 40 firms, the textile sector did not converge in the replication of Table 3.11 using Greene's true-fixed effects methodology. For this reason, the textile sector is excluded from Table 3.17.

With the exception of few cases, most of the results obtained under maximum likelihood dummy variable estimator confirms those obtained under the pairwise difference estimator. For instance, Table 3.16 reports the same direction of significance for worker's age and tenure in all sectors. For all sectors, the lag of two-way trader was not significant. The U-shaped between two-way trade and efficiency is confirmed for food and textiles sectors, while the inverted U-shaped is also confirmed for wood and metal sectors.

Likewise, results in Table 3.17 confirms the general tendencies of those in Table 3.11. The relatively high number of observations for the pooled regression, with respect to regressions for separate sectors, makes it viable to compare results obtained under pooled data for reasons outlined above. Interestingly, results obtained under the pooled data confirms exactly those obtained with the pairwise difference estimator. The lag status of export is confirmed to reduce inefficiency, same as the U-shaped relationship between export experience and efficiency is also confirmed. Lag import status reduces inefficiency, while import experience is not significant in the the first-order polynomial.

Using productive efficiency from the pooled data, I replicate the spillover analysis reported in Table 3.14. Noting that the Chow test in Table 3.6 reject efficiency from a pooled data, it is not surprising that there are few differences between Tables 3.14 and 3.18. With focus on the preferred estimator in column (4), it can be noticed that, the agglomeration variable is statically significant in Table 3.18 at 10% significance level, while it was not significant in column (4) of Table 3.14, yet positive.

Technological distance and absorptive capacity report the same sign of significance. The other control variables have the same significance sign as those reported in Table 3.14 in the main text. The main difference regards the coefficient of technical efficiency. While the variable was negative and not significant in the main text, it was negative and significant in Table 3.18.

Table 3.16: Effect of Two-way Activities on Productive Efficiency (Greene's TFE)

| Variables | Food | Textiles | Wood | Metals | All Sectors |
|---|---|---|---|---|---|
| ***Marginal Effects (Frontier)*** | | | | | |
| Log Capital | 0.00670 | 0.0408 | 0.0362 | 0.179** | 0.0628 |
| | (0.0128) | (0.0778) | (0.101) | (0.0820) | (0.0424) |
| Log Labour | 0.0837** | 0.236*** | 0.0637 | -0.0322 | 0.135*** |
| | (0.0335) | (0.0520) | (0.0497) | (0.0858) | (0.0267) |
| Log Raw Materials | 0.837*** | 0.623*** | 0.721*** | 0.645*** | 0.677*** |
| | (0.00377) | (0.0247) | (0.0209) | (0.0249) | (0.0122) |
| ***Determinants of Inefficiency*** | | | | | |
| Workers' Age | 0.0826*** | 0.175 | 0.301*** | 0.0466** | 0.274*** |
| | (0.0123) | (0.117) | (0.0659) | (0.0208) | (0.0466) |
| Tenure | -0.171*** | -0.305 | -0.282*** | -0.0722* | -0.273*** |
| | (0.0197) | (0.187) | (0.0693) | (0.0382) | (0.0538) |
| Lag Two-way Status | 0.320 | -1.641 | 2.798 | 0.628 | 0.691 |
| | (0.515) | (1.639) | (1.901) | (0.628) | (0.483) |
| Years in Two-way | 0.560*** | 3.707 | -4.455*** | -1.596*** | 0.0903 |
| | (0.213) | (2.502) | (1.628) | (0.267) | (0.380) |
| Years in Two-way Squared | -0.0871*** | -0.832* | 0.797*** | 0.208*** | 0.0382 |
| | (0.0330) | (0.464) | (0.236) | (0.0450) | (0.0575) |
| Constant | -4.013*** | -9.144*** | -12.82*** | -2.835*** | -12.25*** |
| | (0.393) | (3.395) | (2.747) | (0.482) | (1.933) |
| ***Estimated Technical Efficiency*** | | | | | |
| Mean | 0.834 | 0.933 | 0.894 | 0.796 | 0.911 |
| SD | 0.170 | 0.074 | 0.157 | 0.179 | 0.104 |
| Min | 0.209 | 0.572 | 0.112 | 0.217 | 0.172 |
| Max | 1.000 | 0.996 | 0.999 | 1.000 | 0.999 |
| ***Diagnostics and Tests*** | | | | | |
| Scale Elasticity | 0.928 | 0.899 | 0.821 | 0.792 | 0.875 |
| P-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald Test - Z variables | 86.990 | 6.860 | 35.190 | 57.360 | 38.410 |
| P-value | 0.000 | 0.231 | 0.000 | 0.000 | 0.000 |
| Log Likelihood | -135.615 | -21.090 | 1.857 | 91.522 | -21.575 |
| Observations | 270 | 234 | 329 | 264 | 1,097 |
| Number of firms | 48 | 40 | 55 | 45 | 188 |
| Year Dummies | YES | YES | YES | YES | YES |

Standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table 3.17: Effect of Trading Activities on Productive Efficiency (Greene's TFE)

| Variables | Food | Wood | Metals | All Sectors |
|---|---|---|---|---|
| ***Marginal Effects (Frontier)*** | | | | |
| Log Capital | 0.0522 | 0.0136 | 0.134 | 0.0580 |
| | (0.0597) | (0.111) | (0.0849) | (0.0402) |
| Log Labour | 0.0522 | 0.0425 | 0.00454 | 0.123*** |
| | (0.0404) | (0.0600) | (0.0740) | (0.0266) |
| Log Raw Materials | 0.841*** | 0.733*** | 0.667*** | 0.683*** |
| | (0.0253) | (0.0258) | (0.0230) | (0.0119) |
| ***Determinants of Inefficiency*** | | | | |
| Workers' Age | 0.232*** | 0.0662*** | 0.0669*** | 0.331*** |
| | (0.0495) | (0.0168) | (0.0256) | (0.0593) |
| Tenure | -0.484*** | -0.103*** | -0.0999** | -0.367*** |
| | (0.169) | (0.0263) | (0.0425) | (0.0773) |
| Lag Exporters Only | 1.884 | -0.566 | -0.417 | -1.529* |
| | (2.028) | (0.409) | (0.626) | (0.794) |
| Years in Export Only | 1.230 | 0.448*** | 0.602* | 1.529*** |
| | (2.020) | (0.167) | (0.316) | (0.420) |
| Years in Export Only Sqd | -0.397 | -0.0630*** | -0.0935* | -0.211*** |
| | (0.458) | (0.0166) | (0.0545) | (0.0666) |
| Lag Import Only | -0.0203 | 0.140 | -0.386 | -1.600** |
| | (0.599) | (0.281) | (0.239) | (0.689) |
| Years in Import | 1.795* | -0.418*** | 0.551*** | -0.215 |
| | (1.050) | (0.118) | (0.168) | (0.317) |
| Years in Import Squared | -0.404* | 0.0291** | -0.0506*** | 0.0589* |
| | (0.238) | (0.0142) | (0.0162) | (0.0328) |
| Lag Two-way Traders | -1.310 | -0.177 | 12.16** | -0.250 |
| | (1.864) | (0.461) | (5.632) | (0.802) |
| Years in Two-way | -0.609 | -0.127 | -0.535*** | -0.320 |
| | (1.234) | (0.175) | (3.404) | (0.504) |
| Years in Two-way Squared | 0.126 | 0.0484 | 1.105*** | 0.102 |
| | (0.185) | (0.0337) | (0.377) | (0.0767) |
| Constant | -10.00*** | -2.723*** | -4.344*** | -14.02*** |
| | (1.800) | (0.446) | (0.731) | (2.332) |
| ***Estimated Technical Efficiency*** | | | | |
| Mean | 0.920 | 0.760 | 0.790 | 0.928 |
| SD | 0.119 | 0.221 | 0.168 | 0.110 |
| Min | 0.270 | 0.100 | 0.219 | 0.135 |
| Max | 1.000 | 1.000 | 1.000 | 1.000 |
| ***Diagnostics and Tests*** | | | | |
| Scale Elasticity | 0.95 | 0.70 | 0.81 | 0.86 |
| P-value | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald Test - Z variables | 26.16 | 122.54 | 38.63 | 45.86 |
| P-value | 0.006 | 0.000 | 0.000 | 0.000 |
| Log Likelihood | 109.926 | 49.836 | 69.215 | 4.456 |
| Observations | 270 | 329 | 264 | 1,097 |
| Number of firms | 48 | 55 | 45 | 188 |
| Year Dummies | YES | YES | YES | YES |

Standard errors in parentheses $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Considering that the coefficient of productive efficiency computed from true-fixed effects had the same tendency as that from (PDE) in a similar exercise in Chapter 2, there is a high a probability that the use of pooled data result may account for the differences accounted here. All in all, the robustness check confirms result obtained with the pairwise difference estimator.

Table 3.18: Firms Propensity to Trade (Greene's True Fixed Effects)

| VARIABLES | Pooled (1) | Pooled Logit (2) | RE Logit (3) | Dynamic Logit (4) |
|---|---|---|---|---|
| Ratio of Traders to all Firms (By city) | 3.894*** | 2.881 | 7.668*** | 3.502* |
| | (1.276) | (1.846) | (2.490) | (1.956) |
| Technology Distance | -0.357* | -0.787** | -0.526 | -1.164** |
| | (0.215) | (0.314) | (0.582) | (0.510) |
| Absorptive Capacity | 0.336 | 0.723* | 0.587 | 1.284** |
| | (0.230) | (0.369) | (0.659) | (0.604) |
| ln(Wage per Employee) | | 0.113 | 0.166 | 0.00574 |
| | | (0.102) | (0.194) | (0.154) |
| Firm age | | -0.0193 | -0.0364 | -0.0202 |
| | | (0.0129) | (0.0285) | (0.0154) |
| ln(Firm Size) | | 0.681*** | 1.724*** | 0.541*** |
| | | (0.175) | (0.294) | (0.186) |
| Any Foreign Ownership (Dummy) | | 0.0765 | 0.720 | 0.148 |
| | | (0.452) | (0.874) | (0.453) |
| Technical Efficiency | | -2.571 | -1.388 | -6.993*** |
| | | (1.739) | (3.051) | (2.487) |
| Constant | -2.219*** | -2.623 | -10.87** | 0.512 |
| | (0.714) | (2.411) | (4.501) | (3.367) |
| Observations | 848 | 751 | 751 | 748 |
| $PseudoR^2$ | 0.0722 | 0.192 | | |
| Test: $\gamma_2 = \gamma_3$ (P-Value) | 0.109 | 0.025 | 0.361 | 0.026 |
| Industry FE | YES | YES | YES | YES |
| Year FE | No | YES | YES | YES |

Robust standard errors in parentheses clustered at firm-level $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

# Chapter 4

# Markups, Markets Imperfections, and Trade Openness: Evidence from Ghana


## Abstract

This paper examines the impact of trade openness on domestic competition measured by markups, degree of monopsony power and market imperfection in product and labour market. I use firm-level production data to measure markups and market imperfection parameters based on price-cost margins. In the period 1992-2002 showed that median markups on materials reduced by 18%, while those on labour increased by 13%. To draw causal inference, the paper uses Ghana's membership to the World Trade Organisation as an identification strategy in a difference-in-difference estimator to assess the impact of trade openness on market power. Results show firms operating in highly protected sectors have experience a decrease in market power in the product market partly compensated by an increase in their monopsony power in the labour market. The study implies that, firms with monopsony power are likely to compress wages to offset loss of market power on the product market due to trade liberalisation reform, undermining the gains from trade.



***Keywords :*** Markups, Market Imperfections, Trade Openness, Africa, Ghana
***JEL Classification :*** F13, L11, O14, O24

## 4.1 Introduction

Trade liberalization has the potential to boost economic performance in the domestic market through enlarged markets and increased competition. In new-trade theory, increased competition in the domestic market as a result of trade liberalization can lead to a reduction of market power, thereby forcing firms to expand outputs while decreasing their marginal cost (Helpman and Krugman, 1985). Melitz (2003) deduced that trade openness can trigger within-industry resource reallocation causing the least productive firms to exit the market.

Whether the potential of trade openness to increase competition and decrease market power has actually occurred is an empirical question. Many developing countries – including Ghana – undertook massive liberalization policies in the late 1980s and 1990s under the Structural Adjustment Programme. Previous empirical papers in the aftermath of trade reforms in developing countries have focused almost exclusively on the impact of trade on firm productivity (see Pavcnik (2002) on Chile; Amiti and Konings (2007) on Indonesia; Topalova and Khandelwal (2011) on India). Besides the focus on firm productivity a common feature is the focus on Asian and Latin America countries, with the exception of Harrison (1994), leaving one to wonder whether results apply to other developing regions as well.

This paper assesses the impact of trade openness on product and labour markets in Ghana. Assuming product and labour markets were in perfect competition, prices would be equal to marginal costs. However, perfect competition is not the norm and market distortions are prevalent. In particular, industry protection policies pursued over the decades 1950s-1970s in African countries made it possible for inefficient firms to acquire various degrees of market power. In such scenarios, firms do not even need to engage in sophisticated strategies such as product differentiation to have substantive market power.

The general research question of the paper is to ascertain whether trade openness has exerted downward pressure on firm level market power. In particular, does the magnitude of impact differ for product and labour markets? What were the dynamics of market power during the reform period? The role of productivity and other firm level factors in market power will also be assessed.

The paper is related to two strands of the economic literature. First, the paper adopts two recent approaches (De Loecker and Warzynski, 2012; Dobbelaere and Mairesse, 2013) that rely on Hall (1986, 1988) relation between marginal cost and price to derive market power and market distortions. The underlying theoretical framework permits to define firm-level measures of market power. Based on the price-cost relations, I derived markups on materials and labour, as well as the degree of monopsony power a firm holds in the labour market conditional that it is a monopsonist.

Second, the price-cost margins a là Hall (1986, 1988), requires an estimation of production function to measure markups. Standard approaches to estimate production function exhibit biases when factors such as demand shocks, and quality are confounded in productivity estimates (Foster et al., 2008; De Loecker, 2011). Following De Loecker et al. (2016), the paper amends this shortcoming by including input price bias in the production function estimation.

The main results document presence of market imperfections particularly on the labour market. On average, market power on the labour market exceeds that of product market by approximately 73 percent. Dividing market imperfections into different regimes by comparing differences between markups on the product and labour market, I find the distribution of the cases to be evenly split. I also find cases of switching of regimes by firms throughout the sample period. In addition, while markups seem to be reducing on the product market over time, I find the reverse on markups on labour. I also find trade openness to reduce market power on average with distinct effects on product and labour markets.

The remainder of the paper is organised as follows. Section 4.2 discusses trade policy in Ghana from the independence era to liberalisation policies in the 1990s. The section also discusses the sources of data utilised for the analysis. Section 4.3 presents the theoretical framework underlying the definition and derivation of the main variables of market power. Section 4.4 presents estimation methods of the production function addressing the input price bias and other well known biases in the literature. Section 4.5 presents and discusses results on market power and market distortions outlined in the previous sections. Section 4.6 analyses the impact of trade openness on market power through a quasi-natural experiment. Section 4.7 concludes and draws some policy implications.

## 4.2 Institutional Background and Data

In this section, I first describe an overview of trade policy in Ghana from the 1950s and liberalization reforms in the 1980s. Special emphasis is given to the main policy instrument of protection – tariffs – and its evolution during the reform years. Subsection 4.2.2 describes the origins and sources datasets used for the analysis. Both discussions on trade policies and data sources are kept brief.

### 4.2.1 Trade Policy and Liberalization in Ghana

Ghana's trade policy in the aftermath of independence can be divided into two main phases. The first phase comprises a set of protection strategies implemented from 1957 to 1983, while the second phase commenced in 1983. Although Ghana had no trade restriction policies in the later stages of the colonial era, in the early years of independence, thus 1951 – 1960, there were several debates on whether free market policies or a central-control economy suited the development ambitions of newly independent countries. These debates had its effect on subsequent economic policies in developing countries (Laryea and Akuoni, 2012).

On the presumption of insufficient savings from the private sector to spur job creation, the government established state enterprises in the 1960s in its quest for rapid industrialization. Parallel to state enterprises, policy-makers in Ghana, argued that, 'infant' domestic firms ought to be protected against imports from firms in developed countries. This led to import substitution strategy during the 1960s and 70s, of which Ghana was no exception. Irrespective of particular details of actions by successive governments, the main policy instruments applied under the import substitution strategy were: quantity controls and import quota; tariffs; and exchange rate controls.[1]

The fall in commodity prices (especially cocoa for Ghana) and the oil shocks during the 1970s exposed the limitations of the import substitution strategy, prompting a series of economic and political crises from 1970 to 1981.[2] A turning point occurred in 1983 when the then government changed policy direction in response to the economic crises. The government initiated the Economic Recovery Programme (ERP) and the Structural Adjustments Programme (SAP) under the guidance of the International Monetary Fund (IMF) and World Bank. The first phase of the reform initially focused on management of the macroeconomic environment as well as reducing balance of payment imbalances with mild trade liberalization. Appendix A provides brief overview on GDP growth rate, inflation, and evolution of employment to compliment the analysis of the paper.

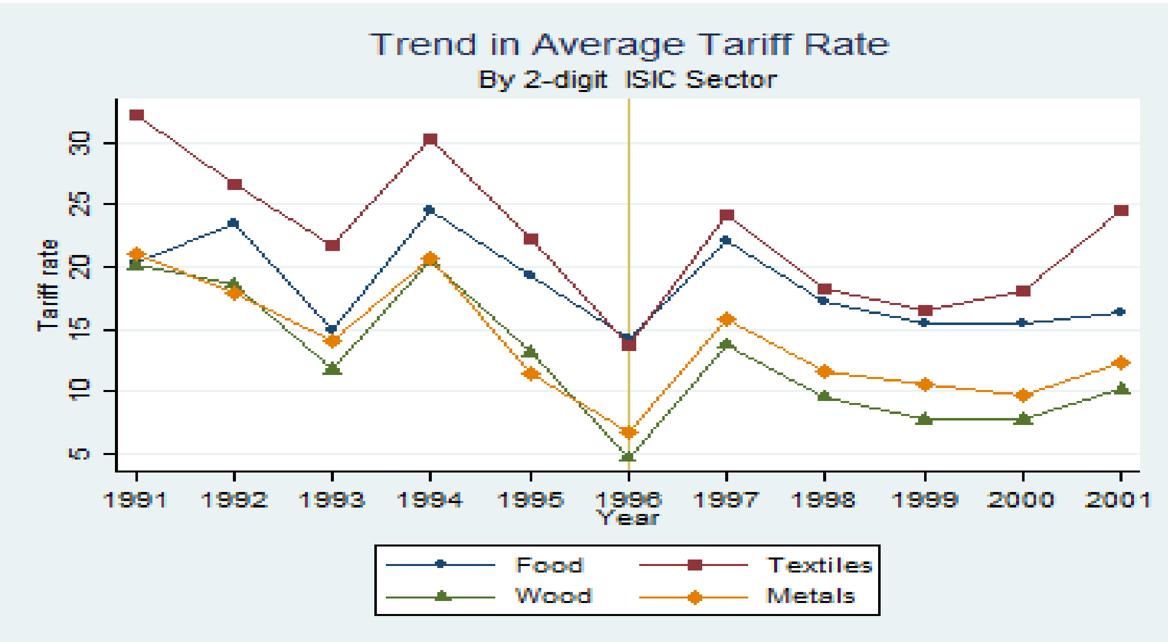



Figure 4.1: Trend in Output Tariff, 1991-2001

Trade openness took a major turn in the 1990s with the abolition of import quotas and removal of exchange rate controls. However, the reform of the tariff structure was prolonged with various revisions throughout the 1990s. Though tariffs were reduced from 1991, the introduction of import sales tax in 1994 contributed to a rise in the tariff rate. From Figure (4.1), it can be observed that though average tariffs went down between 1991 and 2001, it encountered occasional increases according to specific policies during the period.[3] In its effort to deepen trade liberalization, Ghana signed the WTO agreement in 1995. It can be observed

[1]For detail description of policy actions, see Killick (2010).
[2]Ghana had 7 Heads of State during the crises period with an average of 1.42 years in office.
[3]Detail information on the sources of data is given in the next subsection.

from Figure (4.1), that a year after signing the WTO agreement Ghana recorded its lowest tariffs rate during the 1990-2000 decade.[4]

### 4.2.2 Data

As part of the Structural Adjustment Programme, the World Bank launched the Regional Programme on Enterprise Development (RPED) with the aim of collecting manufacturing firm-level survey data in many African countries including Ghana. At the end of RPED in 1994, the University of Oxford, University of Ghana, and Ghana Statistical Service collectively launched the Ghana Manufacturing Enterprise Survey (GMES) from 1995 to 2003 which served as a continuity to RPED . The dataset is a combination of the two surveys, forming a twelve year panel covering 1990-2002. The dataset is freely available through the Centre for the Study of African Economies (CSAE), University of Oxford.

Table 4.1: Summary Statistics

| | Food | | Textiles | | Wood | | Metals | |
|---|---|---|---|---|---|---|---|---|
| | Mean | S.D | Mean | S.D | Mean | S.D | Mean | S.D |
| *Production Function Variables* | | | | | | | | |
| Log (Output) | 17.78 | 2.569 | 15.64 | 2.851 | 17.38 | 2.427 | 17.67 | 2.027 |
| Log (Capital) | 16.62 | 3.191 | 14.46 | 2.965 | 16.79 | 3.017 | 16.40 | 2.711 |
| Log (Employment) | 3.094 | 1.475 | 2.571 | 1.317 | 3.706 | 1.399 | 3.218 | 1.282 |
| Log (Raw Materials) | 17.10 | 2.604 | 14.84 | 2.796 | 16.32 | 2.592 | 16.79 | 2.567 |
| *Firm Characteristics* | | | | | | | | |
| Firm Age | 19.70 | 13.743 | 17.50 | 10.718 | 18.11 | 12.376 | 16.86 | 11.190 |
| Skill Ratio | 0.47 | 0.552 | 0.30 | 0.338 | 0.22 | 0.182 | 0.44 | 0.923 |
| Foreign Ownership (proportion) | 0.19 | 0.393 | 0.11 | 0.307 | 0.22 | 0.416 | 0.25 | 0.433 |
| *Trade Reform Variables* | | | | | | | | |
| Outputs Tariffs | 18.52 | 6.428 | 22.88 | 5.876 | 12.80 | 5.178 | 14.20 | 5.067 |
| Import Penetration | 0.864 | 0.383 | 0.727 | 0.120 | 0.349 | 0.372 | 0.691 | 0.127 |
| Number of Firms | 63 | | 60 | | 76 | | 63 | |
| Number of Observations | 484 | | 447 | | 552 | | 472 | |

Given that the core of trade reform policies occurred during the survey years, one key advantage of the dataset is that, it permits to study the responses of firms to trade liberalization policies. In addition to the survey data, data on tariffs are provided by CEPII research centre[5]. In addition, the World Bank database on trade, production and protection, provides information on industry output level and indexes at 3-digit ISIC level, as well as industry level imports and exports. Using those information, I computed import penetration rate for each sector. Table (4.1) presents summary statistics of key relevant information for

[4] Successive governments from the 2000s have depend trade liberalization policies. In particular, the policy document, Ghana Poverty Reduction Strategy (GPRS II), makes an explicit aim to reduce poverty through export promotion. Other policies include promotion of Foreign Direct Investment (FDI). The paper do not examine post-millennium period due to the sample period of the data.

[5] www.cepii.fr

the analysis.

## 4.3 Theoretical framework

The key point of the analysis in this paper is to evaluate the effect of trade openness on competition. In an institutional environment as described in subsection 4.1, market imperfections and distortions are prevalent and expected. On the other hand, trade liberalization has the potential to increase competition and improve the allocative efficiency of the economy. Indeed, the theoretical model of Melitz (2003) predicts that trade induces competition by raising the minimum productivity survival threshold; consequently, resources of exiting firms will be reallocated towards more productive firms.

The prospect of trade liberalization to induce competition becomes an empirical question that needs to be verified. Previous empirical studies in developing economies have focused on Latin American and Asian countries (Pavcnik, 2002; Amiti and Konings, 2007; Topalova and Khandelwal, 2011) with the exception of Harrison (1994) that studies Cote d'Ivoire. While trade and productivity linkages dominated the past literature in the evaluation of the effect of trade openness, this paper takes a different approach by analysing firms' price-cost margins. Other papers that precedes the present work includes; Brandt et al. (2012) on China, De Loecker et al. (2014) on Belgium and De Loecker et al. (2016) on India.

In view of the above, this section provides a detailed description in the computation of markups and market imperfections parameters using firm-level production data. The theoretical framework is an extension of Hall (1988)'s seminal work on price-cost margins.

### 4.3.1 Markups

In this subsection, I follow the work of De Loecker and Warzynski (2012) to recover firm-level markup. A firm $i$ produces output at time $t$ according to the following production function

$$Q_{it} = F_{it}(L_{it}, M_{it}, K_{it}, \omega_{it}), \tag{4.1}$$

where $L_{it}$, $M_{it}$, and $K_{it}$ represents a vector of labour, intermediate materials, and capital inputs respectively; while $\omega_{it}$ denotes the firm-specific productivity term. Labour and materials are assumed to be variable inputs that the firm can adjust freely while capital is a dynamic input that faces adjustments costs. Two fundamental assumptions are imposed on equation (4.1). First, the production function $F(\cdot)$ is continuous and twice differentiable with respect to its variable inputs. This assumption implies that we can collect the variable inputs into one vector, $V = \{L, M\}$, without loss of generality.

Second, producers active in the market are cost minimizers. The cost-minimization assumption implies that firms will tend to any of their variable input to minimize cost. Hence, the associated Lagrangian function is given by

$$\mathcal{L}(V_{it}, K_{it}, \lambda_{it}) = \sum_{v=1}^{V} P_{it}^{v} V_{it}^{v} + r_{it} K_{it} + \lambda_{it}(Q_{it} - F(\cdot)), \tag{4.2}$$

where $P_{it}^{v}$ and $r_{it}$ represents price of variable inputs and capital respectively. The first-order condition for any variable input is given by

$$\frac{\partial \mathcal{L}_{it}}{\partial V_{it}^{v}} = P_{it}^{v} - \lambda_{it} \frac{\partial Q(\cdot)}{\partial V_{it}^{v}} = 0, \tag{4.3}$$

whereby $\lambda_{it}$ represents the marginal cost of production at a given level of output, since $\frac{\partial L_{it}}{\partial Q_{it}} = \lambda_{it}$. Rearranging terms in equation (4.3) and multiplying both sides by $\frac{V_{it}}{Q_{it}}$, yields the following expression:

$$\frac{\partial Q_{it(\cdot)}}{\partial V_{it}^{v}} \frac{V_{it}^{v}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^{v} V_{it}^{v}}{Q_{it}}. \tag{4.4}$$

The left-hand side of equation (4.4) represents the elasticity of output with respect to variable input, thus, $\theta^{v} = \frac{\partial Q_{it(\cdot)}}{\partial V_{it}^{v}} \frac{V_{it}}{Q_{it}}$. Therefore, optimal input demand is achieved when the output elasticity of a variable input is set equal to the right-hand side of equation (4.4).

By defining markup $\mu_{it}$ as the ratio of price to marginal cost, i.e., $\mu_{it} = \frac{P_{it}}{\lambda_{it}}$; equation (4.4) can be rearranged to derive an expression for markup given as

$$\mu_{it} = \theta_{it}^{v} \left( \frac{P_{it} Q_{it}}{P_{it}^{v} V_{it}^{v}} \right) = \frac{\theta_{it}^{v}}{\alpha_{it}^{v}}, \tag{4.5}$$

where $\theta_{it}^{v}$ is the output elasticity of any variable input and $\alpha_{it}^{v}$ is the share of expenditure of variable input $v$ in total revenue. The expression in equation (4.5) can be expressed explicitly in terms of each variable inputs, materials and labour respectively as;

$$\mu_{it}^{m} = \frac{\theta_{it}^{m}}{\alpha_{it}^{m}} \tag{4.6}$$

$$\mu_{it}^{l} = \frac{\theta_{it}^{l}}{\alpha_{it}^{l}}. \tag{4.7}$$

### 4.3.2 Market Imperfections

The basic intuition behind the derivation of markups in equation (4.5) shows that a competitive firm will increase its use of a variable input until its revenue share equals the output elasticity. Whenever a firm does not increase its variable input use until equality holds but rather increases its output price, such behaviour signals that the firm holds market power in the output market. The presence of market power is the first form of market distortions and thus provides the basis to derive other forms of distortions, which is referred generally as market imperfections.

Notice that the first-order-condition for cost minimization in equation (4.4) can be rewritten as

$$\theta^v_{it} = \mu_{it}\frac{P^v_{it}V^v_{it}}{P_{it}Q_{it}} = \mu_{it}(\alpha^v_{it}). \tag{4.8}$$

In a fully competitive environment where firms act as price takers in both input and output markets, the ratio of price to marginal cost would be unity, i.e., $\mu_{it} = \frac{P_{it}}{\lambda_{it}} = 1$. In that case, the first-order-condition would have been $\theta^v_{it} = (\alpha^v_{it})$.

From the first-order condition in equation (4.8), perfect competition in the product market is unlikely, even in the absence of institutional environments as those explained in subsection 4.2.1. This is because, firms can engage in strategies such as product differentiation, which can permit to obtain positive markups in the product market. It is therefore imperative to assume that firms operate under imperfect competition in the product market. On the other hand, the labour market can result in three scenarios according to specific conditions prevailing in the market. Dobbelaere and Mairesse (2013) define these three possible settings for the labour market (LMS) as: perfect competition (PR), efficient bargaining (EB), and monopsony (MO).[6]

First, for the labour market setting (LMS) to be in perfect competition – thus LMS = PR – implies $\mu^l_{it} = 1$ . Second, the efficient bargaining (EB) outcome, – thus LMS = EB – is a result of Nash bargaining solution, whereby firms and workers bargain over wages and competitive employment level. Third, for the labour market setting to be in monopsony – thus LMS = MO – depends on firms degree of monopsony power.

Hence, the labour market setting is characterised by:

$$\begin{aligned}
\theta^l_{it} &= \mu^l_{it}\alpha^l_{it} \quad \text{if LMS = PR} \\
&= \mu^l_{it}\alpha^l_{it} - \mu^l_{it}\kappa_{it}[1 - \alpha^l_{it} - \alpha^m_{it}] \quad \text{if LMS = EB} \\
&= \mu^l_{it}\alpha^l_{it}\left(1 + \frac{1}{(\varepsilon^l_w)_{it}}\right) \quad \text{if LMS = MO}
\end{aligned}$$

where $\kappa_{it} = \frac{\varphi_{it}}{1-\varphi_{it}}$, represents the relative extent of rent sharing, with $\varphi \in [0, 1]$ being the absolute extent of rent sharing, resulting from the efficient bargaining solution.

From the labour market setting outlined above, the efficient bargaining and monopsony settings require further comment, with particular emphasis on the monopsony case. In efficient bargaining, firms and risk-neutral workers would bargain over wages and employment level leading to an efficient bargaining Nash equilibrium, which is characterized by rent sharing between firms and workers. In this scenario, Dobbelaere and Mairesse (2013) predicted that competition among employers will result in a single market wage whereby a small cut in wage by an employer will result in immediate resignation of all workers. On the other hand, factors such as absence of perfect information on alternative job opportunities, search, and moving costs can give a significant market power for firms over their workers. Such market conditions can readily give rise to situation where a firm can become a monopsony, which we explore below.

[6] The monopsony case is treated in this paper. The interested reader is referred to Dobbelaere and Mairesse (2013) for full discussions on remaining cases.

A monopsonist firm faces a labour supply curve $L_{it}(w_{it})$, which is increasing in wage $w_{it}$. Short-run profit maximization taking the labour supply curve as given is

$$\max_{L_{it},M_{it}} \pi(w_{it}, L_{it}, M_{it}) = R_{it}(L_{it}, M_{it}) - w_{it}(L_{it})L_{it} - p^m_{it}M_{it}$$

where $R_{it} = P_{it}Q_{it}$ represents total revenues.[7] Maximization with respect to materials yields expression (4.8) with the substitution of the superscript $v$ with $m$. Maximization with respect to labour yield the following first-order condition:

$$w_{it} = \gamma_{it}(R^L_{it}), \tag{4.9}$$

where $R^L_{it}$ represents the marginal revenue of labour while $\gamma_{it} = \frac{(\varepsilon^L_w)_{it}}{1+(\varepsilon^L_w)_{it}}$ measures the degree of monopsony power and $(\varepsilon^L_w)_{it} \in \Re_+$ the wage elasticity of labour supply.

From the first-order condition in equation (4.9), the degree of monopsony power is the key variable needed to empirically evaluate whether a firm holds market power in the labour market. To derive the degree of monopsony power empirically, notice that, equation (4.9) can be expressed in terms of elasticity of output with respect to labour as

$$\theta^l_{it} = \frac{\mu^m_{it}\alpha^l_{it}}{\gamma_{it}}, \tag{4.10}$$

from which follows that the degree of monopsony power can be measured directly from the production data as

$$\gamma_{it} = \frac{\alpha^l_{it}}{\alpha^m_{it}}\frac{\theta^m_{it}}{\theta^l_{it}}. \tag{4.11}$$

Finally, given the assumption of imperfect competition on the product market, we can compute a joint parameter of market imperfection $\psi$ as

$$\psi_{it} = \frac{\theta^m_{it}}{\alpha^m_{it}} - \frac{\theta^l_{it}}{\alpha^l_{it}}. \tag{4.12}$$

Accordingly, the joint parameter of market imperfection can result in three cases depending on the labour market setting. That is,

$$\psi_{it} \begin{cases} > 0 & \text{if LMS} = \text{EB}, \\ = 0 & \text{if LMS} = \text{PR}, \\ < 0 & \text{if LMS} = \text{MO}. \end{cases}$$

The main elements needed to compute markups, joint parameter of market imperfection, and degree of monopsony power are: $\alpha^v$, and $\theta^v$ of the production inputs. While information on inputs expenditure shares are readily computed from firm-level production data, we need to estimate the production function in order to recover output elasticities. The next section

[7]All other notations carry the same meaning as before.

describes the estimation procedure to obtain consistent and unbiased estimate of the output elasticities.

## 4.4 Estimation method

In order to obtain $\theta_{it}^v = \{\theta_{it}^m, \theta_{it}^l\}$, I rewrite equation (4.1) in logs and allow for log-additive measurement error and/or unanticipated shocks as

$$q_{it} = f_{it}(\mathbf{x}_{it}; \boldsymbol{\beta}) + \omega_{it} + \varepsilon_{it} \tag{4.13}$$

where $q_{it}$ is production level for firm $i$ at time $t$, $\mathbf{x}_{it}$ is a vector of inputs, specifically, labour, materials and capital; $\boldsymbol{\beta}$ is the vector of production function coefficients to be estimated; $\omega_{it}$ is firm-specific productivity; and $\varepsilon_{it}$ is idiosyncratic error term. The literature on production function estimation has emphasized potential correlation between unobserved productivity term $\omega_{it}$ and the choice of input, termed as simultaneity and selection biases. Seminal contributions from Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2015) have proposed several solutions to overcome the simultaneity and selection biases.

Consistent estimation of equation (4.13) requires all inputs and output to be in physical quantities. Due to lack of data on quantities, a common practice in the literature is to deflate the variables with industry-level price indexes. The Ghanaian dataset contains *firm-specific* input and output price indexes, thus alleviating the necessity to make additional assumptions on potential deviations between industry-level and firm-level prices.

However, firm-specific prices are subject to factors such as differences in quality of inputs, location of the firm and its market shares. It is therefore essential to avoid picking up price differences in the estimation of the production function to recover output elasticities. Recent development in the production function estimation have emphasised that failure to account for price differences in the estimation process leads to biased estimates of the inputs coefficients (Foster et al., 2008; De Loecker, 2011; De Loecker and Goldberg, 2014). This paper follows a recent approach by De Loecker et al. (2016) to control for, simultaneity, selection, and input price biases.

The estimation specification for equation (4.13) becomes

$$q_{it} = f_{it}(\tilde{\mathbf{x}}_{it}; \boldsymbol{\beta}) + B(\mathbf{w}_{it}, \tilde{\mathbf{x}}_{it}, \boldsymbol{\beta}) + \omega_{it} + \varepsilon_{it} \tag{4.14}$$

where $\tilde{\mathbf{x}}_{it}$ denotes the vector deflated (log) inputs and $\mathbf{w}_{it}$ is a vector of firm-specific prices. In order to obtain consistent estimates of output elasticities, the subsections below outline how the estimation procedure accounts for input price, simultaneity and selection biases.

### 4.4.1 Input Price, Unobserved Productivity, and Selection Biases

#### Input Price Bias

Several factors affect the variation of input price vector in $B(\mathbf{w}_{it}, \tilde{\mathbf{x}}_{it}, \boldsymbol{\beta})$. Verhoogen (2008) argued that the choices of inputs is affected by market conditions in local market as well as the quality of inputs used in the production process. Similarly, output prices may also encompass product quality as producers using high quality inputs are likely to sell for high prices (Kugler and Verhoogen, 2012). Given that input prices are increasing in input quality, De Loecker et al. (2016) suggest to control for input price variation using observables such as output prices, market share, location dummies, and export status, that is,

$$\mathbf{w}_{it} = w_t(p_{it}, ms_{it}, G_i, EXP_{it}). \tag{4.15}$$

Substituting the input price control in $B(\mathbf{w}_{it}, \tilde{\mathbf{x}}_{it}, \boldsymbol{\beta})$ for $\mathbf{w}_{it}$ yields

$$B(\mathbf{w}_{it}, \tilde{\mathbf{x}}_{it}, \boldsymbol{\beta}) = B((p_{it}, ms_{it}, G_i, EXP_{it}) \times \tilde{\mathbf{x}}_{it}^c; \boldsymbol{\beta}, \boldsymbol{\delta}), \tag{4.16}$$

where $\tilde{\mathbf{x}}_{it}^c = \{1, \tilde{\mathbf{x}}_{it}\}$; and $\boldsymbol{\delta}$ is an additional parameter to be estimated together with the production function parameters $\boldsymbol{\beta}$.

#### Unobserved Productivity

The firms' choice of inputs is generally affected by its level of productivity, which is unobserved by the econometrician. To proxy for $\omega_{it}$, the paper follows Levinsohn and Petrin (2003) by using input demand control function. Assume the material demand function is affected by

$$\tilde{m}_{it} = m_t(\omega_{it}, \tilde{k}_{it}, \tilde{l}_{it}, p_{it}, ms_{it}, G_i, EXP_{it}) \tag{4.17}$$

where $p_{it}$ is output prices, $ms_{it}$ represents market shares, $G_i$ stands for location dummies, and $EXP_{it}$ denotes export status. Collecting all state variables in $\mathbf{z}_{it} = \{p_{it}, ms_{it}, G_i, EXP_{it}\}$, with the exception of input expenditures, the monotonicity of $m_t(\cdot)$, allows to invert (4.17) to derive the following control function for productivity

$$\omega_{it} = h_t(\tilde{\mathbf{x}}_{it}, \mathbf{z}_{it}). \tag{4.18}$$

#### Correction for Selection Bias

The last standing bias in (4.14) regards the probability of a firm exiting the market based on its productivity level. Given that the dataset is an unbalanced panel, if a firm's exit is correlated with its productivity, then failure to control for exit will create selection bias in the estimation procedure. To correct for selection bias, I follow Olley and Pakes (1996) and define the following selection rule:

$$\chi_{it} = \begin{cases} 1 \quad \text{(remain)} \quad \text{if} \quad \omega_{it} \geq \bar{\omega}_{it}(\mathbf{s}_{it}) \\ 0 \quad \text{(exit)} \quad \text{if} \quad \omega_{it} < \bar{\omega}_{it}(\mathbf{s}_{it}) \end{cases} \tag{4.19}$$

where $\chi_{it}$ is an indicator function equal to 1 if a firm remain active and 0 otherwise; $\bar{\omega}_{it}$ is the productivity cutoff point; and $\mathbf{s}_{it}$ is a vector of state variables determining the cutoff point. Because the cutoff point $\bar{\omega}_{it}$ is not directly observable – creating an endogeneity problem – I control for it using information available at $t-1$. The conditional probability of selection is given by

$$P_{it} = Pr(\chi_{it} = 1|\mathbf{s}_{it}) = Pr(\omega_{it} \geq \bar{\omega}_{it}(\mathbf{s}_{it})|\mathbf{s}_{it-1}), \tag{4.20}$$

with $\mathbf{s}_{it} = \{\tilde{k}_{it}, a_{it}, \zeta\}$; where $a_{it}$ represents firm age and $\zeta$ denotes time. I therefore estimate the probability of surviving, using probit, as a function of the lags of, firm's capital value, firm age, and time trend. The probit model includes both the 1st and 2nd order polynomials of the variables as well as their interactions.

### 4.4.2 Productivity Process and Moment Conditions

To recover the parameter vectors $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$, firm productivity is assumed to follow a first-order Markov process. The law of motion underlying the Markov process is derived as:

$$\omega_{it} = g(\omega_{it-1}, EXP_{it-1}, P_{it}) + \xi_{it}, \tag{4.21}$$

where $\xi_{it}$ is an idiosyncratic shock, and $EXP_{it-1}$ indicates the export status of a firm. The export status is included in the productivity process to control for market demand conditions in export market, which may differ from domestic market and hence affect the productivity process. In addition, the probability of survival is included in the law of motion to address selection bias as discussed above.

Finally, based on the law of motion expressed in (4.21), plugging the input price control function in (4.16) and the expression for unobserved productivity in (4.18) into the production function in (4.14), yields the following estimation equation

$$q_{it} = \phi_{it} + \varepsilon_{it}, \tag{4.22}$$

where

$$\phi_{it} = f_{it}(\tilde{\mathbf{x}}_{it}; \boldsymbol{\beta}) + B\left((p_{it}, ms_{it}, G_i, EXP_{it}) \times \tilde{\mathbf{x}}^c_{it}; \boldsymbol{\beta}, \boldsymbol{\delta}\right) + \omega_{it}. \tag{4.23}$$

The predicted output in the first stage regression $\hat{\phi}_{it}$ permits to compute productivity $\omega_{it}(\boldsymbol{\beta}, \boldsymbol{\delta})$ as

$$\omega_{it}(\boldsymbol{\beta}, \boldsymbol{\delta}) = \hat{\phi}_{it} - f_{it}(\tilde{\mathbf{x}}_{it}; \boldsymbol{\beta}) - B\left((p_{it}, ms_{it}, G_i, EXP_{it}) \times \tilde{\mathbf{x}}^c_{it}; \boldsymbol{\beta}, \boldsymbol{\delta}\right). \tag{4.24}$$

Likewise, the moment conditions used to estimate the parameters are

$$E(\xi_{it}(\boldsymbol{\beta}, \boldsymbol{\delta})\mathbf{Y}_{it}) = 0, \tag{4.25}$$

where $\mathbf{Y}_{it}$ incorporates lagged materials current capital and labour, as well as their higher order and interaction terms; lagged output prices, lagged market shares and their appropriate interactions (see De Loecker et al. (2016) for further exposition details). Finally, I use a translog specification of the production function represented by $f_{it}(\tilde{\mathbf{x}}_{it}; \boldsymbol{\beta})$ in expression (4.23). The translog expression is given by[8],

$$\begin{aligned} f_{it}(\tilde{\mathbf{x}}_{it}; \boldsymbol{\beta}) = {} & \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_l l_{it}^2 + \beta_k k_{it}^2 + \beta_m m_{it}^2 + \beta_{lk} l_{it} k_{it} \\ & + \beta_{lk} l_{it} k_{it} + \beta_{mk} m_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} \end{aligned}$$

from which we can compute output elasticities of the inputs as;

$$\hat{\theta}_{it}^k = \hat{\beta}_k + 2\hat{\beta}_{kk} k_{it} + \hat{\beta}_{lk} l_{it} + \hat{\beta}_{mk} m_{it} + \hat{\beta}_{lmk} l_{it} m_{it} \tag{4.26}$$

$$\hat{\theta}_{it}^l = \hat{\beta}_l + 2\hat{\beta}_{ll} l_{it} + \hat{\beta}_{lm} m_{it} + \hat{\beta}_{lk} k_{it} + \hat{\beta}_{lmk} m_{it} k_{it} \tag{4.27}$$

$$\hat{\theta}_{it}^m = \hat{\beta}_m + 2\hat{\beta}_{mm} m_{it} + \hat{\beta}_{lm} l_{it} + \hat{\beta}_{mk} k_{it} + \hat{\beta}_{lmk} l_{it} k_{it}. \tag{4.28}$$

## 4.5 Empirical Results

This section presents results from the production function estimation as well as parameters of market imperfections. A separate production function was estimated for each sector in the sample thus allowing technology to vary across sectors.

### 4.5.1 Output Elasticities

Table 4.2 reports results from the production function estimation outlined in the previous section. Each row represents result by sector. Columns (2) - (4) report output elasticity computed using expressions (4.26) - (4.28) for capital, labour, and materials respectively. The last column in the table reports returns to scale for each sector. Panel A reports average output elasticities while panel B reports median output elasticities.

From panel A, the food and wood sector reported the lowest output elasticities for capital input, 0.02 and 0.09 respectively[9]. Another characteristic of the estimation methodology regards the output elasticity of labour, which seems to be small. In the original application of the methodology on India, De Loecker et al. (2016) reported average output elasticities for labour on various sectors within the range 0.09 – 0.25. Therefore, results in Column (3) of

[8] The translog permits output elasticities to vary across firms while such flexibility is unavailable under the Cobb-Douglas specification.

[9] While this is characteristic of the methodology, Collard-Wexler and De Loecker (2016), argued in a related work that the unstable coefficient for capital found in production function estimation is due to measurement error in capital stock. They proposed to instrument capital with lagged investment expenditure in a hybrid IV-Control function. However, due to a lot of missing values on investment, the proposed correction cannot be applied in this dataset.

Table 4.2: Average and Median Output Elasticities, By Sector

| ISIC Rev.2 | Sector | Obs. (1) | Capital ($\hat{\theta}^k_{it}$) (2) | Labour ($\hat{\theta}^l_{it}$) (3) | Materials ($\hat{\theta}^m_{it}$) (4) | Returns to Scale (5) |
|---|---|---|---|---|---|---|
| PANEL A: Average Output Elasticities | | | | | | |
| 31 | Food | 390 | 0.02 | 0.27 | 0.74 | 1.04 |
| | | | [0.26] | [0.36] | [0.21] | [0.23] |
| 32 | Textiles | 364 | 0.16 | 0.18 | 0.78 | 1.12 |
| | | | [0.14] | [0.23] | [0.18] | [0.10] |
| 33 | Wood | 462 | 0.09 | 0.20 | 0.76 | 1.04 |
| | | | [0.17] | [0.19] | [0.14] | [0.24] |
| 38 | Metals | 391 | 0.16 | 0.17 | 0.82 | 1.15 |
| | | | [0.22] | [0.12] | [0.16] | [0.16] |
| PANEL B: Median Output Elasticities | | | | | | |
| 31 | Food | 390 | 0.08 | 0.26 | 0.76 | 1.03 |
| 32 | Textiles | 364 | 0.18 | 0.15 | 0.79 | 1.11 |
| 33 | Wood | 462 | 0.11 | 0.21 | 0.77 | 1.11 |
| 38 | Metals | 391 | 0.21 | 0.17 | 0.84 | 1.16 |

Column (1) refers to number of observations for each production function by sector. Columns (2) - (4) report average (median) estimated output elasticity with respect to each production input for firms in the sector in panel A and (B). In panel A, results in brackets report standard deviations (not standard errors). Column (5) reports returns to scale, which is given by the sum of the average (median) elasticities of the three inputs.

Table 4.2 falls in line with expected outcome. In addition, it can be noted from Column (5) that all sectors report increasing returns to scale.

In order to cross-check whether the average output elasticities are affected by outliers, panel B of Table 4.2 reports median elasticities for all inputs and returns to scale. From the results, there seems not to be substantial differences between mean and the median output elasticities across sectors. A slight increase in the capital output elasticities for food and metal sectors can be noted.

### 4.5.2 Markups and Market Imperfection Parameters

Moving on to the main interest of analysis, Table 4.3 reports the mean and median of markups computed on materials and labour, and the joint parameter of market imperfection. Across all sectors, the mean and median for $\hat{\mu}_{it}^{m}$ are 1.56 and 1.33 respectively, while that of $\hat{\mu}_{it}^{l}$ was 2.74 and 2.09 respectively. Moreover, markups computed on labour appears to be high compared to that of materials almost across all sectors.

Table 4.3: Markups and Market Imperfections, By Sector

| ISIC | | $\hat{\mu}_{it}^{m}$ | | $\hat{\mu}_{it}^{l}$ | | $\hat{\psi}_{it}$ | |
|---|---|---|---|---|---|---|---|
| Rev.2 | Sector | Mean | Median | Mean | Median | Mean | Median |
| 31 | Food | 1.28 | 1.16 | 3.63 | 2.79 | -2.21 | -1.59 |
| 32 | Textiles | 1.45 | 1.27 | 2.55 | 1.85 | -1.06 | -0.38 |
| 33 | Wood | 1.87 | 1.52 | 2.19 | 1.72 | -0.17 | 0.07 |
| 38 | Metals | 1.62 | 1.37 | 2.60 | 2.01 | -1.06 | -0.56 |
| | Average | 1.56 | 1.33 | 2.74 | 2.09 | -1.13 | -0.61 |

Table report mean and median markups computed on materials and labour; as well as the joint parameter of product/labour market imperfection from 1992-2002.

Results in Table 4.3 clearly suggests firms have higher market power in the labour market than they do in the product market. It can be noted that, the food and wood sector reversed positions in terms of highest and lowest value of markups on materials and labour respectively. Based on the results of markups on materials and labour, unsurprisingly, all four sectors reported negative mean values for the joint parameter of market imperfections, $\hat{\psi}_{it}$, while three out of four reported negative median values.

To shed further lights on the composition of the market according to the joint parameter of market imperfection, three possible regimes based on $\psi \gtreqless 0$, provides the starting avenue. The three regimes are: perfect competition (PR) obtained when $\psi = 0$; efficient bargaining (EB) obtained if $\psi > 0$, and monopsony (MO) obtained when $\psi < 0$. To classify firms according to regimes, I compute a 90% confidence interval for $\mu_{it}^{m}$ and $\mu_{it}^{l}$ in order to consider intersections between the two measures of markups rather than their difference based on point estimate.

Table 4.4 presents mean and median markups for each sector in each regime. Using confidence intervals to compute the regimes, the observations are distributed by the following, 36.50% in perfect competition, 3.81% in efficient bargaining, and 59.69% in monopsony. One

Table 4.4: Markups and Market Imperfections Based on Regimes, By Sector

PANEL A: Regime: Perfect Competition (PR)

| | | $\hat{\mu}_{it}^{m}$ | | $\hat{\mu}_{it}^{l}$ | |
|---|---|---|---|---|---|
| | | Mean | Median | Mean | Median |
| 31 | Food | 1.60 | 1.46 | 1.69 | 1.57 |
| 32 | Textiles | 1.54 | 1.34 | 1.53 | 1.28 |
| 33 | Wood | 2.02 | 1.70 | 1.79 | 1.57 |
| 38 | Metals | 1.69 | 1.52 | 1.40 | 1.17 |
| | Average | 1.71 | 1.50 | 1.60 | 1.40 |

PANEL B: Regime: Efficient Bargaining (EB)

| | | $\hat{\mu}_{it}^{m}$ | | $\hat{\mu}_{it}^{l}$ | | $\hat{\psi}_{it}$ | |
|---|---|---|---|---|---|---|---|
| | | Mean | Median | Mean | Median | Mean | Median |
| 31 | Food | 2.64 | 2.64 | 0.70 | 0.70 | 1.95 | 1.95 |
| 32 | Textiles | 1.83 | 1.70 | 1.28 | 0.69 | 1.06 | 0.99 |
| 33 | Wood | 3.86 | 4.04 | 2.48 | 1.66 | 2.81 | 2.37 |
| 38 | Metals | 2.47 | 1.76 | 0.79 | 0.69 | 1.73 | 1.06 |
| | Average | 2.70 | 2.54 | 1.31 | 0.94 | 1.88 | 1.59 |

PANEL C: Regime: Monopsony (MO)

| | | $\hat{\mu}_{it}^{m}$ | | $\hat{\mu}_{it}^{l}$ | | $\hat{\psi}_{it}$ | | $\hat{\gamma}_{it}$ | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean | Median | Mean | Median | Mean | Median | Mean | Median |
| 31 | Food | 1.18 | 1.07 | 4.66 | 4.33 | -3.54 | -3.37 | 0.29 | 0.24 |
| 32 | Textiles | 1.40 | 1.24 | 4.33 | 3.59 | -3.10 | -2.32 | 0.35 | 0.33 |
| 33 | Wood | 1.54 | 1.38 | 4.46 | 3.96 | -3.14 | -2.70 | 0.35 | 0.34 |
| 38 | Metals | 1.53 | 1.29 | 4.27 | 3.73 | -2.95 | -2.38 | 0.36 | 0.38 |
| | Average | 1.41 | 1.25 | 4.43 | 3.90 | -3.18 | -2.69 | 0.34 | 0.32 |

Observations are distributed between regimes as follows: Perfect Competition (PR) 36.50%, Efficient Bargaining (EB) 3.81%, and Monopsony (MO) 59.69%.

can deduce that the Ghanaian manufacturing sector is characterised by majority of firms exercising monopsony power compared to few cases where workers can engage in efficient bargaining of wages with employers.

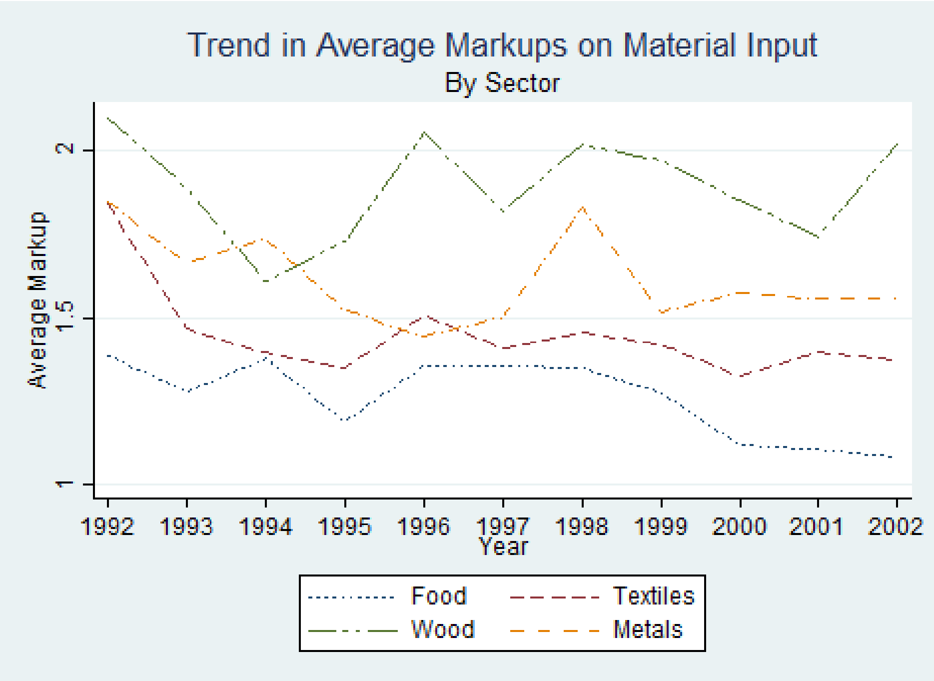
Figures 4.2 and 4.3 present trends in markups to shed more light on yearly variation. In panel (a) of Figure 4.2, three sectors recorded an immediate drop in markup level between 1992 and 1993, while the metal sector extended its drop to 1994. The food sector had the lowest level of markup on materials during the sample period. Despite some increases in the early years, it began to drop remarkably from 1998. Average markups for the food sector decreased by 28% from 1992 to 2002. The textile sector dropped significantly by 26% from 1992 to 1995. Although there was a slight increase afterwards, the yearly variations did not reach pre-reform levels. Over the whole period, average markup for the textile sector shrank by 25%.

The wood and metal sectors recorded some volatility in yearly variations of markup levels. The metal sector variations can be divided into two phases: 1992-1996 and 1997-2002. After dropping significantly in the first period, (despite a slight increase in 1994) average markups started an upward trend with some volatility. Notice that there was a decrease of 22% between 1992 and 1996, whilst the sector recorded a decrease of 15% over the total period. The wood sector was the most volatile. After dropping sharply by 23% between 1992 and 1994, average markup started to increase with the final figure almost close to the initial levels.

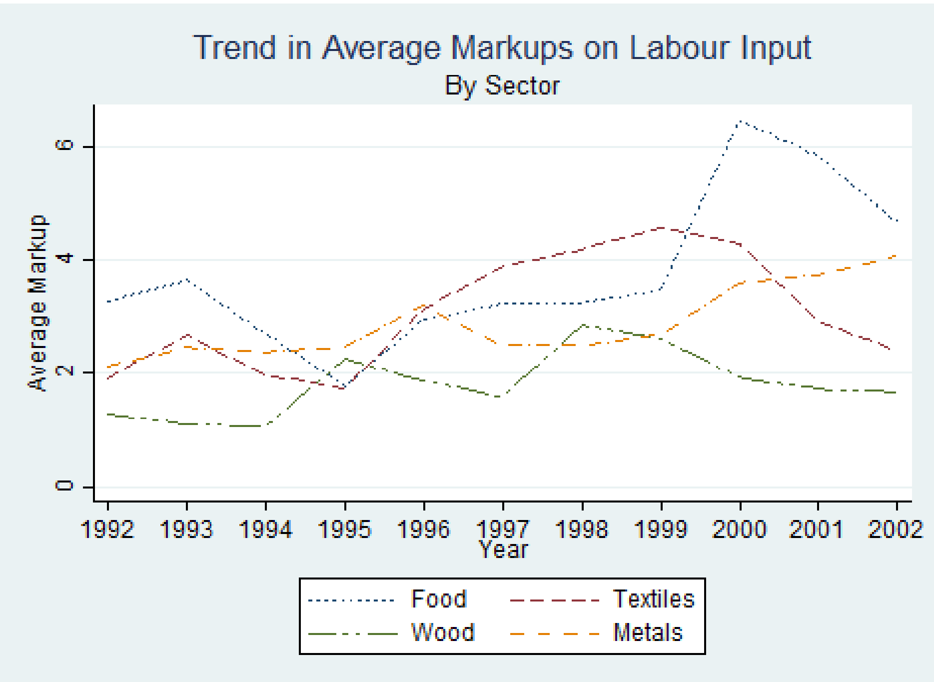
Panel (b) of Figure 4.2 displays average markups computed on labour input over time. The dynamic seems to be generally the same for all sectors. However, average markup computed on labour tends to increase over the years. The food, textiles, wood, and metal sectors grew by 43%, 25%, 32%, and 92% respectively from their starting values in 1992 to 2002. As mentioned previously, the food sector had the highest level of markup on the labour market while it had the lowest on the product market.

Figure 4.3 performs a similar exercise as of Figure 4.2, focusing on firm size. Based on the cumulative distribution of the sample, the following size classification was adopted: small, 1-10 employees; medium, 11-50 employees; and, large, more than 50 employees. From panel (a) of Figure 4.3, both large and medium firms started at the same level of markup in 1992. The two categories of firm sizes registered some volatility in markup level throughout the sample period. While medium firms recorded the largest drop in markup by 22% over the period, markup level for large firms almost returned to the same level of 1992, with a reduction of just 4%. On the other hand, small firms had the lowest average level of markup on materials throughout the period. Overall, small firms recorded a decrease of 17% in markup levels.

Echoes of panel (b) in Figure 4.2 are repeated in panel (b) of Figure 4.3 when average markups on labour seems to be rising rather decrease. Medium firms were the big gainers recording 160% increase in average markup on labour between 1992 and 2002. Although large firms had the highest level of markup, their overall total increase stood at 65% over the decade. The dynamics of average markup for small firms in panel (b) of Figure 4.3



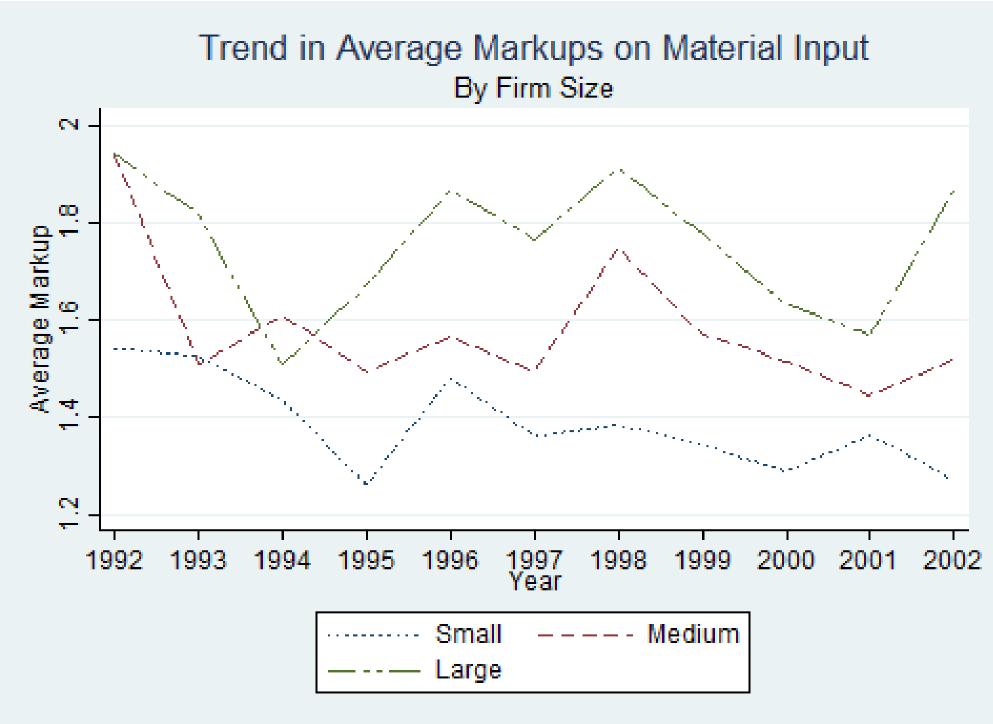

(a)



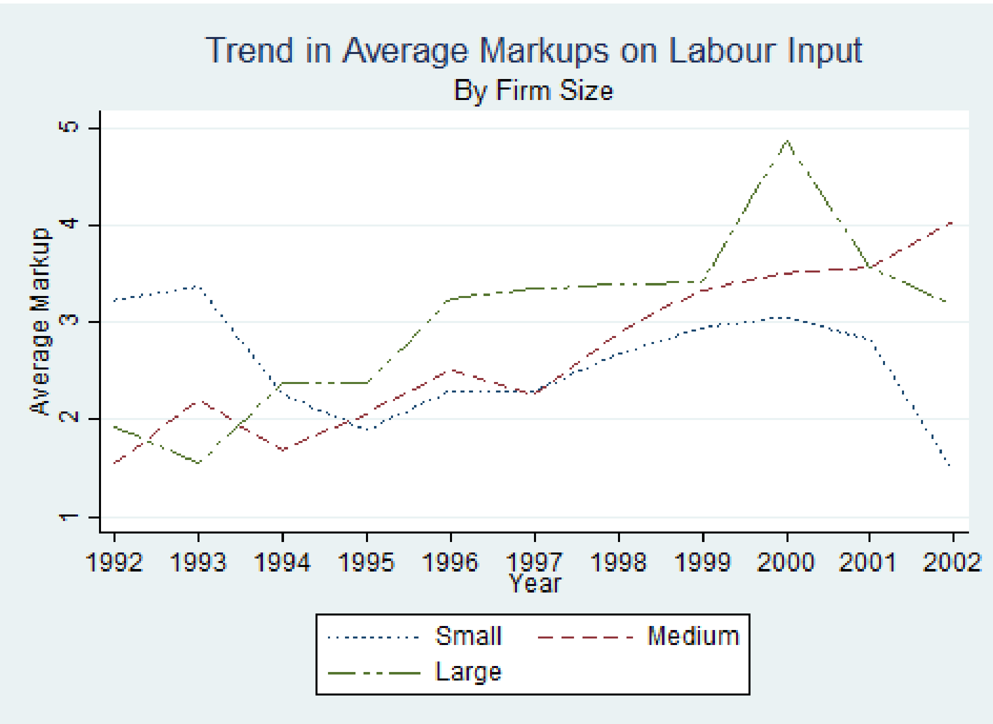

(b)

Figure 4.2: Trend in Markups Level, By Sector

was different compared to the other categories of firm sizes. Small firms started as the category with high markup level in the initial period. Between 1992 and 1995, average markup decreased by 41%. However, over the following five years, the trend started to be positive with an overall increase of 62%. The positive trend did not go beyond year 2000 as markup started to decrease again with sharp decline between 2001 and 2002.




(a)




(b)

Figure 4.3: Trend in Markups Level, By Firm Size

Figures 4.2 and 4.3 showed that while average markup computed on materials declined over the decade, markup computed on labour increased with the exception of small firms. This seems to suggest that firms hold different market power on the product and labour market.

We can formulate a trade-off hypothesis, firms that faced higher competition compress wages to make up for lost margins on the product market. This hypothesis is the starting point to analyse resource misallocation commonly found in Africa and other developing regions (Restuccia and Rogerson, 2013).

## 4.6 Trade Openness and Market Power

This section assesses the effects of international competition on firms' market power. Two measures of international competition are central to this section: outputs tariffs and import penetration. I measure import penetration at sector level, $\text{IMP}_{jt}$, as:

$$\text{IMP}_{jt} = \frac{Import_{jt}}{Import_{jt} + Prod_{jt} - Export_{jt}}$$

where production, import and export are defined at three-digit sector level.

To identify the impact of international competition on firms' domestic market power, I use Ghana's membership to the World Trade Organisation (WTO) in 1995 as a quasi-natural event to detect any changes to market power during the reform years. Using the difference-in-difference estimator to assess the impact of trade openness on market power, I defined a dummy variable $Post_{1995}$ equal to 1 after 1995, which captures before and after differences in market power during the reform period 1991-2002. (see, Guadalupe (2007) for similar approach).

Sectors differ in starting values of tariffs and import penetration at the beginning of the decade. For each international competition variable, I estimate a separate difference-in-difference equation on the outcome variable. To assess the effect of tariffs and import penetration on market power, I estimate

$$y_{ijt} = \alpha_i + \lambda_1(Post_{1995}) + \lambda_2(\tau_{ij1991}) + \lambda_3(\tau_{ij1991} \times Post_{1995}) + \mathbf{X'}_{it}\boldsymbol{\xi} + \delta_t + \epsilon_{ijt}, \tag{4.29}$$

$$y_{ijt} = \alpha_i + \lambda_1(Post_{1995}) + \lambda_2(Imp_{ij1993}) + \lambda_3(Imp_{ij1993} \times Post_{1995}) + \mathbf{X'}_{it}\boldsymbol{\xi} + \delta_t + \epsilon_{ijt}, \tag{4.30}$$

where the dependent variable is the market power of firm $i$ in sector $j$ at time $t$; $\tau_{ij1991}$ is the tariff rate for firm $i$ in sector $j$ in 1991; while $Imp_{ij1993}$ is the import penetration rate for firm $i$ in sector $j$ in 1993;[10] $Post_{1995}$ takes value 1 from year 1995 onwards, and 0 otherwise; $\mathbf{X'}_{it}$ is a vector of the following firm characteristics: predicted productivity, skill ratio, and firm size categories; $\delta_t$ is the year fixed effects; $\alpha_i$ is unobserved firm-specific component; and $\epsilon_{ijt}$ is an idiosyncratic error.

The coefficient $\lambda_1$ captures differences in market power before and after 1995. It also controls for any variations in market power that may correlate with competition, either due to trade liberalisation or any other reason. The coefficient $\lambda_2$ captures differences in market power across sectors with different levels of trade protection in 1991 or trade penetration

[10] The first observable year for tariffs was 1991, while that of import penetration was 1993.

in 1993. The coefficient $\lambda_3$ is the main coefficient of interest, which captures any impact of foreign competition either through falling protection or increasing import penetration on market power.

The expected sign of $\lambda_3$ depends on the kind of market power under examination. Market power in the product market is measured by markups computed on materials, that is, $\mu^m_{it}$. On the other hand, market power in the labour market is measured by the degree of monopsony power, that is, $\gamma_{it}$. One could argue that markups computed on labour equally represent market power in the labour market. While this is generally true, by the first-order-condition exhibited in equation (4.3), a firm with significant power may choose not to vary the quantity of labour input but may choose to compress wages as exhibited in equation (4.9). By virtue of this, the degree of monopsony power accurately represents market power on the labour market.

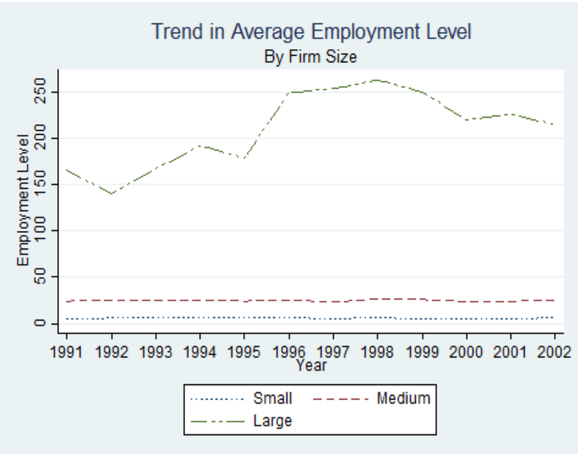
From the theoretical assumptions underling market power in the product and labour markets, as well as the trends in markups exhibited in Figures 4.2 and 4.3, $\lambda_3$ is expected to have negative impact on $\mu^m_{it}$, thus a reduction of market power in product market in the aftermath of trade openness. On the other hand, the effect of $\lambda_3$ on $\gamma_{it}$ is likely to be positive. This is because, firms facing higher competition on the product market are likely to compress wages to be able to stay on the market.

Furthermore, the vector $\mathbf{X'}_{it}$ contains firm covariates that are likely to be correlated with firm level market power. The first of this is predicted productive efficiency obtained using the procedure outlined in subsection 4.4.2. Most productive firms are likely to have high market power with respect to their less productive counterparts. The ratio of skill workers to all workers is included in the vector $\mathbf{X'}_{it}$ to account for the effect of the intensity of skilled workers on firms market power. To capture the effect of firm size on market power, small, medium, and large firm sizes categories are included in the covariates vector.

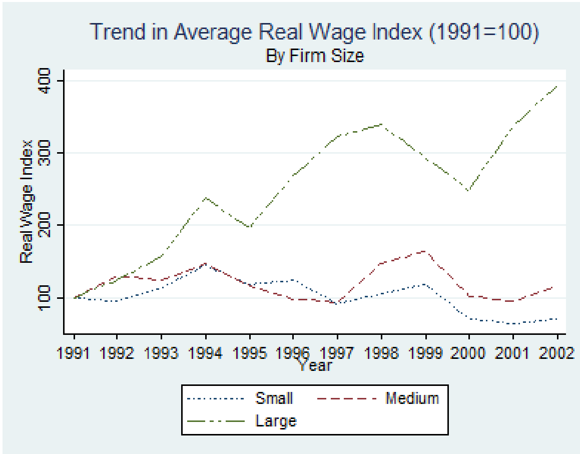
It can be notice that the degree of monopsony power is attainable in panel C of Table 4.4, thus, $\psi < 0$. Therefore, I implemented the sample selection correction procedure – Heckit method – due to Heckman (1979) to study market power in the labour market. For the purpose of the selection criterion, a firm is defined as monopsonist if it falls under panel C of Table 4.4. In the first stage, I estimate the probability of being a monopsonist conditional on: productive efficiency, firm size categories, skill ratio, location dummies, foreign ownership, unionisation of workers, average years of education of workers, and number of apprentices. Results for the selection equation are presented in appendix B. The inverse mills ratio computed in the first stage is then added to the second stage, only for the degree of monopsony power.

Results of the probit estimate show that, productive efficiency has a negative impact on the likelihood of being a monopsonist indicating that productive firms are less likely to compress wages. On the other hand, small size and medium size firms are more likely to be monopsonist compared to large firms. The number of apprentices at a firm increases the likelihood of being a monopsonist. On the contrary, the ratio of skill workers to all employees reduces the likelihood of being a monopsonist so as foreign ownership. Unionisation of workers and average years of education of the workforce had no significant impact on the likelihood of being a monopsonist.

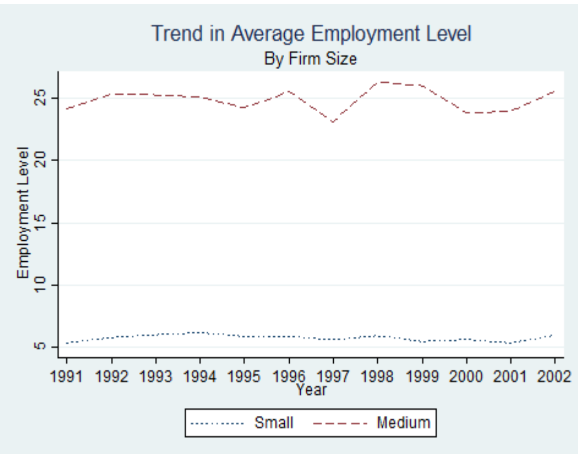
Why do small and medium size firms are more likely to be monopsonist with regards to large firms? To fully comprehend this result, recall the first-order-condition exhibited in equation (4.9): $w_{it} = \gamma_{it}(R^L_{it})$. It follows that the degree of monopsony power is given by $\gamma_{it} = \frac{(\varepsilon^L_w)_{it}}{1+(\varepsilon^L_w)_{it}}$ where $(\varepsilon^L_w)_{it} \in \Re_+$ is the wage elasticity of labour supply. Hence, if wages tend to be inelastic with respect to labour supply, then firms are likely to compress wages when faced with increased competition.



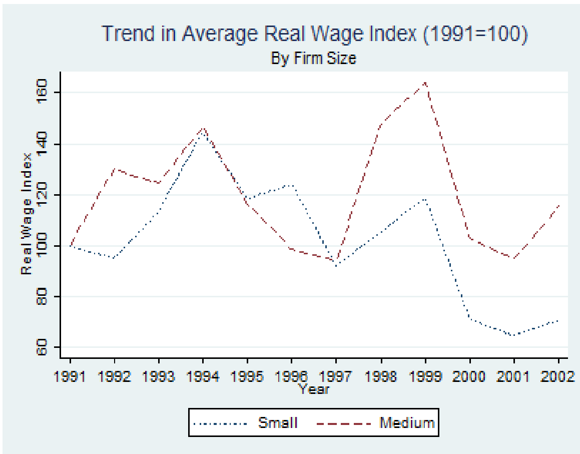

(a)




(b)




(c)




(d)

Figure 4.4: Trends in Employment Level and Real Wage

Figure 4.4 present trend in average employment level and real wages across the three categories of firm sizes.[11] It can be observed from panel (a) of Figure 4.4, that, large firms increased their average employment level over the decade. On the other hand, average employment level for small and medium firms almost remained constant. In panel (b) of the same figure, there is an increased in real wage with respect to the base year for large firms.

Panels (c) and (d) are repetitions of panels (a) and (b) without large firms, in order

[11] Due to large differences in wage levels, I converted real wage into an index with 1991 as the base year.

to put the dynamics for small and medium firms in evidence due to differences in scale. Medium firms registered a cyclical movement in real wages. However, small firms registered a downward spiral in real wages over the decade. As argued above, while there is little variation in employment level for small and medium firms, both categories have resorted to compress wages, more intensively by small firms than medium firms.

Table 4.5: Main Results

| Variables | $\mu^m_{ijt}$ (1) | $\gamma_{ijt}$ (2) | $\gamma_{ijt}$ (3) | $\mu^m_{ijt}$ (4) | $\gamma_{ijt}$ (5) | $\gamma_{ijt}$ (6) |
|---|---|---|---|---|---|---|
| $\tau_{1991} \times Post_{1995}$ | -0.0181*** | 0.0111*** | 0.0112*** | | | |
| | (0.00597) | (0.00286) | (0.00271) | | | |
| $Imp_{1993} \times Post_{1995}$ | | | | -0.0716 | 0.0729 | 0.0723 |
| | | | | (0.349) | (0.149) | (0.149) |
| $\omega_{it}$ | 1.570*** | 0.154*** | 0.153** | 1.556*** | 0.163*** | 0.158** |
| | (0.125) | (0.0457) | (0.0478) | (0.130) | (0.0484) | (0.0477) |
| Skill Ratio | 0.0665 | 0.264 | 0.269 | 0.0661 | 0.236 | 0.235 |
| | (0.139) | (0.175) | (0.177) | (0.143) | (0.180) | (0.181) |
| Small size firms | 0.101 | 0.251*** | 0.237** | 0.0985 | 0.241*** | 0.196* |
| | (0.0847) | (0.0680) | (0.102) | (0.0786) | (0.0657) | (0.102) |
| Medium size firms | 0.0559 | 0.102* | 0.0773* | 0.0474 | 0.103* | 0.0828* |
| | (0.0668) | (0.0508) | (0.0391) | (0.0650) | (0.0499) | (0.0372) |
| $\omega_{it}$ × Small size firms | | | 0.00176 | | | 0.00486 |
| | | | (0.00789) | | | (0.00867) |
| $\omega_{it}$ × Medium size firms | | | 0.00281 | | | 0.00212 |
| | | | (0.00364) | | | (0.00356) |
| Inverse Mills Ratio | | 0.0834 | 0.0829 | | 0.0916 | 0.0847 |
| | | (0.0592) | (0.0671) | | (0.0539) | (0.0574) |
| Constant | -12.44*** | -1.541** | -1.537** | -11.81*** | -1.340* | -1.311** |
| | (1.089) | (0.554) | (0.584) | (1.115) | (0.597) | (0.559) |
| Observations | 1,574 | 601 | 601 | 1,555 | 593 | 593 |
| $R^2$ | 0.483 | 0.119 | 0.119 | 0.475 | 0.105 | 0.106 |
| Number of firm | 223 | 152 | 152 | 220 | 149 | 149 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

Robust standard errors clustered at three digit industry level in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1$.

Table 4.5 reports main results of the estimation equations. Columns (1) and (2) report results for the impact of tariffs on market power in product and labour markets respectively. The main coefficient of interest, $\lambda_3$, has the expected sign and is significant in columns (1) and (2). The result show a decrease of market power on the product market following the reduction of protection levels. With regards to monopsony power, the coefficient of $\lambda_3$ in column (2) shows an increase of market power in labour market after trade liberalization episode. As pointed out in the hypothesis, this can be due to firms compressing wages to offset lost of market power in the product market.

Firm-level productive efficiency, $\omega_{it}$, is positive and significant under both columns (1) and (2), indicating that firms with lower marginal cost have a higher market power on both product and labour markets. One can notice that, the magnitude of impact of productive efficiency is higher on the product market than on the labour market. The ratio of skill workers to all workers is not significant under both cases of market power. Firm size categories are not significant determinant of market power in the product market but they are significant in the labour market.[12] In particular, small and medium firms have approximately 25% and 10% monopsony power, respectively, than large firms.

The result for firm size categories in column (2) suggest that small firms are more likely to compress wages than medium and large firms.[13] To ascertain whether results on firm size categories reported in column (2) could be driven by productivity differentials between small, medium, and large firms, I re-estimate the equation in column (2) interacting productivity and firm size categories.[14] Results reported in column (3) show that potential productivity differentials between firm size categories do not account for the results reported in column (2).

Columns (4) and (5) report result on the effect of import penetration on market power. In column (4), the coefficient of, $Imp_{1993} \times Post_{1995}$, is negative while it is positive in column (5), although both are not statistically significant. Comparing the results of $Imp_{1993} \times Post_{1995}$ and that of $\tau_{1991} \times Post_{1995}$, it can be deduced that tariffs have a significant impact on firm-level market power than import penetration based on results in Table (4.5).

Some factors may account for such result. Import penetration was computed on the assumption that all firms in a given industry faces the same level of import penetration irrespective of their level of internationalisation. This is commonly referred as horizontal import penetration. However, firms may face different exposure to import penetration based on the products they produce and their imports. Unfortunately, the dataset do not provide detail information to enable a construction of input-output tables at either firm-level or sector level, so as to correct for such shortcoming by constructing a vertical import penetration.

Controlling for year fixed effects wipes out $\lambda_1$ from the estimation equation. However, the coefficient, $\lambda_1$ , is needed to evaluate the marginal effect of foreign competition on market power. To this end, I re-estimate the equations in Table 4.5, substituting time dummies for time trend.[15]

From Table 4.6, the coefficient of $Post_{1995}$, $\lambda_1$, is negative in columns (1) and (2) indicating a general reduction of market power due to tariffs after Ghana's membership to the WTO. Using the results in column (1) of Table 4.6, we can compute the marginal effect of trade openness on market power in product market by: $\frac{\partial Y}{\partial X} = \lambda_1 + \lambda_3 \cdot \tau_{1991}$. From the results,

[12]Recall the wage elasticity of labour supply offers possibility for firms to compress wages gaining market power in the process. Firms compete on the same input markets for materials. Recall that the possibility of input bias have been corrected in the estimation of the production function.

[13]See Figures (4.4) and (**??**) for evidence on the evolution of real wages by firm sizes.

[14]Large firms category is omitted due to collinearity.

[15]I controlled for non-linearity in time trend by including time squared in the estimation equations. The t-statistic was not significant in four columns. Additionally, a further test on equality of the coefficients of time and time squared was not rejected. Hence, time squared was dropped from the final results.

Table 4.6: Effect of Trade Openness on Market Power

| Variables | $\mu^m_{ijt}$ (1) | $\gamma_{ijt}$ (2) | $\mu^m_{ijt}$ (3) | $\gamma_{ijt}$ (4) |
|---|---|---|---|---|
| $Post_{1995}$ | -0.407** | -0.250*** | 0.0452 | 0.0313 |
| | (0.164) | (0.0481) | (0.173) | (0.0918) |
| $\tau_{1991} \times Post_{1995}$ | -0.0179*** | 0.0112*** | | |
| | (0.00603) | (0.00241) | | |
| $Imp_{1993} \times Post_{1995}$ | | | -0.0537 | 0.0597 |
| | | | (0.347) | (0.146) |
| $\omega_{it}$ | 1.544*** | 0.151** | 1.533*** | 0.162** |
| | (0.125) | (0.0536) | (0.130) | (0.0573) |
| Skill Ratio | 0.134 | 0.227 | 0.128 | 0.204 |
| | (0.116) | (0.165) | (0.118) | (0.172) |
| Small size firms | 0.102 | 0.251*** | 0.101 | 0.243*** |
| | (0.0865) | (0.0644) | (0.0809) | (0.0621) |
| Medium size firms | 0.0567 | 0.104* | 0.0484 | 0.107* |
| | (0.0750) | (0.0548) | (0.0733) | (0.0551) |
| Inverse Mills Ratio | | 0.0827 | | 0.0958 |
| | | (0.0713) | | (0.0703) |
| Time | -0.0356** | -0.0152* | -0.0362** | -0.0151 |
| | (0.0137) | (0.00798) | (0.0138) | (0.00826) |
| Constant | -11.85*** | -1.074 | -11.68*** | -1.175 |
| | (1.089) | (0.608) | (1.127) | (0.647) |
| Observations | 1,574 | 601 | 1,555 | 593 |
| $R^2$ | 0.463 | 0.105 | 0.454 | 0.091 |
| Number of firm | 223 | 152 | 220 | 149 |
| Firm FE | Yes | Yes | Yes | Yes |

Robust standard errors clustered at three digit industry level in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1.$

there was a massive reduction in the average market power – on the product market – by 82.02% across all sectors.

Breaking down the results at two-digits sector levels, the textiles sector registered the biggest decease on average market power (in product market) by approximately 98.39% over the decade 1991-2002. Median market power also reduced by 76.83%, 76.67% and 78.09% for food, metals, and wood sectors respectively.[16] It can be observed from Figure 4.2 that, the textile sector had the highest level of tariffs in 1991 compared to the other sectors. Hence, the magnitude of the impact on textile sector suggest that, the most protected sector recorded a significant drop in protection levels resulting in a such decline in market power.

Applying the same procedure to evaluate the impact of trade openness on monopsony power as above, the overall average impact across all sector was a positive 0.91% while the median impact was negative 2.11%. The result indicate differences at the sector level, which derive a positive average effect and a negative median effect. At the sector level, the food, wood, and metal sectors recorded a reduction in degree of monopsony power by 2.33%, 2.44% and 1.56 respectively. Although the overall effect was negative for three out of the four sectors, the level of reduction was modest compared to that in product market.

The textile sector, however, recorded an overall increase in monopsony power by 11.18%. To put the result into perspective, recall that, the textile sector had the highest level of tariffs in 1991 and recorded the biggest drop in market power in the product market by 98.39% over the period 1991-2002. Hence, being the only sector that recoded an increase in market power in the labour market, offers evidence of firms offsetting loss of market power in the product market by compressing wages. By so doing, firms can remain on the market despite losing considerable market power in the product market.

As robustness check to the results presented above, I extended the analysis in Table 4.6 to markups on labour to evaluate the overall impact of trade openness on market power. Results of estimation equations are reported in Table 4.8 in appendix B. On tariffs, the coefficient of $Post_{1995}$ is positive indicating an increase in market power after 1995. On the other hand, the coefficient of tariffs interacted with $Post_{1995}$ is negative indicating a drop in market power. The overall marginal effects translate into a reduction of market power by 8.85% due to tariffs. In column (2) of Table 4.8, the overall marginal effect translate into an increase in market power by 25 percent across all sectors. Generally, market power tends to increase in the labour market, while when there are reductions, it turns to be modest.

In summary, reduction in the level of protection during Ghana's trade reform era reduced market power in the product market. However, the likelihood of firms to compress wages when they posses significant monopsony power can undermine the gains from trade openness.

[16] Although these figures seems to be huge and driven by sample size, the point estimates gives consistent results.

## 4.7 Conclusions

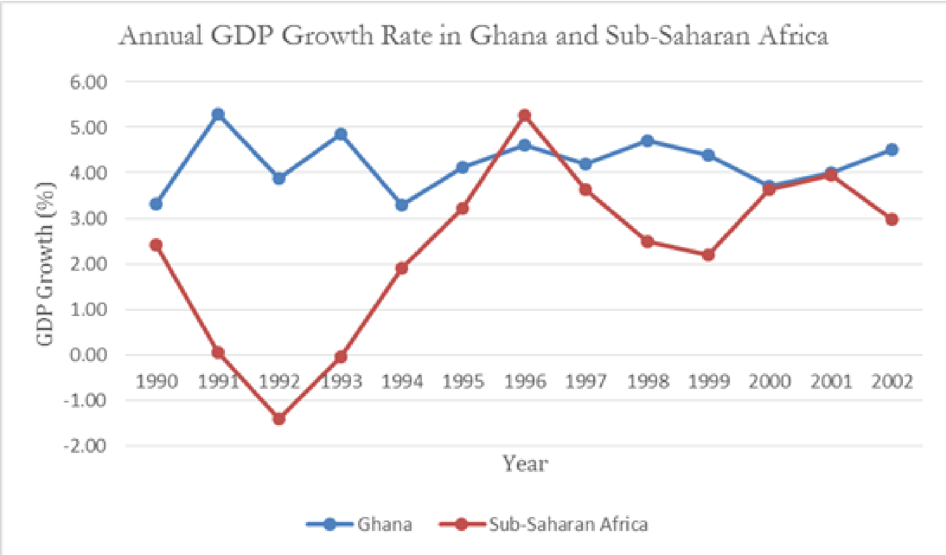
The gains from trade, either potential or realised, have been a persistent topic for the past two decades. Improvements in productive efficiency gains have been the most investigated channel in literature. This paper examines the impact of trade openness on market power. Two dimensions of market power are used; markups on materials, and the degree of monopsony power. To infer markups from price-cost margins relations, it is necessary to estimate a production function.

Analysis of the trends in firm-level markups show different dynamics on the products and labour markets. Markups computed on materials gradually reduced over the decade, while that on labour took an upward direction with the exception of small firms. To draw casual inference on the impact of trade openness on market power, the paper used Ghana's membership to the World Trade Organisation in 1995 as an identification strategy to apply a difference-in-difference estimator. Results showed that trade openness reduced market power on the product market but less so on the labour market. For example, the textile sector, which was the most protected – measured by tariffs rate – recorded a reduction of market power on the product market by approximately, 50%, while market power on its labour market increased by 20%.

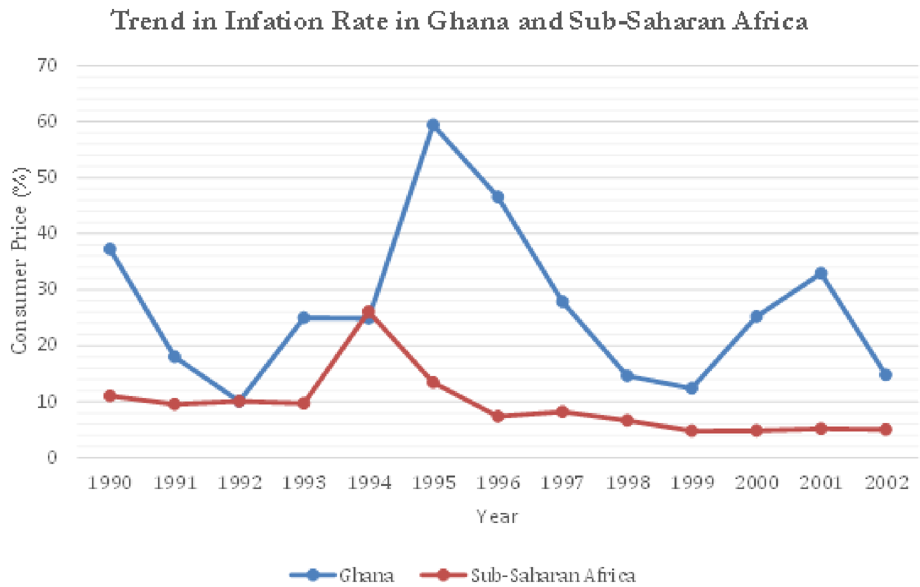
The main policy implications of the results suggest that trade liberalisation policy must be accompanied by appropriate labour market reform to avoid firms shifting sources of market power from product market to labour market. If such scenario occurs, the gains of trade liberalisation will be distorted. Another implication is to access the effect of firms offsetting market power loss in the product market with increased market power in labour market on industry dynamics of entry and exit as well as allocation of resources. Such assessment is beyond the scope of the present paper and hence left for future research.

## Appendix A: Macroeconomic Overview of Ghana

This appendix presents brief overview of Ghana's macroeconomic indicators with focus on unemployment, inflation, and GDP during the period 1990-2002. The aim of this, is to provide additional information against which results presented under this chapter can be interpreted. Using data retrieved from World Development Indicators, Figure 4.5 presents evolution of GDP growth and inflation rate in Ghana and Sub-Saharan African.[17]




(a)




(b)

Figure 4.5: Trend in GDP Growth Rate and Inflation Rate in Ghana and Sub-Saharan Africa

Panel (a) of Figure 4.5 shows that Ghana experienced cyclical growth between 1990 and 1994 after which GDP growth remained stable for the remaining parts of the period. Ghana

[17] http://databank.worldbank.org/data Last accessed: 23/03/2017.

performed better compared to the average of all income levels in Sub-Saharan Africa. Panel (b) of Figure 4.5 compares trend in consumer prices in Ghana and Sub-Saharan Africa over the period 1990-2002. Ghana experienced turbulent inflation trend compared to Sub-Saharan Africa average. Though beyond the scope of the present work, one can argue whether the spike in inflation rate between 1994-1995 and 1999-2001 windows are related to the 1996 and 2000 general elections in Ghana as done in political business cycle literature (Block, 2002).

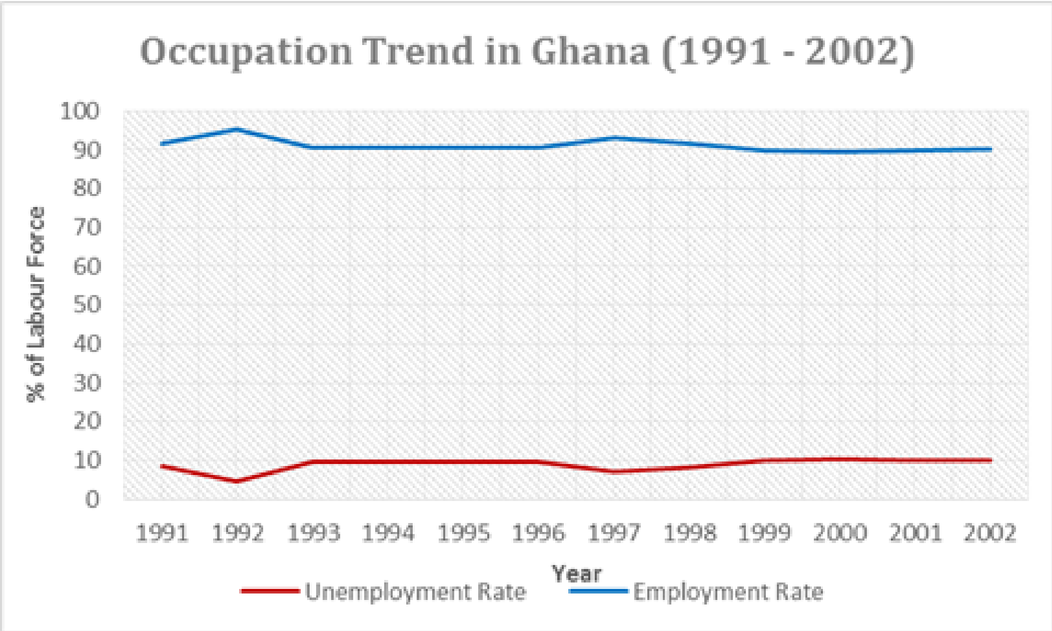



Figure 4.6: Occupation Trend in Ghana

Figure 4.6 presents the evolution of occupation between 1991 and 2002. Using data from World Development Indicators, I compute employment rate as a ratio of total employment to total labour force multiplied by 100. On the other hand, unemployment rate was based International Labour Organization (ILO) estimate and readily available in the data. The two series shows a stable trend in Ghana's occupation level.

## Appendix B: Selection Equation

Table 4.7: Probability of being a Monopsony, Probit Estimate

| VARIABLES | Monopsony |
|---|---|
| $\omega_{it}$ | -0.251*** |
| | (0.0760) |
| Small Size Firm | 1.160*** |
| | (0.145) |
| Medium Size Firm | 0.381*** |
| | (0.108) |
| Skill Ratio | -0.729** |
| | (0.304) |
| Foreign Ownership | -0.286*** |
| | (0.105) |
| Unionisation of Workers | -0.170 |
| | (0.113) |
| Firm Average Years of Education | -0.0150 |
| | (0.0174) |
| Number of Apprentices | 0.0135** |
| | (0.00550) |
| Location: Kumasi ★ | -0.0980 |
| | (0.0800) |
| Location: Takoradi | 0.0789 |
| | (0.143) |
| Location: Cape Coast | -0.275 |
| | (0.203) |
| Time | 0.0754 |
| | (0.0581) |
| Time Squared | -0.00327 |
| | (0.00413) |
| Constant | 3.389*** |
| | (0.962) |
| Observations | 1,531 |
| Pseudo $R^2$ | 0.2038 |
| Log Likelihood | -824.825 |
| Sector Dummies | Yes |

Robust standard errors in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$.
★ The capital city, Accra, is used as the base variable.

# Appendix C: Robustness Check

Table 4.8: Robustness Check Using Markups on Labour

| VARIABLES | $\mu^l_{ijt}$ (1) | $\mu^l_{ijt}$ (2) |
|---|---|---|
| $Post_{1995}$ | 0.890** | -0.601** |
| | (0.420) | (0.225) |
| $\tau_{1991} \times Post_{1995}$ | -0.0422** | |
| | (0.0156) | |
| $Imp_{1993} \times Post_{1995}$ | | 1.136** |
| | | (0.478) |
| $\omega_{it}$ | 0.363 | 0.321 |
| | (0.242) | (0.230) |
| Skill Ratio | -0.814 | -0.681 |
| | (1.028) | (1.035) |
| Small Size Firm | -1.562*** | -1.483*** |
| | (0.230) | (0.233) |
| Medium Size Firm | -0.551** | -0.512* |
| | (0.262) | (0.275) |
| Time | 0.0661* | 0.0540* |
| | (0.0321) | (0.0289) |
| Constant | -0.822 | -0.392 |
| | (2.427) | (2.323) |
| | | |
| Observations | 1,020 | 1,007 |
| R-squared | 0.042 | 0.041 |
| Number of firm | 198 | 195 |
| Firm FE | Yes | Yes |

Robust standard errors clustered at three digit industry level in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1$.

# Chapter 5

# Conclusion and Policy Implications

This thesis analysed productive efficiency, firm internationalisation, and impact of trade openness on domestic market power. The main text discusses specific conclusions related to each paper. This concluding chapter summaries main messages as well as policy implications deriving from the study.

Suppose the objective of a policy-maker is to increase the number of African manufacturing firms participating in foreign markets. According to the conventional models of estimating productive efficiency, this would require the policy-maker to draw up policies that urge or nudge manufacturing firms to increase their productive efficiency. However, the thesis have shown in chapter 2, that such policy is less likely to yield expected results since productive efficiency is not a determinant of export participation for African firms. For example, financial constraints could be the main factor that prevent firms from participating in the export market.

In chapter 3 the thesis showed that imports are mostly likely to increase productive efficiency than other modes of trade participation. The first policy implication of such result would require the policy to abolish import tariffs. Unfortunately, given that the revenue generation capacity of most African governments are limited, it has become a praxis for most governments to impose various taxes and levies on import. For example, as recent as 2013, the government of Ghana introduced special import levy with the aim of generating additional revenue to supplement the government budget plans.

The second conclusion from chapter 3 showed that trade experience is important for productive efficiency feedback from trade. Policy-makers can set up government agencies in their most relevant foreign market to act as a bridge between their trading firms and host countries. The absence of such agencies gives extra burden to firms which may discourage them to continue trading in foreign markets.

In chapter 4 the thesis showed that market power in the product market reduced after trade liberalisation policies. On the other hand, there was little variation in market power in the labour market which tended to increase with regards to the textile sector. That suggest the possibility of firms offsetting lost market power in the product market with market power in the labour market. This can simply be archived by compressing wages. The most likely consequence of this would be inefficient firms, which ought to be out of the market get to remain using their monopsony power. In the long run, this will affect expected reallocation of resources benefits. In view of this, trade liberalisation policies must be accompanied by appropriate policies for the labour market to decrease firms monopsony power.

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