DISSERTATION

TECHNICAL EFFICIENCY AND FIRM GROWTH DYNAMICS IN THE ETHIOPIAN MANUFACTURING SECTOR

KIDANEMARIAM BERHE HAILU

2014

National Graduate Institute for Policy Studies

TECHNICAL EFFICIENCY AND FIRM GROWTH DYNAMICS IN THE ETHIOPIAN MANUFACTURING SECTOR

A Dissertation

Submitted to the Faculty of the National Graduate Institute for Policy Studies (GRIPS) in

Partial Fulfillment of the Requirements for the Degree of

DOCTOR OF PHILOSOPHY IN PUBLIC POLICY

by

Kidanemariam Berhe Hailu

September, 2014

Abstract

Technical efficiency and firm growth dynamics in the Ethiopian manufacturing sector

by: Kidanemariam Berhe Hailu

Dissertation Director: Professor Kenichi Ohno

September, 2014

In the face of mounting competition in domestic and international markets the survival and success of firms depend on their business performance. Thus, to maintain competitive advantage, firms need to assess their performance periodically. This study examines the performance of manufacturing firms in Ethiopia in terms of technical efficiency and firm growth dynamics using establishment-level census panel data over the period of 2000 to 2009. The "true" random effects stochastic frontier model (Greene, 2005a, 2005b), which can disentangle time-varying technical inefficiency from time-invariant unobserved heterogeneity, and the conventional fixed and random effects models are used to estimate efficiency for the aggregated and individual industry groups. The results indicate that efficiency estimates are sensitive to model specifications of firm-specific unobserved heterogeneity. We find a significant gap in efficiency estimates between the "true" random effects model and the fixed and random effects models, which would imply considerable heterogeneity of manufacturing firms in Ethiopia. Our results suggest that firm-specific heterogeneity would be particularly significant in the food and beverages,

non-metals, and furniture industries. We also show that the production of the Ethiopian manufacturing sector is largely responsive to changes in intermediate inputs compared to labor and capital inputs. The mean technical efficiency varies considerably across firms within an industry. On average, technical efficiency for the whole manufacturing sector is estimated to be 74 percent in the study period.

We investigate if efficiency variation among firms is systematically associated with firm size and age. The results indicate that the effect of these variables on efficiency varies from industry to industry. However, overall, their relationship with efficiency seems to be insignificant. We further qualitatively discuss that the major problem for the variation in efficiency among firms is the inability of firms to operate at their full production capacity, which is mainly caused by shortages of raw material supply. We also found that firms in the manufacturing sector have shown positive technological progress in the study period.

We also examined the efficiency of manufacturing industries in Ethiopia from the DEA perspective. In the DEA analysis, we first proposed a handicap setting model for fair evaluation of the manufacturing industries in Ethiopia. The manufacturing industry comprises many sectors which include many companies in the category. Thus, there is a "two-layered" structure. The statistics of a sector is the sum of those of its member companies. In order to evaluate the relative efficiency of industrial sectors, we need to take account of performance of their membership companies. For this purpose, we proposed a handicap model that enabled us to compare industries under a *handicap race*. Using the model, we classified industries into *no-handicap* and *with-handicap* groups. Since we use an input-oriented model, we modify inputs using the handicaps and evaluate the sectoral efficiency. We found four sectors belonging to the *with-handicap* group the most handicapped sector being the Machinery and equipment. If this industry could be improved by innovation, it would become the top industry in the manufacturing sector, while the other three handicapped sectors remain inefficient even after taking account of handicaps.

The above DEA analysis did not consider any statistical noise in the data. However, a growing concern over DEA is that results may be biased in the presence of statistical noise such as measurement errors. To address this problem, three recently proposed DEA resampling models which account for measurement errors in the data are utilized in a separate chapter. Using these three resampling models, we gauge the confidence interval of the efficiency scores of each industry. Unlike previous studies which tried to estimate past and present efficiency of decision-making units, we further evaluate the future efficiency of the industries using future forecasting model. This enables us to assess the future potential of the industries.

This dissertation also studies firm size and growth rate distribution patterns and growth persistence of manufacturing firms in Ethiopia using a quantile regression approach. This approach has unique advantages over the standard econometric techniques in that it allows the impact of the independent variables to vary over the entire conditional distribution of the dependent variable. Our findings indicate that the distributional properties of firm size and firm growth rate show significant deviations from a Gaussian distribution. Particularly, while firm size exhibits a right-skewed distribution, growth rate distributions are highly leptokurtic that resemble a fat-tailed Laplace distribution. The empirical results indicate that firm growth decreases with size suggesting that small firms have faster growth than larger firms in terms of employment. This highlights the ability of small firms to create significant job opportunities in the Ethiopian manufacturing sector. Furthermore, we find high negative autocorrelation of growth rates in consecutive years. This means that any high positive or negative growth events of employment in any given year are unlikely to be repeated the following year. In other words, there is lack of persistence in employment growth. Our results are robust to size, temporal and sectoral disaggregation of the data. Generally, all these results suggest that Gibrat's law of proportionate effect is rejected in the case of Ethiopian manufacturing.

The research findings can be helpful for industrial policy makers as background information for further development of the sector.

Keywords: **S**tochastic frontier analysis, "true" random effects, unobserved heterogeneity, technical efficiency, Data Envelopment Analysis, resampling, measurement error, firm size distribution, firm growth rate distribution, autocorrelation, quantile regression, growth persistence, Ethiopian manufacturing

Dedication

To my parents Berhe Hailu and Tideg Gebrehiwet, and daughters Lidya and Sidona

Table of Contents

List of Tables

List of Figures

Acknowledgements

This doctoral dissertation would not have been completed without assistance, encouragement and guidance of several people for whom I feel honor to extend my profound appreciation at this stage.

First and for most, I would like to express my sincere gratitude to my principal supervisor, Prof. Kenichi Ohno, for his continuous guidance and encouragement from the inception to the completion of the dissertation. His timely advice, constructive comments and suggestions were crucial in the successful completion of this dissertation. Despite the busy time he had with other academic and professional commitments, he was available at all times and devoted significant amount of his time to supervise me. I have gained a lot from his profound expertise and experience in the field of industrial policy.

I am very grateful to my dissertation committee members: Professors Tatsuo Oyama, Makoto Tanaka, Takashi Tsuchiya, and Abu Girma for their insightful comments and suggestions that were helpful in shaping my dissertation. Prof. Oyama has been very cooperative and kind to provide me assistance even beyond his role as dissertation committee member. Prof. Oyama is known for his role in providing support for students at GRIPS. He was really quick to deal with administrative matters related to my study. It would have been very difficult for me to reach this stage without his immense support. Prof. Tanaka has also been very helpful in providing me advice any time I need assistance. His wonderful thoughts and comments have greatly contributed to improve the quality of the dissertation. I have immeasurably benefited from his inputs during seminar, formal, and informal consultation meetings that I have had with him. Prof. Abu's contribution to improve the quality of the dissertation has also been very crucial. I also extend my gratitude to Prof. Tsuchiya for his comments to further improve the dissertation.

I am also deeply thankful to Prof. Kaoru Tone for his invaluable contribution in the course of producing this dissertation. His constructive comments, guidance and suggestions helped me to successfully complete my dissertation. Through his guidance and advice, I have gained an understanding of the fundamental knowledge of Data Envelopment Analysis in empirical research. Words are not enough to express my gratitude to Prof. Tone. I have also benefited from the insightful comments I received from Dr. Miki Tsutsui. My special gratitude also goes to Prof. Roberto Gonzalez for his unreserved support during my study. Many thanks go to Professor Jim Elwood for his editorial advice. I am deeply indebted to fellow colleagues Dr. Temesgen Kassamun, Dr. Girum Abebe, Dr. Berihu Assefa, Dr. Thanabalasingam Vinayagathasan, Kefyalew Adane, Atakilti Adugna, Philemon Kiprono, and Hansa Reda for their support throughout my study.

My heartfelt appreciation also goes to all GRIPS administrative staff for their kind cooperation during my stay in Japan. Special thanks go to Ms. Makiko Nakamichi and Ms. Mieko Iizuka for their cooperation throughout my study. I am also highly indebted to GRIPS for the fellowship award I was offered to study my doctoral program. Special thanks also go to Aksum University for granting me study leave.

Last but not least, I am greatly indebted to my parents Berhe Hailu and Tideg Gebrehiwot whose prayers, encouragement and moral support enabled me to accomplish my study. Most importantly, I am deeply grateful to my wife, Eliana Assegid for providing me prayers, love, inspiration and for the huge endurance to enable me to complete my study.

Chapter 1

Introduction

1.1. Background to the study

The manufacturing sector has historically played a significant role in the economic transformation of nations. The manufacturing sector is considered to be a special deriver of economic transformation because it has the potential to impact the economy via various channels. First, manufacturing output is characterized by value addition and higher productivity, and hence it has the potential to create job opportunities for both skilled and unskilled workforce by producing wage increases. Second, technical skills obtained from manufacturing jobs can be transferred into the economy and reinforce increases in general productivity levels, thereby raising wages in other sectors. The East Asian experience, which has passed this virtuous circle, is a manufacturing success story. For example, Page (2012) noted that the development of the manufacturing sector in East Asian countries has been of paramount importance in their economic growth. It is also argued that East Asian countries were able to rapidly and successfully retrain their farmers as manufacturing workers.

However, it seems that Africa has thus far failed to bring about the structural change that has recently been seen in East Asian countries. The manufacturing sector has not been performing up to expectations. The development of the sector in most African countries has virtually stagnated in the last two decades. The declining performance of the sector is manifested in terms of its contribution to GDP and its share of global manufacturing. A report by UNIDO (2011) showed that the contribution of manufacturing to GDP has seen a significant decline from 15.3 percent in 1990 to 12.8 percent in 2000 and 10.5 percent in 2008. Africa's share of global manufacturing (with the exception of South Africa) fell from 0.4 percent in 1980 to 0.3 percent in 2005, and its share of world manufactured exports from 0.3 to 0.2 percent. Africa still accounts for a very low share of global manufacturing (UNIDO, 2009). The absence of well-functioning markets, poor infrastructure facilities, and poor managerial and technological capabilities coupled with unfavorable government policies in the manufacturing sector are often considered to be the main stumbling blocks of the manufacturing sector in Africa.

Nevertheless, it is believed that Africa has the potential to develop its manufacturing sector and can become competitive in the global market. Particularly, Ethiopia has great potential to revitalize its manufacturing sector. As discussed by Dinh et al. (2012) and Sonobe (2009), Ethiopia, with its abundant low-cost labor force, has a comparative advantage in less-skilled, labor-intensive sectors. In such light manufacturing areas as textiles, wood products, leather products, and apparel, Ethiopia can produce low-cost manufacturing exports. Furthermore, Ethiopia has abundant resources, including cattle, which are vital for making leather and leather products, forests, which can provide wood for the furniture industry, cotton, which supplies the garment industry, and agricultural land and lakes that are readily available for use by agro-processing industries (Dinh et al., 2012).

Ethiopia's preferential duty-free trade access to US and EU markets also provides strategic opportunities to further enhance its manufacturing sector.

Mindful of this potential, since 2002 Ethiopia has been undergoing significant policy changes in the manufacturing sector to create a favorable environment to attract foreign direct investment (FDI) and encourage domestic investment. The government has been seriously engaging itself in industrial policy learning, mainly from the experiences of East Asian countries. In a bid to transform its mostly agrarian economy into an industry-based economy spearheaded by light manufacturing industries, Ethiopia is currently implementing the first five-year Growth and Transformation plan (GTP) covering the period from 20100-2011 to 2014-2015.In this GTP, promoting exports in the priority sectors; textiles, apparel, leather and leather products, and agro-business industries will likely help the Ethiopian manufacturing hub develop. To exploit this opportunity, a number of foreign companies from China, India, Turkey, and Japan are currently exploring opportunities in the country, which has led to a sudden upsurge in FDI inflow in the last two to three years.

Despite the policy changes and the enormous potential that could boost the industrialization process in the country, the manufacturing sector still remains underdeveloped. Notwithstanding the fact that Ethiopia has been one of the fastest growing economies in the world in the past decade, the performance of the industrial sector has been disappointing with no significant change in its contribution to the GDP and generation of employment. Its share of GDP has remained relatively static, amounting to between 13 and

14 percent. In particular, the share of the manufacturing sub-sector, a crucial sector in transforming an economy, remained stagnant (African Development Bank, 2010).

A number of structural bottlenecks are inhibiting the development of the sector. Structurally, the manufacturing industry is dominated by simple agro-processing activities and the production of basic consumer goods. Industries that help to create technological capabilities and dynamism such as chemical, electrical and electronics, metal-processing and other engineering industries are almost non-existent. All manufacturing exports are agriculture-based, including such commodities as clothing, semi-processed hides, footwear, and beverages. More specific factors also contribute to this malaise. For example, the most serious problem facing the manufacturing sector is shortages of raw materials. Complaint about shortage of supply of raw materials may seem something bizarre, particularly, in the priority sectors, given Ethiopia's potential in the availability of inputs to be used in these sectors. However, the problem is not about the availability of inputs. The root cause of the problem is a fragmented and lengthy input marketing system that involves many parties, thus resulting in high transaction costs. Faced with this high transaction/ input cost, firms in the sector are forced to set high prices for their products, which puts them into difficult competitive positions in the domestic and global markets. Other bottlenecks in the sector include irregularities in the implementation of government rules and regulations, an erratic electric power supply, a lack of management capability, and shortage of working capital which can be manifested by difficulty accessing credit. In addition, the technological level of firms in the sector is, by any standards, very low. The cumulative effect of these problems has made firms operate at far less than their full production capacity. Firms in the sector are unable to produce the maximum possible output.

Given this background, the main objective of this dissertation is to evaluate the performance of the Ethiopian manufacturing sector using an establishment-level census panel data set collected annually by the Central Statistical Agency (CSA) over the period 2000 to 2009. The term performance in this dissertation is defined as technical efficiency and firm growth dynamics. The performance of firms determines the overall economic environment. For instance, macroeconomic growth rates, unemployment, and standards of living are strongly linked with the economic performance of firms. Without analyzing micro performance, it is not possible to explain the overall performance of an economy. Evaluating the performance of Ethiopian manufacturing is therefore important to understand the potential of the sector to emerge as a manufacturing base. In particular, performance evaluation of the target sectors upon which high hopes are placed to emerge as exporters in the face of heightening competition in the global market is of great importance to see if they are performing up to expectations.

Measuring the efficiency of firms is particularly important in that it helps to identify the sources of inefficiency and thus allow further investigation of how firms can utilize resources optimally to enhance their efficiency. Enhancing efficiency is an important source of productivity growth. Hence, developing economies like Ethiopia where technological capability of firms is low can opt to increase production or reduce costs by improving efficiency. This can be achieved with available resources and technological capability. Policy endeavors aiming at reforming and promoting the manufacturing sector need to consider how to increase the efficiency and productivity level of firms in the sector. In this regard, the analysis of technical efficiency in the sector can be used as background information for policymakers in formulating industrial policy.

In this dissertation, we also study the growth dynamics of Ethiopian manufacturing firms. We are particularly interested in studying the dependence of firm growth rate on size and the persistence of firm growth rate in a dynamic context from which important policy implications can be drawn. The study of the dependence of firm growth rate on size is helpful to identify whether small firms or large firms are growing faster and hence design policy accordingly (Wagner, 1992). Similarly, the study of growth persistence carries important information on firm growth trajectories in that it enables us to know whether job creation in one period is repeated in the following year (Coad & Holzl, 2009).

This study contributes to the existing literature in general and to the literature on Ethiopian manufacturing in many ways (for similar studies on Ethiopian manufacturing, see chapter 3). This dissertation makes use of a relatively large data set and covers the entire set of Ethiopian manufacturing firms that employ 10 persons or more. Despite the fact that such studies that use large census data sets for manufacturing are common in developed economies, they are rare for developing countries due mainly to a paucity of data. Empirically, this study looks into Ethiopian manufacturing using recent models of Stochastic Frontier Analysis (SFA) and Data Envelopment analysis (DEA). The details of the methodological and empirical innovations are given in the respective chapters. Furthermore, this study may provide some insights into Ethiopian manufacturing from other perspectives, namely, efficiency and firm grow dynamics.

Finally, we would like to note here that due to a lack of data, this study does not include the recent upsurge in FDI in Ethiopia. We also do not address the difference in performance between domestic and FDI firms. By highlighting the recent developments in the sector, this study contributes background information for further development of the sector.

1.2. Data and methodology

In this section, we briefly describe the data and methodological approaches used in this study. However, the detailed data description and methodology used in each chapter are presented in the respective chapters.

1.2.1. Data description

The data for the present study have been taken from the census data of large and medium-sized manufacturing industries (LMMIS) which use power for production; these data are collected annually by the Ethiopian Central Statistical Agency (CSA) from all manufacturing establishments with 10 or more employees. The full dataset covers the period 2000 to 2009 unbalanced panel data and covers both private and public manufacturing establishments across the country, which obviates the need to consider sampling variability. This census comprises data about employment, wages, sales, total production, taxes, export sales, asset, capital structure, varieties of inputs used, investment, and other related information at the establishment level. The data also have detailed establishment level regarding location indicators from region to the smallest administrative location. The types of industries from which the data were collected include food, beverage, textile, apparel, leather, footwear, wood, furniture, paper and printing, chemicals, rubber and plastic and metal industries.

Based on the literature and data availability, we use a single-output and 3-input production technology for Ethiopian manufacturing. Output is measured by the gross value of all outputs produced by the firm. The inputs include (a) the number of employees measured by the sum of permanent and temporary workers, (b) capital input measured by the net value of fixed assets at the end of the survey year, and (c) intermediate inputs aggregated as the sum of the values of raw materials, fuel and lubricating oil, electricity, wood and charcoal for energy, and other industrial costs. For the purpose of this study, data were aggregated to 2-digit level industries according to the "International Standard Industrial Classification of All Economic Activities" (ISIC).

Price adjustment

While dealing with panel data, it is important to make the necessary adjustment for price changes to remove price effects in each period prior to embarking on efficiency and productivity analyses. Coelli et al. (2005) suggested that appropriate deflators should be used to remove the price effects for the selected outputs and inputs. Accordingly, we can find different approaches to deflate inputs and outputs in the literature. For instance, for Bangladesh manufacturing, Hossain & Karunaratne (2004) used wholesale price index of industrial products to deflate gross value-added, the wholesale price index of manufacturing which excludes fuel and lighting to deflate capital input, and the wholesale price index of raw materials to deflate intermediate inputs. For Korean manufacturing, Kim (2003) deflated the value-added of each firm by an industry-specific wholesale price index deflator.

Similarly, since this study is based on ten years of panel data, and there was a high level of inflation in Ethiopia during 2008 and 2009, we have made price adjustments prior to our analysis. Coelli et al. (2005) suggested that when adjusting for price changes, it is imperative to select a deflator that relates to the commodities that constitute the aggregate. Given the availability of data, we have computed separate price deflators that suit our problem best. Accordingly, we deflate gross output by sectoral GDP deflator for LMMIS which was computed by dividing the nominal gross out value of LMMIS to the real gross value of LMMIS. We deflate capital input using capital deflator from the World Bank's Africa Development Indicator (ADI). We obtained the capital deflator by dividing nominal gross capital formation to real gross capital formation. However, for intermediate inputs, in the absence of sectoral input deflators, we use GDP deflator. While the source of data for the sectoral GDP deflator for the LMMIS output was MoFED[1], the GDP deflator for intermediate inputs came from National Bank of Ethiopia. All the variables are expressed using 1999/00 prices as base.

Output and inputs are expressed in 1999/00 Ethiopian birr. Observations with missing output and/or input variables were deleted. Moreover, since the CSA census was conducted only for establishments which employ ten persons or more, observations of establishments with fewer than 10 persons were also deleted.

[1] Ministry of Finance and Economic Development of Ethiopia. The data from MoFED comprise sectoral outputs and inputs at current and constant prices for the period under consideration.

1.2.2. Methodology

We apply two competing methodological approaches in the efficiency analysis, namely, Stochastic Frontier Analysis (SFA) and Data Development Analysis (DEA). In the firm growth analysis, quantile regression approach which is more appropriate for growth rate distributions is used. Details of the methods and materials can be found in the respective chapters.

1.3. Organization of the dissertation

The rest of the dissertation is structured as follows: Chapter 2 provides a detailed review of Ethiopian manufacturing. It begins with an overview of the Ethiopian economy and moves on to discuss Ethiopia's industrial learning process from East Asian countries, which includes industrial policy dialogue and institutionalization of *Kaizen* as a management tool. The chapter also gives some insight into the *ease of doing business* in Ethiopia by highlighting Ethiopia's global rank relative to comparator economies and regional average in *ease of doing business.* Issues pertaining to the firm entry process, trends of output, and employment growth in the manufacturing sector are also discussed. The performance of the sector's exports and imports, labor productivity, and the potential that Ethiopia has to jump-start its manufacturing are also points of discussion in this chapter. Finally, some recent developments in the manufacturing sector are also highlighted in this chapter.

Existing literature is presented in Chapter 3. Some theoretical and empirical discussions related to measuring technical efficiency and firm growth dynamics are discussed. In the first part of this chapter, we present the fundamental analytical tools used to conceptualize and measure efficiency; those tools include production technology, production frontiers, and distance functions. Previous studies on technical efficiency in Ethiopian manufacturing are also dealt with in this part of the chapter. The second part of the chapter deals with firm size and growth rates distributions, the dependence of firm growth rate on its size, and firm growth persistence.

In Chapter 4, we estimate and analyze the technical efficiency of firms in Ethiopian manufacturing using SFA. Efficiency variations across industries and among firms within an industry are also addressed. Factors that might have caused efficiency differences among firms are also explained in this chapter. Finally, the chapter concludes and offers some policy implications that policymakers may use as background information for further development of the sector.

In chapter 5, we propose a handicap model in DEA that enables us to compare the efficiency of the industries under *handicap race*. After setting the handicap model, we illustrate it using data from the Ethiopian manufacturing sector. Chapter 6 also consists of a DEA investigation of the technical efficiency of the sector. A newly developed approach on resampling in DEA that takes account of measurement errors in the data has been used. Using three resampling models, we estimated efficiency scores along with their confidence interval for each industry.

In Chapter 7, the dynamics of firm growth in Ethiopian manufacturing are examined. The chapter begins with a discussion of the distributional characteristics of firm size and firm growth rate and looks into the relationship between the two. We further investigate the persistence of the firm growth as measured by the autocorrelation of the coefficients of firm growth rate. Based on the results in this chapter, we provide some policy recommendations.

Chapter 8 concludes the dissertation by summarizing the main findings from Chapters 4 to 7 and provides policy recommendations.

Chapter 2

The Ethiopian manufacturing sector

2.1. Introduction

While Ethiopia's population is the second-largest in Africa with more than 90 million people, it has one of the lowest levels of GDP per capita in the world. Agriculture still remains the mainstay of the Ethiopian economy, which is heavily dependent on rainfall and is dominated by smallholder farmers. Despite the potential of agriculture in Ethiopia, agricultural productivity has been stagnant, leaving millions of people to depend on external aid.

The contribution of the industrial sector to GDP has been stagnant for a long period of time. Its share of GDP has remained relatively static, amounting to between 13 and 14 percent. In particular, the share of the manufacturing sub-sector, a crucial sector in transforming an economy, has remained stagnant (African Development Bank, 2010). The manufacturing industry is dominated by simple agro-processing activities and production of basic consumer goods. Industries that help to create technological capabilities and dynamism such as chemical, electrical and electronics, metal-processing and other engineering industries have not yet developed. The technological level of firms is by any standards very low. All manufacturing exports are agriculture-based, which include clothing, semi-processed hides, footwear, and beverages.

The rest of the chapter is organized as follows. Section 2.2 presents the experience of industrial policy learning and the introduction of *kaizen* (continuous quality and productivity improvement) from Japan. After showing the performance of the sector's export and import performance in Section 2.3, we present a snapshot of labor productivity and unit labor cost in the sector in Section 2.4. Ethiopia's window of opportunity to jump-start its manufacturing is examined in Section 2.5. Section 2.6 discusses some recent developments in the manufacturing sector during the past three years of GTP implementation period. Section 2.7 concludes the chapter.

2.2. Industrial policy learning

Following the demise of the military regime in 1991, Ethiopia embarked on liberalizing its economy from the previous centrally-planned economy toward a free market one by selectively pursing the structural adjustment programs put forward by the IMF and WB. In the mid-1990s the government unveiled its Agricultural Development Led Industrialization (ADLI) as its development vision. In 1998, the government further launched an Export Promotion Strategy in which some manufacturing and agro-industry sectors were chosen for preferential treatment (Gebreeyesus & Iizuka, 2010).

The industrial sector has gradually been deregulated and liberalized, thus allowing entry of the private sector and foreign competition into the manufacturing. A comprehensive Industrial Development Strategy (IDS) was implemented in 2002. The key elements included in the IDS are linkage of industry and agriculture, selection of certain strategic sub-sectors, integration of the country's trade sector, export promotion, private sector development, and the indispensable role of the government as the leader in the development agenda.

2.2.1. Industrial policy dialogue with Japan[2]

In order to achieve the objectives stipulated in the IDS, Ethiopia started to learn industrial policy making from the experience of East Asian countries through self-learning and sending government officials to, for example, the Korean Development Institute (KDI) of South Korea. Moreover, an attempt was also made to learn western-style industrial policy (Ohno, 2013).

However, attracted by their successful experience, Ethiopia finally turned to seriously and systematically learn industrial policymaking from East Asian countries through industrial policy dialogue with Japan. With the aim to transfer the methodology of industrial policy formulation (in a way that is suited to Ethiopia) from East Asia, Ethiopia entered into a two-year bilateral cooperative agreement with Japan in 2009. The cooperation consists of two components: policy dialogue and a *kaizen* project. From the Japanese side, while the GRIPS Development Forum (GDF here after) policy dialogue team led by Professor Kenichi Ohno was in charge of the former, the Japan International cooperation Agency (JICA) was in charge of the latter (GDF, 2011; Ohno, 2013). As a first-phase project, the two components were implemented from June 2009 to May 2011.

The policy dialogue team met with high government officials several times and discussed a range of issues related to the implementation of the two components of the bilateral cooperation. Several sessions of policy dialogue were held at different levels in which the following issues (among others) were discussed:

---

[2] The text in this section and section 1.3.2 is largely taken from Kenichi Ohno (2013) and GRIPS Development Forum (2011). A detail report of the industrial policy dialogue and the *Kaizen* project can be found in these materials

"Concept and practice of kaizen, basic metal and engineering industries, industrial strategy in the next five-year development plan, methods of drafting industrial master plans and action plans, national productivity movements in East Asia and Africa, international best practices in industrial policy procedure and organization" (Ohno, 2013).

Impact of policy dialogue:

The GDF report (2011) showed that the industrial policy dialogue produced a number of encouraging impacts for Ethiopia, including the following:

- Creation of accelerated policy learning;
- Identification and communication of weaknesses in policy procedure and organization; and
- Policy dialogue at all levels, including the operational people who made it possible for Ethiopia both to relay its policy intention precisely and raise issues flexibly with Japan.

2.2.2. Introduction of *Kaizen*

As mentioned before, Ethiopia has introduced a *Kaizen* project as a management tool in collaboration with JICA together with the policy dialogue to address problems associated with management practice in the industrial sector. *Kaizen* is a Japanese management philosophy aiming at continuous quality and productivity improvement. It is based on incremental change and a participatory decision-making approach. The *Kaizen*

Project was implemented in close coordination with the industrial policy dialogue. The *kaizen* was first implemented as a two-year (2009 to 2011) pilot project in 30 selected companies in the areas of agro-processing, leather, chemical, and textile industries. Continuous on-the job and off-the job training were given by the *kaizen* team to the implementing companies to deepen understanding of *kaizen*. The *kaizen* team closely monitored the progress of the pilot project during the two-year period and the progress and achievements of the Project were regularly reported to relevant bodies in parallel with GDF policy dialogue.

Achievements of *Kaizen*

Some remarkable qualitative and quantitative achievements were seen during the two-year implementation period. Examples include cleaner working environments, better team spirit, cost reduction, labor saving, and an increase in labor productivity. The first phase of the cooperation ended in 2011 with the establishment of the "Ethiopian Kaizen Institute" (EKI).

Encouraged by the results of the first phase of the cooperation, both components were extended into second phase for three more years that will run from 2011 to 2014. On the *kaizen* project, unlike the first phase which was confined to LMMIS, the second phase is aimed at disseminating *kaizen* to both LMMIS and micro- and small-scale enterprises across Ethiopia and building capacity at EKI in a sustainable manner. Reports about the results of the second phase are encouraging. Sourcing the general manager of the EKI, BBC reported that kaizen is being applied in 160 companies so far, and in 2013 alone EKI trained around 11,000 people in the country (BBC, 2014). The GTP annual progress report also shows that in the 2012/13 fiscal year major activities of the dissemination and institutionalization of *kaizen* were conducted in the manufacturing sector. For example, improvements in working procedures, organizational restructuring, human resource capacity building, creating critical mass and establishing teams based on one to five twining were undertaken in such manufacturing sectors as textile and garment, leather and leather products, agro-processing, chemical, and metal industries (MoFED, 2014). The report showed that such efforts have led to improvement in the efficiency, productivity, quality, and competitiveness of these industries.

Regarding the policy dialogue, the modality in the first phase has continued in the second phase. Some of the main issues discussed in the meetings of the policy dialogue include assessment of existing Ethiopian investment and export policies, policy directions for export promotion, introduction of proactive FDI policy in Ethiopia (with suggestion from an East Asia perspective) and technology transfer from FDI to local firms.

2.3. Performance of export and import

Despite the general increase of manufacturing exports in Ethiopia, the manufacturing exports are dominated by agriculture-based primary products including textiles, leather, footwear, and beverages. Table 2.1 reports the share of export in total sales, share of imported raw materials in total raw materials consumed, and the ratio of export to import (export coverage of import) by industrial group in the LMMIS. The overall export to total sales ratio of the LMMIS accounted for about 6 percent in 2010/11. This is a decline from about 7 percent in 2003/04, but an increase compared to the 2009/10 performance (3 percent). Despite the decline in export share in 2009/10 and 2010/11 as compared to that of 2003/04, export in absolute values has been increasing, implying that firms have become more domestic oriented than export oriented. For example, the value of exports increased from 734,419 million in 2003/04 to 3,578,779 million Ethiopian birr in 2010/11. However, the ratio of export to sales differed considerably from sector to sector. For instance, in 2010/11, the tanning, leather and footwear sector took the lead with an export-to-sales ratio of about 52 percent textile, followed by the textile industry with a share of about 14 percent. About 4 percent of the total sales in the wearing apparel sector came from export revenue. This figure is an improvement compared to 2003/04 (export share about 1%), but a decrease compared to 2009/10 (export share about 13%)

As far as imports area concerned, Ethiopia imports most capital goods and manufactured consumer goods. Moreover, the manufacturing sector is highly dependent on the import of raw materials. For instance, in Table 2.1, we see that the overall volume of imported raw materials accounts for about 47 percent of the total raw materials consumed in the LMMIS. This implies that the sector is heavily dependent on imported raw materials although the degree of dependence varies by sector. In reference to 2010/11, the dependence is relatively lower in the food and beverages, textiles, tanning, leather and footwear, non-metals wood and furniture industries, which account for a minimum of about 25 percent in the non-metals sector to a maximum of about 46 percent in the wood industry. Among the sectors that are heavily dependent on imported raw materials are paper and printing, chemicals, rubber and plastics, machinery and equipment, basic iron and steel, and motor vehicles, whose consumption of imported materials ranges from 73 percent to 93 percent of the value of total raw materials.

Table 2.1: Export-Import Performance in the LMMIS

	Share of export in sales (%)			Share of imp. raw materials (%)			Ratio of export to import (%)	
Industry	2003/04	2009/2010	2010/11	2003/04	2009/10	2010/2011	2003/04	2010/11
Food & beverages	3.14	1.78	5.47	21.35	24.85	26.65	41.95	50.83
Tobacco	0.00	0.45	0.47	36.79	5.54	53.34	0.00	1.41
Textiles	11.49	9.19	14.37	31.07	37.01	40.79	58.50	53.29
Wearing apparel	1.30	12.92	3.58	16.25	50.30	33.40	15.75	23.56
Tanning, leather & footwear	63.87	36.27	52.36	18.35	34.36	29.51	507.76	337.71
Wood	0.00	0.05	0.00	56.42	21.11	45.76	0.00	0.00
Paper & printing	0.00	0.00	0.00	71.22	59.48	73.69	0.00	0.00
Chemicals	0.07	1.02	3.12	77.87	70.53	76.94	0.17	7.46
Rubber & plastics	0.00	0.13	12.17	93.96	92.32	92.97	0.00	24.29
Non-metals	0.07	0.07	0.55	17.01	58.13	25.46	1.68	9.72
Basic iron & steel	0.00	2.42	1.29	99.02	79.13	78.55	0.00	2.69
Fabricated metals	0.13	1.53	0.02	84.95	84.60	52.40	0.29	0.17
Machinery & equipment	0.00	2.04	0.00	94.23	85.06	87.02	0.00	0.00
Motor vehicles	0.00	0.00	0.00	92.56	98.48	86.60	0.00	0.00
Furniture	0.00	0.00	0.00	44.17	50.10	36.00	0.00	0.00
Total	7.08	3.03	6.05	50.56	51.04	47.40	34.46	31.33

Source: Own computation based on CSA survey reports (various years)

Another point we can learn from Table 2.1 is how much of the cost of imported raw materials are covered by exports. This is measured by the ratio of exports to imports. Accordingly, the overall coverage of exports has declined from 34 percent in 2003/04 to 12 percent in 2009/10, but then increased to 31 percent in 2010/11 in the LMMIS. The increase in export coverage in 2010/11 was also evident in the major export sectors (textiles, tanning, and footwear sectors). Although the increment is not that significant, this encouraging sign might be the result of the government's effort to promote the sectors.

2.4. Labor productivity and labor cost

Labor productivity is computed as the ratio of value added (VA) per person engaged.[3] The VA in turn is calculated as the difference between gross value of production and intermediate consumption adjusted for tax on product measured at a basic price[4]. Similarly, labor cost has been computed by dividing the labor cost (total wages and salaries and other labor related costs) by the VA. VA is measured in Ethiopian birr (ETB) and hence labor productivity is measured as ETB per person engaged.

Table 2.2 reports labor productivity and labor cost by industrial group in the LMMIS. The overall average labor productivity in the LMMIS has shown an increasing trend from ETB 25,058 in 2000/01 to ETB 83,671 in 2010/11. Although it differs by sector, the increasing trend in labor productivity has been experienced by all of the sectors except the fabricated metals sector. The result of the improvement could be due to the exerted efforts by companies to introduce various types of management training such as *kaizen* as a management tool.

Table 2.2 reports the labor productivity and labor cost by industrial group in the LMMIS. The overall average labor productivity in the LMMIS has shown an increasing

[3] Persons engaged comprise paid employees including seasonal and temporary workers and working proprietors. Active partners and unpaid family workers are also included here.

[4] VA at basic price represents the difference between gross output and intermediate consumption net of taxes on production (i.e., taxes on product less subsidies). Moreover, VA is not adjusted for price change, meaning its value is nominal, not real.

trend from ETB 25, 058 in 2000/01 to ETB 83, 671 in 2010/11. Although it differs by sector, the increasing trend in labor productivity has been experienced by all of the sectors except in the fabricated metals sector. The result of the improvement could be due to the exerted efforts by the companies to introduce various management trainings such as *kaizen* as a management tool.

Table 2.2: Labor Productivity and Labor Cost in the LMMIS

	Labor productivity (VA in ETB/Worker)			Labor cost (total wages and salaries/VA)		
Industry	2000/01	2009/10	2010/11	2000/01	2009/10	2010/11
Food & beverages	43,838	65,596	117,605	0.182	0.216	0.137
Tobacco	79,511	-16,018	166,671	0.174	-1.324	0.101
Textiles	5,794	33,197	16,473	0.807	0.298	0.857
Wearing apparel	3,647	16,259	36,586	1.209	0.511	0.261
Tanning, leather & footwear	15,951	2,292	29,336	0.534	0.45	0.164
Wood	15,827	55,467	72,856	0.401	4.795	0.433
Paper & printing	25,032	55,467	72,856	0.341	0.29	0.233
Chemicals	25,589	82,118	133,984	0.278	0.196	0.147
Rubber & plastics	39,479	60,332	67,608	0.21	0.224	0.218
Non-metals	27,250	107,986	115,108	0.263	0.114	0.132
Basic iron & steel	43,765	42,699	104,940	0.292	0.37	0.2
Fabricated metals	14,502	77,795	-168,126	0.504	0.215	-0.11
Machinery & equipment	12,774	64,238	102,406	0.441	0.244	0.2
Motor vehicles	95,338	157,725	96,275	0.147	0.126	0.353
Furniture	8,719	52,465	42,237	0.585	0.191	0.267
Total	25,058	60,538	83,671	0.278	0.219	0.188

Source: CSA survey reports (various years)

In Table 2.2, we see that the overall average unit labor cost declined from 0.278 in 2000/01 to 0.188 in 2010/11. Focusing on the priority sectors, this trend is true particularly in the wearing apparel and tanning, leather, and footwear sectors where it is believed that Ethiopia has a labor cost advantage in comparison to the rest of the world. This is good news for attracting foreign companies, which are facing spiraling labor costs in the home country. However, while our analysis may give a snapshot of the labor cost trend, a further rigorous analysis may be necessary to arrive at a robust conclusion. Labor cost in the textiles sector, on the other hand, has shown an increase from 0.298 in 2009/10 to 0.857 in 2010/11.

2.5. Can Ethiopia jump-start its manufacturing?

An initial factor endowment plays an important role in starting industrialization. In developing countries like Ethiopia where capital is scarce and labor is relatively abundant, labor-intensive industrialization can be pursued as a strategy for structural transformation of the economy. Cognizant of this fact, the Ethiopian government has been pursuing an industrial policy that promotes labor-intensive manufacturing industries. For example, in the GTP period, focus has been on the development of light-manufacturing industries and priority sectors have been identified. The list of priority sectors include textile and apparel, leather and leather products, agro-processing, chemical and pharmaceutical, metal, and the food and beverage sectors. These sectors have been selected based on the fact that they are labor intensive, the availability of raw materials, and their ability to form a strong linkage with the agricultural sector and their potential as key sectors for export promotion. Hence, these sectors are believed to play a leading role in the growth of the manufacturing sector and thus drive the industrialization and transformation of the economy.

While Ethiopia has the potential for labor-intensive industrialization, the manufacturing sector is still in a nascent stage. There are a number of internal and external problems surrounding the sector. Because the Ethiopian manufacturing sector is still in an underdeveloped state, it is generally dominated by simple agro-processing activities and the production of basic consumer goods; moreover, the technological capabilities of firms are very low. Despite Ethiopia's abundant human resources, the quality of the labor force involved in the sector is generally low. The sector is largely dominated by an unskilled workforce. There is a lack of practical, systematic, and targeted worker training programs and implementation methods that can improve workers' production efficiency and productivity in the companies. Firms in the sector are generally characterized by their lack of modern management practice, poor product design, and a lack of exposure to international markets. While most of the problems mentioned above can be addressed by the firms themselves, there are also a number of external problems that are beyond the control of the firm. These include a lack of working capital, unfavorable infrastructure facilities, a shortage of raw materials supply, and a limited availability of spare parts. From a policy perspective, despite the fact that the government seems determined to improve the investment climate in the sector, its implementation still remains worrisome. A lack of coordination among the policy-implementing bodies is widespread in the sector. A lack of competitiveness with foreign products is another distinguishing feature of the sector. For example, firms in the sector are unable to compete with Chinese products in price, thus driving them out of the market. The cumulative effect of these factors has led firms to operate at less than their installed capacity (full capacity). Moreover, the availability of foreign exchange also affects the production capacity of firms. The US Department of Commerce (USDC) (2013) reported that private sector actors engaged in importing inputs for production have been facing difficulty in getting foreign exchange. The report also shows that importers are required to wait for more than three months to get foreign exchange and make a payment for their import. Thus, in the absence of foreign exchange, enterprises may be forced to stall or scale down their production capacity, thereby reducing their efficiency.

However, despite the current problems facing the manufacturing sector, there seems to be a consensus that Ethiopia has a window of opportunity to become a manufacturing hub in labor-intensive light manufacturing by attracting FDI. Attracted by a decade of sustained economic growth in general and the development taking place in the manufacturing sector in particular, foreign investors are eyeing Ethiopia. Manufacturing FDI in labor-intensive industries is growing in size and number. In what follows, we discuss some of the attractive features of Ethiopia's manufacturing.

Labor cost advantage

Labor costs constitute a significant portion of production costs in a typical factory. With about 85 percent of Ethiopia's population living in rural areas, Ethiopia has labor force reserves that can be transferred into industry and work at a minimal cost. Dinh et al. (2012) and Sonobe (2009) noted that Ethiopia has abundant low-cost labor, which gives it a comparative advantage in less-skilled, labor-intensive sectors such as light manufacturing.

On the other hand, labor cost in the Asian counterparts is mounting. In some Asian countries like China, Thailand, the Philippines, and Malaysia, manufacturing wages have reached a point beyond which no new labor-intensive manufacturing FDI could be interested in coming. For instance, Hellen Hai, former manager of the Huajian Group[5] in Ethiopia, noted that labor costs in China have reached as much as USD 500 per month. Ethiopia's wages for manufacturing workers are currently about USD 50 per month. This wage is even low by African standards. This allows Ethiopia to have a wage advantage competitive enough to attract FDI into its labor-intensive industries.

However, the availability of an abundant and cheap labor force may not be a sufficient condition to maintain competitiveness. Labor productivity also matters in keeping wage competitiveness. As can be seen in Table 2.2, although there is an increasing trend of labor productivity in the Ethiopian manufacturing, the figures still are low by regional and international standards. Unless labor productivity is enhanced, Ethiopia's competitiveness in the labor-intensive light manufacturing may be seriously constrained. The wage advantage might be neutralized by the low productivity. It should be taken into consideration that wage increases should not overtake labor productivity. Once wage increases exceed labor productivity growth, it becomes difficult (in terms of labor costs) for firms to invest in light manufacturing. Thus, efforts that increase labor productivity in particular and total factor productivity in general should also be in place.

---

[5] Huajian Group is a Chinese shoemaker which was established in January 2012 in Ethiopia and became a major exporter of shoes in about a year.

Serious policy attention and political stability

On the policy side, the government, with the aim of transforming the country from an agrarian to an industrialised nation, has been preparing an environment conducive to attracting FDI. Strategic policies have been implemented that define sector-specific targets and adopt a carrot-and-stick approach that rewards enterprises compliant with the government's developmental state agenda and penalizes those enterprises engaged in rent-seeking behaviour. Generous incentives that include tax breaks, duty-free import of capital goods, soft loans, and cheap land lease rates have been put in place in certain preferred sectors. As a policy direction, the government has already designated what came to be known as priority sectors that include textile, leather and leather products and apparel industries for FDI. Ethiopia expects many FDI firms to become involved in those sectors and thus provides them with special treatment. However, there are concerns associated with such government-guided targeted industrial policies that they may instead create a new source of rent-seeking behavior if not well managed. Altenburg (2010) argued that there is a high possibility of firms which are fortunately engaged in areas designated as target sectors, firms that benefit from restricted licenses, firms working around import or export bans to become rent-seekers. Hence, policies that adopt a carrot-and-stick approach need to pursue transparent rules and a mechanism by which policymakers could be held accountable should be in place.

As a macroeconomic policy intervention, in order to promote the export sector, the government keeps depreciating the value of the birr against the USD by 5 percent each year.

In September 2010, the Birr was devalued against the USD by 20 percent and further devaluation is expected. Such a devaluation policy encourages export competitiveness.

On the political condition, Ethiopia is a relatively stable country in the volatile Horn of Africa region making it to be preferred by investors.

Large population

Ethiopia has cheap labor force that can be employed in the labor-intensive industries. Moreover, one of the driving forces for structural change in an economy is the change in domestic demand. This seems evident in the current situation of Ethiopia. With a population of more than 90 million (the majority of which are young) and a rapidly growing number of middle-class families, Ethiopia provides a big market for high-value processed consumer goods. This situation offers another prospect for investment in domestic market-focused manufacturing such as food, beverages, and plastic products.

Natural resource

A firm’s decision to invest is also affected by the availability of local raw materials. To a great extent, Ethiopia is gifted with ample natural resources that can provide valuable inputs for light manufacturing industries serving both domestic and export markets. Among its abundant resources are cattle, which can be used as an input for making leather and leather products, forests, which can be used in the furniture industry, cotton, which can be expanded to further develop the garments industry, and agricultural land and lakes that are readily available to provide inputs for agro-processing industries (Dinh et al., 2012).

Given these opportunities, Ethiopia is currently receiving considerable FDI from China, India, Japan, and Turkey. Therefore, we believe that if Ethiopia addresses the obstacles mentioned above and uses all available opportunities, there is a possibility of becoming a manufacturing base in the labor-intensive light manufacturing sectors. Ethiopia can utilize FDI inflow as an initial driver of industrialization and hence pursue structural transformation. However, the availability of these opportunities may not be an end by itself. In order to continue attracting FDI, Ethiopia needs to maintain its comparative advantage. In particular, as long as its diligent, cheap, and high-quality workforce and political stability are extant, FDI will continue to flow into the country. Global experience shows that such advantages can more than offset other unfavourable business conditions. For instance, despite the widespread policy irregularities and corruption that have been seen in China, Vietnam, and Indonesia, FDI still continues as investors remain attracted by the availability of the domestic market and a quality workforce.

Given all these current discussions in the sector and the policy changes that have been taking place, it is therefore imperative to conduct a robust performance evaluation of the sector at this stage. Such a study will be helpful to understand the level of resource utilization and can be used by policymakers as background information for further development of the sector.

2.6. Recent developments in the manufacturing sector

Ethiopia is keen to transform its mostly agrarian economy into an industry-based economy spearheaded by light manufacturing industries. In a bid to foster broad-based development, the government is implementing the first five-year GTP covering the period from 2010/11 to 2014/15. Following the implementation of GTP, Ethiopia has made great strides in the industrial sector, particularly in the manufacturing industries, in the past three GTP implementation periods.

2.6.1. Industrial development

Micro- and small-scale enterprise development

For poor countries like Ethiopia, the development of micro- and small-scale enterprises (MSEs) plays an important role in providing ample job opportunities, thereby reducing poverty. Mindful of this fact, the development of the sector is given priority in the GTP period**.** In the last three years of the GTP period, efforts have been made to promote the MSEs. The establishment of new micro- and small-scale enterprises and the promotion of the existing ones into medium-scale enterprises were among the main accomplishments done in the sector during the last three years of the GTP. As a result, it was possible to create over 3.96 million new temporary and permanent jobs in the sector throughout the country (MoFED, 2014).

LMMIS development

In the GTP period, focus has been on the development of light manufacturing industries. Hence, it is expected that the performance of the sector will improve in the GTP period. On this sub-topic, we briefly discuss the performance of the LMMIS during the past three years of the GTP.

The average annual growth rate of large and medium manufacturing during the last three years stood at 14.9 percent. Despite that encouraging growth rate, its share of GDP still remained low at about 3 percent. As part of the GTP, emphasis was given to increasing manufacturing export earnings from the priority sectors and targets were set in each year of the plan period with USD 2 billion manufacturing export earnings expected to be achieved by the end of the GTP period. Table 2.3 reports the export performance of selected manufacturing industries in the past three years of the GTP period. The concerned efforts towards export promotion in the past three years of GTP period have brought a large increase in export earnings from the selected sectors. The total export earnings have increased from USD 118.4 million in the base year (2009/10) to USD 281.1 million in 2012/13, an increase of USD 162.7 million. Sectoral disaggregation also shows that the performance of manufacturing export earnings. Notwithstanding the increase in export earnings, the performance still remains below the planned targets. For instance, in 2012/13, a total of USD 542.1 million was the target. However, the actual export earning was USD 281.1, just 51.8 percent of the target. This indicates that there is still a lot to do to achieve the targets.

Table 2.3: Performance of Manufacturing Export Earnings (in million USD)

Sector	Base year (2009/10)	2010/11	2011/12	2012/13
Textile & garment	23.2	62.2	84.6	99
Leather & leather products	56.5	104.3	112.1	123.4
Agro-processing	35.2	34.45	51.8	50.8
Pharmaceuticals & chemical products	3.5	6.9	7	7.9
Total	118.4	207.9	255.45	281.1

Source, MoFED (2014)

2.6.2. Private sector development

Although, the government plays an important role in investing in areas where it believes there is a market gap, it also recognizes that the private sector is an engine of economic growth. The government has taken measures that include creating a conducive policy environment and supportive regulatory measures as well as improving infrastructure and public service delivery to enhance the competitiveness of the private sector (MoFED, 2014).

Industrial zone development

In an effort to promote industrial development, the government recognizes the establishment of industrial zones. Thus, the government allocated demand-based industrial zones in different parts of the country. A total of 3,537 hectares of land was made ready for the establishment of industrial zones in Addis Ababa, Kombolcha, Dire Dawa and Hawassa; of these four areas, the Bole Lemi Industry Zone site in Addis Ababa is under construction. Other privately-owned industrial zones that are under development include the Eastern Industrial Zone around Dukem (owned by a Chinese investor) and the Sendafa Industry Zone around Finfine area (owned by a Turkish investor).

Domestic private investment

In the past three years of GTP implementation period, a total of 16,807 domestic investors with a total capital of birr 132 billion have obtained licenses to invest in the country. Of the total projects, 208 projects with a capital of birr 1.89 billion are in operation and under construction. Of the 208 projects, 115 projects (55.3%) with capital of birr 1.55 billion, 19 projects (9.1%) with capital of birr 0.2 billion, and 74 (35.6 percent) with capital of birr 0.14 billion are engaged in the service, manufacturing, and agriculture sectors, respectively (MoFED, 2014). This shows that the majority of the domestic investors are engaged in the service sector.

Foreign direct investment (FDI)

Under the export-led industrialization strategy that Ethiopia is pursuing, labor-intensive light manufacturing industries such as textile and garment, leather and leather products and agro-processing are the sectors to which foreign investor are attracted. Previous studies have shown that these sectors have the potential to be competitive in the export market. The potential competitiveness of the sectors can be justified on two grounds. First is the labor cost advantage: while labor productivity in some of the sectors in Ethiopia can approach that of China and Vietnam, Ethiopia's wages are a quarter of those in China and half of wages in Vietnam (Dinh et al, 2012). The second reason is Ethiopia's abundance of natural resources to be used as raw materials in these sectors. For example, Ethiopia is endowed with cotton resources that can be used as inputs in the textile and garment industries. Moreover, in the leather and leather products industry, Ethiopia's hides and skins are known for their high quality. These advantages can give Ethiopia a comparative advantage in the export market. To realize this objective, in the past three years of GTP implementation, the government of Ethiopia has been exerting concerted efforts toward improving the general investment climate to attract FDI. Beyond improving the general investment climate, it has also made customized negotiations targeting such well-known foreign manufacturers as Ayka, Huajian, George shoe, and H & M, whose presence could attract more foreign firms and improve Ethiopia's reputation among investors. In the past two to three years, there has been a sudden and large labor-intensive export-oriented FDI inflow to Ethiopia.

Table 2.4 summarizes FDI inflow and the number of jobs created in the manufacturing sector. A total of 1,865 projects with about birr 172 billion have been registered in all the sectors in the past three years. Of the total projects, the majority of them (about 46 percent) with a total capital of Birr 87 billion (about 50 percent of the total FDI) are engaged in the manufacturing sector. FDI inflow increased in the manufacturing sector as we move from 2011 to 2012, but there was a slight decline in 2013. These registered projects have created a total employment of 154, 275 during the three years of GTP period. Employment opportunities have increased from 39,777 in 2011 to 66,926 in 2012. However, the jobs created seem to be few in light of the fact that the industries are the most labor-intensive, which provide ample employment opportunities for the unemployed.

Table 2.4: Licensed FDI in the Manufacturing Sector in the Past three Years

			Employment		
Year	No. of projects	Capital in thousands birr	Permanent	Temporary	Total
2011	224	27,208,359	20,096	19,681	39,777
2012	294	33,456,399	27,529	20,043	47,572
2013	344	26,258,868	48,693	18,233	66,926
Total manufacturing FDI	862	86,923,627	96,318	57,957	154,275
Total FDI	1,865	171,550,342	190,887	315,682	506,569

Source: Ethiopian Investment Agency

Some of the foreign companies that invested in the leather industry are now reaping the benefits from exports. A notable example is the Huajian Group, a Chinese shoe factory which has become a major exporter of Western brand shoes to the US and Europe. The China Daily Africa news media reports that the company made 837,400 pairs of shoes in in the first 10 months of 2013 alone and generated revenue of USD13.06 million (China Daily Africa, 2013). Currently the company employs 3,200 people and is planning to expand its investment in machinery and to take on thousands more local workers. The factory has been praised by the IMF as an exemplary investment in creating job opportunities. There are other successful foreign export-oriented companies in the sector. This is a new trend in the Ethiopian manufacturing and a sign that Ethiopia's labor-intensive light manufacturing can realize its future industrialization.

2.7. Conclusion

In this chapter, we explored a range of issues descriptively and qualitatively. We began by presenting Ethiopia's experience of industrial policy learning and implementation of *kaizen* from Japan and the achievements so far. We then examined the export performance of the sector. A close look at the export performance of the sector revealed an increasing trend in the export-to-sales ratio, particularly in the priority sectors of textiles, apparel, and tanning, leather and footwear sectors. We also showed that Ethiopia has a window of opportunity to jump-start its manufacturing in the light manufacturing sectors. Finally, we discussed recent developments in the manufacturing sector in which we examined the performance of the sector in the past three years of GTP period. The government was committed to support development of the industrial sector and particularly the labor-intensive light manufacturing in such areas as the textile and garment, leather and leather products and agro-processing industries. New domestic and foreign investments have been added into the sector and job opportunities created. The sector has performed well in terms of attracting FDI and of its export earnings during the three years. This has shown Ethiopia's potential to become a light manufacturing hub in the years to come.

Chapter 3

Empirical literature review

3.1. Literature on technical efficiency

Given the importance of efficiency as performance indicator, there is a large body of technical efficiency studies in the literature for manufacturing industries in both developing and developed countries. Examples for developed countries include: Caves and Barton (1990) for the US, Green and Mayes (1991) for United Kingdom, Caves (1992) for Australian manufacturing, and Martin-Marcos and Suarez-Galvez (2000) for Spanish manufacturing. Some of the empirical studies on the question of efficiency in African manufacturing industries include Söderbom and Teal (2004) for Ghana's manufacturing, Aggrey et al. (2010) for Kenyan, Tanzanian and Ugandan manufacturing industries, Ngui-Muchai and Muniu (2012) for Kenyan manufacturing. However, since the main objective of this study is to investigate the technical efficiency performance of Ethiopian manufacturing, we are more interested in literature that is relevant to Ethiopian manufacturing. Generally, technical efficiency is under-researched in the sector. In what follows, we briefly describe some of the available technical efficiency literature in the sector.

Gebeyehu (2003) evaluated the technical efficiency of firms in the leather industry during the period from 1996 to 1999. The main methodology used in the study was stochastic frontier analysis (SFA). The author found that inefficiency was widespread in the sector. The mean technical efficiency of the firms was found to be 83 percent for the period under study. The author found a general decline of the overall technical efficiency in the tanning industry mainly due to the use of obsolete machinery coupled with limited attempts to modernize production systems. Kuma (2002) examined the technical efficiency for the period 1984/85–1999/00 and showed that widespread inefficiency existed in the manufacturing sector in Ethiopia.

Bekele and Belay (2007) also studied the technical efficiency of grain mill products in Ethiopian manufacturing using a stochastic frontier production function. The study covered large and medium-scale establishments that employ 10 or more persons for the period 1999/2000. The estimated technical efficiency of the sample firms varied from a minimum of 18.9 percent to 95 percent. The overall mean technical efficiency was found to be 75.6 percent implying that there was a room for improvement. If factors that negatively affect efficiency could be addressed, efficiency could be expanded in the industry by about 24 percent.

Using World Bank data, a comparative analysis of labor productivity, total productivity and technical efficiency of 22 developing countries from Middle East and Northern Africa, SSA, Latin America, East Asia, and South Asia was made by Kinda et al. (2009). The study was done on eight manufacturing industries. However, in the case of Ethiopia only 5 industries (textile, leather, garment, agro-processing and wood and furniture) were included in the study. In terms of technical efficiency, Ethiopia ranked 20th among the 22 countries and six among the seven African countries. This indicates the low performance of the sector in terms of technical efficiency. For that matter, Ethiopia's rank in terms of labor productivity and total factor productivity also stood at 20^{th}.

Abegaz (2013) recently studied technical efficiency for Ethiopian manufacturing (LMMIS) that employ 10 or more persons during the period from 1996 to 2009. The author used a SFA to evaluate the sector's technical efficiency. The mean efficiency estimates indicated by the study ranged from a minimum of 10 percent in the food industry to 88 percent in the tanning and dressing industry.

While the above studies helped us to understand the condition of the manufacturing sector in the country, they have weaknesses in different areas that need to be addressed in this study. First, with the exception of Abegaz (2013), the data used in most of the studies appears to be rather old. Following these studies, Ethiopia has made significant policy changes in the industrial sector in general and the manufacturing sector in particular which might have greatly affected the performance of the firms in the sector. In terms of study coverage, most previous studies were limited to specific industries, thus giving only a partial view of the sector which may not be representative of the entire manufacturing sector. Most importantly, the methodological approach that previous studies employed raises issues of concern that directly affect the estimation procedure of the technical efficiency in the sector.

Most of these studies use stochastic frontier models of the type Battese & Coelli (1992, 1995) used to estimate technical efficiency. However, the inherent problem of these models is that they do not exploit the panel nature of the data to control for unobserved heterogeneity, which means firm-specific unobserved heterogeneity is not treated explicitly in the analysis. This generates a misspecification bias in the presence of time-invariant unobservable factors (e.g., firm-specific innate ability). The effect of these factors, unrelated to the production process but affecting the output, may be captured by the inefficiency term, thereby producing biased results. Kumbhakar et al. (2012) noted that the Battese & Coelli (1992, 1995) models are somewhat restrictive and mix firm effects with the inefficiency term. Particularly, despite the relatively longer panel data he used, Abegaz (2013) applied Battese & Coelli (1992) model while assuming time-invariant efficiency. However, the assumption of time-invariant efficiency seems to be unrealistic, especially with such a longer unbalanced panel data set (14 years). In the current study, it may also be difficult to assume that efficiency has remained unchanged in the manufacturing sector. A number of policy changes that could affect the efficiency of the firms in the sector have taken place in the 14 year under consideration. Hence, it may be important to consider that efficiency performance of the firms in the sector has changed over time and apply a model with time-varying efficiency.

Greene (2005a, b) has recently proposed a new time-varying stochastic frontier model called the "true" random effects (TRE) model. This model not only assumes time-varying efficiency, but also addresses the issue of unobserved heterogeneity. Unlike previous models, the TRE model disentangles firm-specific time-invariant unobserved heterogeneity from inefficiency. This dissertation exploits this opportunity to address these issues that have not previously been addressed. Greene's approach enables us to disentangle time-varying inefficiency from firm-specific time-invariant unobserved heterogeneity, which is particularly useful for an analysis of diverse and heterogeneous manufacturing firms in Ethiopia. We also use the conventional fixed effects (FE) and random effects (RE) stochastic frontier models to examine how the specification of the unobserved heterogeneity affects the estimation results.

Moreover, in addition to the SFA method, we also employ a / the DEA approach to further investigate the technical efficiency of the firms in the sector. DEA is a nonparametric linear programming approach to efficiency analysis which is popular in the literature. Despite its popularity, DEA has been criticized on the ground that it does not take measurement error and other statistical noise into consideration. In the presence of measurement error and other statistical noise, efficiency estimates from DEA may be biased (Coelli et al., 2005). Many attempts such as the bootstrapping method by Simar & Wilson (2000) have been devised to address this problem. More recently, Tone (2013) proposed a new resampling method in DEA which deals with measurement errors in inputs and outputs and resamples data depending on the empirical distribution of the errors; moreover, it estimates confidence intervals within which the estimated efficiency score of an individual firm occurs. In this paper, we exploit the unique advantages of the new resampling models by Tone (2013) that consider measurement errors in inputs and outputs to measure the efficiency of Ethiopian manufacturing industries.

This study contributes to the existing literature in different ways. First, previous studies on efficiency performance in the Ethiopian manufacturing sector are scarce, and their scope is limited to specific industries, thus giving only a partial view of the sector which may not be representative of the whole manufacturing. We thus fill this gap by providing evidence on efficiency performance based on a comprehensive and more recent dataset covering the entire Ethiopian manufacturing sector. This will provide policy implications on possible areas for further improvement in the manufacturing sector. Second, with regard to econometric methodology, this study builds upon previous SFA studies by explicitly taking into account the effect of firm-specific unobserved heterogeneity in measuring technical efficiency. Focusing on the Ethiopian manufacturing sector, we examine the extent to which technical efficiency estimates are affected by the different econometric specifications of the unobserved heterogeneity.

Measure of inputs and outputs in efficiency analysis

In efficiency analysis, a precise definition and measurement of both input and output variables determine the accuracy of results. Coelli et al. (2005) note that estimation of technical efficiency requires data on input and output quantities. Hence, in this section we discuss input and output variables frequently used in the existing literature of efficiency analysis and select appropriate variables to be used in this study.

A) **Selection of Inputs**

In a production process, labor, capital and intermediate inputs are used to produce certain level of output or outputs. In the empirical literature, company-based inputs are commonly classified into five categories for analysis purpose: (i) capital (K); (ii) labor (L); (iii) energy (E); (iv) material inputs; (M) and (v) purchased services (S) which are sometimes called the KLEMS approach in efficiency and productivity analysis. Coelli et al. (2005) documented that in most cases, energy, material inputs and purchased services are summed to form a single "other input" group (intermediate inputs). Accordingly, in this study, three inputs, namely; capital, labor and intermediate inputs. Intermediate inputs are the sum of energy, material inputs, purchased services and other administrative and production costs. A detail explanation of these inputs is given as below.

Capital

Capital is one of the essential inputs in measuring efficiency and productivity. As discussed in Coelli et al. (2005), a proper measurement and treatment of capital input is needed to explain efficiency and productivity variations across firms as well as the changes in the structure of industry. It is not easy to measure the quantity and price of capital input, because unlike material or labor inputs which are consumed in the production process within an accounting period, capital is a durable input used throughout the life of the asset. There are a number of alternative measures for capital input. OECD (2001) summarizes them as:

(i) Total capital service flows from different assets

(ii) Replacement value

(iii) Net capital stock

(iv) Physical measures

(v) Perpetual inventory method

A number of capital input measures have been used in various empirical studies. For example, Hossain & Karunaratne (2004) defined capital input as the gross fixed assets aggregated from book values of land, buildings, machinery, tools, transport, and office equipment for the Bangladesh manufacturing sector for the period 1978–94. Kim (2003) also measured capital input by the amount of tangible fixed assets for Korean manufacturing firms. Lundvall & Battese (2000) used the replacement cost of existing machinery and other equipment as the capital input for Kenyan manufacturing. Very recently, Ngui-Muchai & Muniu (2012) also employed the replacement value of machinery and other equipment as a capital input. Sehgal & Sherma (2011) used gross fixed capital stock as a measure of capital input for Indian manufacturing. Aggrey et al. (2010) defined capital stock as the replacement cost of existing machinery and equipment.

The CSA dataset used in this study provides book value of fixed assets at the beginning and end of the survey year, fixed assets sold and disposed during the year and depreciation rate. Hence, In this study, following the existing literature and the availability of the data, the net value of fixed assets (net capital stock) at the end of the survey year is used as capital input and is deflated using the implicit capital formation deflator. The net capital stock is the current market value of the firm's productive capital (OECD, 2001). Abegaz (2013) also used the same measure of capital input from the same source of data for estimating efficiency in the Ethiopian manufacturing.

Labor

Labor is also one of the important inputs in a firm's production and hence constitutes a considerable share of a firm's expenditure on inputs. The proxy variables used to measure labor input include; (i) number of employees; (ii) numbers of hours worked; (iii) total wages and salaries bill. Labor input can further be classified as skilled and unskilled workers, and production and non-production workers (Coelli et al., 2005).

Accordingly, many scholars have used these approaches to measure labor input. For example, Hossain & Karunaratne (2004) and Kim (2003) have used number of employees as a measurement of labor input for Bangladesh and Korean manufacturing sector, respectively. Keramidou & Mimis (2011) also adapted number of full-time employees as labor input for the Greek poultry sector for the period of 1994–2007. Aggrey et al. (2010) used annual total wage bill for the firm in the East African manufacturing. Lundvall & Battese (2000) and Ngui-Muchai & Muniu (2012) also used the total cost for labor (total wage bill) for the firm in the year as labor input in the Kenyan manufacturing sector. Sehgal & Sherma (2011) used total persons engaged involving of both production and non-production workers as a measure of labor input for Indian manufacturing.

In this study we use total labor as measured by the sum of annual permanent and temporary workers. Quality of labor can be very different in terms of education, training, experience, etc. However, since measuring quality of labor is not an easy matter, our assumption in this study is that there is no remarkable difference in labor quality.[6]

Intermediate inputs

Intermediate inputs are another important category of inputs in efficiency and productivity analysis which mainly includes energy, material inputs and purchased services and outsourcing. Energy and material inputs constitute the largest share in input costs of an enterprise. In recent years, expenditure on purchased services and outsourcing has also

[6] OECD (2001) also notes that the distinction of the quality of labor input by type of skills is particularly important if our purpose is to know the effects of a changing quality of labor on the growth of output and productivity.

become an important part of input cost and is often considered to be intermediate input. This is often observed for companies outsourcing a number of services such as cleaning, security and computing and IT-related services. Coelli et al. (2005) noted that in empirical analysis, these three inputs are commonly aggregated into one category called "other inputs". Accordingly, many empirical studies have aggregated material, energy and fuel costs as intermediate inputs. For example, Aggrey et al. (2010) used costs for raw materials, solid and liquid fuel, electricity, and water as intermediate inputs for East African manufacturing. Similarly, Lundvall & Battese (2000) also used the aggregated value of raw materials, solid and liquid fuel, electricity, and water as intermediate inputs for Kenyan manufacturing.

Our data contain the values of raw materials, fuel and lubricating oil, electricity, wood, and charcoal for energy for each establishment. Moreover, the dataset comprises other industrial expenses such as cost of water consumed, cost of contract work done by others for the establishment, cost of goods bought and resold, and cost of repair and maintenance work done by others for the establishment. In this study, we define intermediate input as the aggregated value of these items, which is deflated by a GDP deflator.

B) Selection of outputs

The measures of output commonly used in the literature are value-added and gross output as a measure of output.[7] For instance, Salim & Kalirajan (1999), Kim (2003), and

[7] Output measures based on value-added exclude intermediate inputs (materials, energy, purchased services and outsourcing, used up in the process of production), while the output measures based on gross output include those inputs.

Hossain & Karunaratne (2004) utilized value-added output measures. Nevertheless, value-added measures of output have been criticized by many authors. For example, Cobbold (2003) argued that value-added measures of output may be theoretically flawed because they provide biased estimates of industry growth rates. The value-added measure of productivity growth is not a measure of overall improvements in efficiency. It is rather viewed as the capacity of an industry to convert its technological change into final output (Cobbold, 2003; OECD, 2001).

The exclusion of intermediate inputs from the analysis using a value-added approach has been subject to debate. Cobbold (2003) noted that since intermediate inputs are the major source of output growth at the industry level, the gross output approach as a measure of output is conceptually more appealing than the value-added approach. There are also concerns over the validity of the value-added measures given the separability assumption of primary inputs (labor and capital) from intermediate inputs. For instance, Berndt and Wood (1975) argued that the separability assumption is restrictive because it is unlikely that the primary and intermediate inputs in most production process are independent. Considering these concerns, for output, the present study adopts gross output as measured by the value of all outputs produced by a given firm in the Ethiopian manufacturing sector. To correct for price changes, we deflate gross output using the output deflator for large and medium manufacturing industries. Output and all the inputs (except labor) are expressed using 2000 prices as the base.

3.2. Firms size distribution, firm growth rate distribution and persistence of growth

This section presents a brief theoretical foundation of and empirical literature on industrial dynamics. In particular, the distributional properties of firm size and firm growth and the autocorrelation of firm growth are dealt with in the subsequent sections.

3.2.1. Firm size distribution

Firm size distribution is often the starting point into the study of industrial dynamics. A pioneering work of firm size distribution is attributed to Gibrat (1931), who investigated the size distribution of French firms and concluded that the logarithm of firm size distribution can be approximated by a log-normal (Gaussian) distribution. He then proposed a model of firm growth independent of firm size that came to be known as Gibrat’s law (also called the Law of Proportionate Effect). Since then, the law has been used as a common benchmark in empirical studies of firm dynamics.

Several studies have tested the validity of Gibrat’s proposition of log-normal distribution of firm size. Despite the fact that the size distribution of firms has been a topic of interest for many researchers, a definitive shape has not yet been reached (Bottazzi & Secchi, 2005). While some studies suggest that the firm size distribution can be approximated by right-skewed log-normal, others have found the emergence of alternative shapes. Empirical studies on the firm size distribution suggested that firm growth dynamics evolve over the course of industry evolution. Using data from Portuguese manufacturing, Cabral and Mata (2003) observed that firm size distribution begins as right-skewed and gradually converges over time toward a log-normal distribution. A number of other studies (e.g., Angelini & Generale, 2008; Bottazzi et al., 2011; Coad, 2007, 2009; Ribeiro, 2007) also found that firm size distribution is right skewed.

Even though the right-skewed nature of the firm size distribution could be considered a robust finding, other features of the size distribution are also emerging in the literature. Bottazzi et al. (2007) examined the dynamics of large Italian manufacturing firms using panel data over the period from 1987 to 1997. Applying a nonparametric Kernel density method and using number of employees as a proxy for firm size, the size distribution exhibited a significant bimodal shape at the aggregate level. A sectoral-level analysis, however, revealed several sectors exhibited multimodal shape while others were characterized by a unimodal shape. This result evidenced the coexistence of firms of different size even within industries with similar activities. Bottazzi & Secchi (2005) also observed a bimodal shape of the size distribution of the top firms in the worldwide pharmaceutical industry during the period from 1987 to 1997. The authors argued that the observed bimodal nature may be peculiar to the pharmaceutical industry due to the existence of firms of different average size. Demirel & Mazzucato (2010) also examined the evolution of the firm size distribution for quoted US pharmaceutical firms observed over the period from 1950 to 2003. Unlike the log-normal distribution proposed by Gibrat (1931), their main result showed the existence of a bimodal distribution in the pharmaceutical industry, which indicated that the structural difference of the firms could be explained by the emergence of small innovative pharmaceutical firms in the industry.

In the Ethiopian manufacturing case, using CSA LMMIS data for the period from 1996 to 2003, Bigsten & Gebreeyesus (2007) have shown the departure of firm size distribution in the sector from log-normality. However, since their main focus was not on firm size distribution, their result was just a snapshot of the aggregate picture of the size distribution in the sector. They did not give a detailed analysis of the firm size distribution in the sector. Hence, in this study, a more rigorous analysis of the subject matter is presented. We show firm size distribution not only at an aggregate level, but also at a sectoral level. Previous studies have shown that features of any firm size distribution observed at an aggregated level do not hold at the sectoral level. This will shed some light on the evolution of firm size distribution in the Ethiopian manufacturing sector.

3.2.2. Firm growth rate distribution

The starting point in studying distributional properties of any firm growth rate is still Gibrat's proposition that firm growth rates are purely random draws from independent and identical Gaussian distributions (Reichstein & Jensen, 2005). However, empirical research into the distributional properties of firm grow rates have shown significant departures from Gaussian distribution which tend toward a fat-tailed and 'tent-shaped' distribution that resembles a Laplace distribution (Reichstein & Jensen, 2005).

Amaral et al. (1997) studied the distribution of firm growth rate for US manufacturing firms over the period 1974 to 1993. They observed that the distribution of firm growth rate exhibits a "tent-shaped" form that resembles the Laplace or "double-exponential" distribution. Growth rate distributions with fat tails resembling the Laplace density have also been found by Bottazzi et al. (2002) for Italian manufacturing, Bottazzi and Secchi (2003) for US manufacturing, Bottazzi & Secchi (2005) for the worldwide pharmaceutical industry, Reichstein and Jensen (2005) for Danish manufacturing, Reichstein et al. (2010) for Danish manufacturing, service, and construction sectors, and Coad & Holzl (2009) for Australian service industries. What is more interesting with the Laplace distribution of firm growth rate is that, unlike firm size distributions, it seems to be a robust feature of the industrial dynamics that they display a high degree of homogeneity across different levels of data aggregation (Bottazzi et al., 2011). As a result, the 'tent shape' Laplace distribution of firm growth rates is emerging as a 'stylized fact' in the industrial dynamics literature. To this end, Bottazzi & Secchi (2003, 2006) have introduced theoretical models explaining the appearance of such a behavior.

The emergence of growth rate distributions with fat tails resembling the Laplace distribution has implications for the use of econometric models. Under such circumstances, conventional regression estimators that target the average firm but ignore extreme events as outliers may not be robust (Coad, 2007). The author argued that a quantile regression model is characteristically robust to outliers and fat-tailed distributions. Moreover, a quantile regression model is advantageous in that there is no need to assume that the error terms are identically distributed at all points of the conditional distribution. Finally, quantile regression also provides a richer characterization of the data, allowing consideration of the effect of the independent variables varying across the entire distribution of the dependent variable instead of merely on its conditional mean.

However, the reported empirical studies have been undertaken in the developed world. Such a topic is minimally researched in SSA countries, mainly due to a lack of data availability. In this study, we exploit the CSA data to examine the distributional properties of firm growth rate in Ethiopian manufacturing. This will contribute to the literature the shape of the firm growth rate distribution when viewed from the perspective of low-income countries. Moreover, our methodological approach is also novel in the Ethiopian manufacturing context in that we apply a quantile regression model to capture distributional characteristics of the firm growth rate.

3.2.3. Firm growth rate and firm size

Another aspect of Gibrat's 'Law of Proportionate Effect' is the relationship between firm growth rate and firm size. The law states that firm growth rate is independent of its size, which implies that the growth of firms is proportional to their size. A number of empirical studies have been undertaken to test the validity of Gibrat's law (e.g., Evans, 1987; Kumar, 1985; Yasuda, 2005). The findings were inconclusive with some supporting the law while others rejecting it. Among the earlier studies that found results supporting Gibrat's law were Hart & Prais (1956) and Simon & Bonini (1958), who independently confirmed the independence of firm growth rates on size. However, several other studies reject Gibrat's law (see for example, Evans, 1987; Kumar, 1985; Oliveira and Fortunato, 2005; Yasuda, 2005). These studies suggested that firm growth is negatively associated with firm size, which indicates that small firms grow faster than larger ones. Similarly, Hymer & Pashigian (1962) found evidence contravening Gibrat's law after observing an inverse correlation between the variance of growth rates and firm size for the 1000 largest

US manufacturing firms. Some researchers investigated the law by age cohorts. For instance, Lotti et al. (2001) tested whether Gibrat's law is valid for new Italian firms. The main finding of their study was that in the early stages of the firm's lifecycle the law did not hold, yet the growth rate converged toward Gibrat's law as time went by. Having classified by size and age groups, Fotopoulos and Giotopoulos (2010) found an inverse relationship between firm growth rate and its size for micro, small and young manufacturing firms in Greece on the basis of which the authors rejected Gibrat's law. However, they failed to reject the law for medium and large firms.

Studying the relationship between firm growth and its size has important policy implications. Wagner (1992) emphasized the industrial policy implications of such a test, arguing argues that if the findings reveal that small firms grow faster than larger ones, it would help policymakers design policies that promote the entry and growth of small firms into the market, thereby prompting employment. If, on the contrary, large firms appear to grow faster than small ones, industrial policymakers might be motivated to design policies that encourage the expansion and growth of large firms in the market.

To the best of our knowledge, the only reported studies testing the relationship between firm growth rate and firm size in the Ethiopian manufacturing sector are Admasu (2006) and Bigsten & Gebreeyesus (2007) in a static analysis context. No study examines the relationship between firm growth and firm size in the context of growth persistence. Moreover, our methodological approach is different in that it takes into account the distributional properties of growth rate examined earlier. We use a quantile regression model, which is not limited only to regressions against averages, but also enables us to see the effect of firm size over the entire distribution of the firm growth rate.

3.2.4. Firm growth persistence

According to Gibrat's law of proportionate effect, firm growth rate is independently and identically distributed, which implies that growth rates at time t are not affected by the previous period's growth rates. Despite the fact that a number of studies have been conducted on the relationship between firm growth rate and firm size, there have been a relatively limited number of studies of the persistence of firm grow rates. Often growth persistence is considered to be simply a nuisance to be controlled for.

Early empirical studies on this subject began with the work of Ijiri and Simon (1967). The authors studied the growth persistence of 90 US large business firms and found strong evidence of positive autocorrelation (persistence) that contradicts Gibrat's law. Similarly, for 2000 UK quoted companies over the period 1948 to 1960, Singh and Whittington (1975) also found that firms that show an above or below average growth rate in the past would tend to experience above or below average growth rate in the following period. Subsequent studies that confirmed the existence of positive growth persistence include Chesher (1979) for the same UK quoted firms, Wagner (1992) for Germany manufacturing firms, and Bottazzi et al. (2001) for the world's top 150 pharmaceutical firms. This positive growth persistence implies that firms that experience high growth in one year will likely experience high growth the following year. Bottazzi & Secchi (2005) also observed a relatively weaker autocorrelation for the top firms in the worldwide pharmaceutical industry during the period 1987 to 1997.

Contrary to the above findings, a number of studies that showed negative growth persistence have emerged in the literature. Goddard et al. (2002) tested Gibrat's law for a sample of 443 quoted Japanese manufacturing firms for the period 1980 to 1996. The authors concluded that negative growth persistence appeared to characterize Japanese manufacturing. Oliveira and Fortunato (2006), who studied growth persistence using an unbalanced panel of Portuguese manufacturing firms over the period 1990 to 2001, found negative serial correlation in growth. Bottazi et al (2007) also found negative autocorrelation for Italian manufacturing firms using number of employee and value-added as proxies for the size of the firm. A negative serial correlation in the growth process suggested that high growth in one period is likely to be followed by a decline in the subsequent period.

The studies examined thus far applied the standard econometric models that estimate the average relationship between the dependent variable and the regressors based on the conditional mean function. However, with a fat-tailed firm growth rate distribution in which we find extreme growth events, the conventional regression estimators that focus on the average firm and ignores extreme events as outliers may not be robust (Coad, 2007). To address such a concern, other strands of studies that use quantile regression have emerged. The use of quantile regression enables us to study how growth persistence varies over the entire distribution of the growth rate distribution as opposed to point estimation.

Some of the recent papers which applied quantile regression to assess serial correlation (growth persistence) include Coad (2007), Coad and Rao (2008), Coad & Holzl

(2009), and Reichstein et al. (2010), Ribeiro (2007). Coad (2007) examined the serial correlation in 10,000 French manufacturing firms that employ 20 employees or more using panel data that cover the period 1989 to 2002. They observed that autocorrelation dynamics vary with firm size such that while the growth process of small firms is characterized by negative autocorrelation, large firms display positive autocorrelation in their growth process, which indicates that small and large firms operate in different environments. Similar trends have also been noted in Coad & Holzl (2009), who studied serial correlation for Australian micro, small and large service industries for the period 1975 to 2004. Using data for more than 9,000 Danish manufacturing, services, and construction firms for the period 1994 to 1996, Reichstein et al. (2010) suggested that studies of firm growth should focus more on the other parts of firm growth rate distributions than on the conditional mean behavior.

All the above studies were conducted in developed counties. Such studies are scant in developing countries, particularly in SSA, mainly due to a lack of data. To the best of our knowledge, there is no reported study of firm dynamics in the context of growth persistence for Ethiopian manufacturing. Hence, this dissertation contributes to filling this gap by providing an empirical study on the issue of autocorrelation in Ethiopian manufacturing. Such a study has important policy implications. Autocorrelation has a lot of information on the growth process of firms. Coad & Holzl (2009) noted that autocorrelation in the firm growth process allows us to study the persistence of chance in firm growth trajectories. This in turn helps to know whether new jobs created will disappear the following year or the growth process will remain healthy.

Chapter 4

Technical efficiency and heterogeneity of manufacturing firms in Ethiopia: A stochastic frontier analysis

4.1. Introduction

Efficiency occupies a central place in the production process of a firm. One of the objectives of an economic unit (firm) is to avoid waste by producing the maximum possible output from a given vector of inputs (output-oriented) or by minimizing input usage to produce a given level of output vector (input-oriented). Such a concept in production is what we call technical efficiency and firms can attain a high degree of technical efficiency by pursuing the waste avoidance objective (Krumbhakar & Lovell, 2000). Hence, technical efficiency is an important indicator of firm performance. Empirical studies have revealed that at different levels of disaggregation, there exist considerable variations of technical efficiency among firms with some firms becoming more efficient than the others. While firms that perform better grow and survive, firms that experience poor performance decline and are gradually driven out of the market (Jovanovic, 1982). The main purpose of this study is to investigate the technical efficiency performance and determine the relationship between firm size, age, and technical efficiency of firms in the Ethiopian manufacturing sector using unbalanced panel data (census data) over the period of 2000 to 2009.

There are various compelling reasons to measure efficiency. Fried et al. (2008) suggested that by measuring efficiency, we can identify and separate controllable and uncontrollable sources of performance variation. The authors also argued that since micro performance drives macro performance, the later depends on the former. For most firms, the ultimate concern is success as indicated by financial performance indicators. Improved efficiency performance leads to improved financial performance (Fried et al., 2008). Similarly, Kalirajan & Shand (1999) suggested that quantification of efficiency is helpful in three ways. First, it facilitates comparison among firms. Second, where measurement reveals efficiency variations among firms, additional analysis can be conducted to identify the source of such variations. Third, the result of the analysis can be used in policy formation to take further actions to improve efficiencies.

There is a large body of technical efficiency studies in the literature for the manufacturing industries in developed countries. Examples include Caves and Barton (1990) for the US, Green and Mayes (1991) for the United Kingdom, Caves (1992) for Australian manufacturing, and Martin-Marcos and Suarez-Galvez (2000) for Spanish manufacturing. Some of the empirical studies on the question of efficiency in African manufacturing industries include Söderbom & Teal (2004) for Ghana's manufacturing, Aggrey et al. (2010) for the Kenyan, Tanzanian and Ugandan manufacturing industries, and Ngui-Muchai & Muniu (2012) for Kenyan manufacturing. Söderbom &Teal (2004) argued that manufacturing firms in Africa are less efficient compared to their counterparts in the developed world. However, there have been only limited attempts to study the technical efficiency efficiency performance of the manufacturing sector in Ethiopia. Gebeyehu (2003), Kuma (2002), Belay (2007), Kinda et al. (2009) and Abegaz (2013) are some of the reported technical efficiency studies on the Ethiopian manufacturing sector. These studies use stochastic frontier models of the type by Battese & Coelli (1992, 1995).

However, the inherent problem of these models is that firm-specific unobserved heterogeneity is not treated explicitly in the analyses. This generates a misspecification bias in the presence of time-invariant unobservable factors (e.g., firm-specific innate ability). The effect of these factors, unrelated to the production process but affecting the output, may be captured by the inefficiency term, thereby producing biased results. Moreover, the study by Abegaz (2013) assumes time-invariant efficiency. However, given the relatively longer panel data set he used and substantial policy changes that could affect the efficiency of the firms in the sector have taken place within the study period, the assumption of time-invariant efficiency seems to be unrealistic. Hence, it is important to consider that the efficiency performance of the firms in the sector might have changed over time and apply a model with time-varying efficiency. To address these problems, the present study applies a recently proposed stochastic frontier model called a "true" random effects (TRE) model (Greene, 2005a, b). This approach enables us to disentangle time-varying inefficiency from firm-specific time-invariant unobserved heterogeneity. This is particularly useful for the analysis of diverse and heterogeneous manufacturing firms in Ethiopia. We also use the conventional fixed effects (FE) and random effects (RE) stochastic frontier models to examine how the specification of the unobserved heterogeneity affects the estimation results.

This study contributes to the existing literature in different ways. First, previous studies on efficiency performance in the Ethiopian manufacturing sector are scarce, and their scope is limited to specific industries, which allows only a partial view of the sector which may not be representative of the entire manufacturing sector. We thus address this gap by providing evidence on the efficiency performance based on a comprehensive and more recent dataset covering the entire population of manufacturing firms in Ethiopia that employ 10 or more persons. It will provide policy implications on possible areas for further improvement in the manufacturing sector. Second, with regard to econometric methodology, this study explicitly accounts for the effect of firm-specific unobserved heterogeneity in measuring technical efficiency. Focusing on the Ethiopian manufacturing sector, we examine to what extent the technical efficiency estimates are affected by the different econometric specifications of the unobserved heterogeneity. Moreover, the available efficiency studies in the Ethiopian manufacturing sector have focused on estimating efficiency scores. We further examine the association between firm size, age and technical efficiency. Particularly, the study of size-efficiency relationship has policy implication as to whether to promote small firms or large ones. Supporters of small firms promotion argue that since there is more competitive pressure in small firms, they tend to be more efficient than large firms. Moreover, it is also argued that the promotion of small firms can be justified on the ground that it plays an important role in creating job opportunities and reducing income inequality. On the contrary, the specialized human resources and economies of scale inherent in large firms can make them more efficient than small ones.

Our results indicate that efficiency estimates are sensitive to model specifications of the firm-specific unobserved heterogeneity. We find a significant gap in efficiency estimates between the TRE model and the FE and RE models, which would imply considerable heterogeneity of manufacturing firms in Ethiopia. The conventional FE and RE models seem to underestimate the efficiency estimates since the firm-specific unobserved heterogeneity is confounded with the inefficiency term. Our results suggest that the firm-specific unobserved heterogeneity would be particularly significant in the food and beverages, non-metals, and furniture industries due to the more heterogeneous mix of firms in these industries. Our results also show that production of the Ethiopian manufacturing sector is largely responsive to changes in intermediate inputs compared with labor and capital inputs. We also found that firms in the manufacturing sector have shown positive technological progress in the study period. The mean technical efficiency varies considerably across the industries and among firms within an industry. On average, technical efficiency for the whole manufacturing sector is estimated to be 74 percent in the study percent.

The rest of the chapter is organized as follows. Section 4.2 describes the data used in this chapter. In Section 4.3, we deal with the methodology and estimation strategy followed by the discussion of the empirical results in Section 4.4. Section 4.5 concludes the chapter.

4.2. Data description

The overall data description for the whole dissertation is given in Chapter 1 Sub-section (1.3.1). However, since data used in each chapter have been adjusted according to the models used in the particular chapter, we briefly describe here the data adjustment made for the purpose of this chapter. The data for this chapter cover an unbalanced panel data annually collected by CSA of Ethiopia during the period 2000 to 2009. Three inputs (capital, labor and intermediate inputs) and a single output (total value of production) are used to estimate the production frontier in the Ethiopian manufacturing sector. For the purpose of this chapter, we have undertaken certain data cleaning procedures. Since the CSA survey was conducted for establishments that employ 10 or more persons, observations in our data set that slip below 10 employees were deleted (1218 observations). Furthermore, all inputs and output with missing values were also excluded from our analysis. Since we are using panel data models that require firms to be observed in / over at least two time periods, all observations that appear only once in the data (1034 observations) were also not considered in the analysis. These procedures were unavoidable for the purpose of our analysis. After cleaning the data, our observations had been reduced from a total of 11217 to 8300.   .

4.3. Stochastic frontier model specification and estimation methods

Two popular approaches are used in the literature to estimate technical efficiency: stochastic frontier analysis (SFA) and data envelopment analysis (DEA). The two methods have their own distinguishing features. SFA is a parametric approach that has a stochastic nature requiring the specification of functional form assumptions about the relationship between inputs and outputs. The quality of SFA is dependent on the parameterization. DEA, on the other hand, is flexible in the sense that it is a nonparametric approach that does not require any functional form assumptions. However, the main drawback of the DEA framework is that factors such as measurement errors are attributed to inefficiency. In contrast, SFA has the advantage that statistical noise and random variation of the frontier across firms can be distinguished from inefficiency by specifying parameters in the error term.

Exploiting that advantage, this chapter makes use of SFA to evaluate the performance of the Ethiopian manufacturing sector, as measured by technical efficiency. SFA was originally and independently proposed by Aigner et al. (1977) and Meeusen and van der Broeck (1977) in the context of cross-sectional data. With the availability of panel data sets, there are varieties of SF panel data models in the literature.[8] Schmidt and Sickles (1984) estimated a stochastic production function with panel data using the conventional fixed-effects (FE) and random effect (RE) models. Their basic SF panel data model can be expressed as follows:

$$y_{it} = \beta_0 + x_{it}'\beta + v_{it} - u_i \tag{4.1}$$

where y_{it} is output (or cost) of firm i; x_{it} and β are vectors of inputs and parameters, respectively; v_{it} is an error term; and u_i is a one-sided non-negative disturbance representing time-invariant inefficiency ($u_i \geq 0$). Model 1 in Table 4.1 shows the specification of the FE model proposed by Schmidt and Sickles (1984). In this model, the firm-specific intercept, denoted by $\beta_{0i} = \beta_0 - u_i$, is allowed to correlate with the explanatory variables and v_{it}, and can be estimated by a "within-firm" estimator. Model 2 represents Schmidt and Sickles' RE model, which can be estimated by the conventional feasible generalized least squares (GLS) method. The firm-specific component, u_i, is assumed to be random and uncorrelated with the frontier regressors and v_{it}. The FE and

[8] See, for example, Belotti et al. (2012) for a detailed review of panel data models in stochastic frontier analysis.

GLS-based RE models can avoid the restrictive distributional assumptions about the inefficiency term.[9]

Table 4.1: Econometric Specification of the SF Models

	Model 1 FE	Model 2 RE (GLS)	Model 3 TRE
Firm specific component	Fixed (group dummies)	$u_i \sim \text{iid}(\mu, \sigma_u^2)$	$\alpha_i \sim \text{iid}(0, \sigma_\alpha^2)$
Random error term	$v_{it} \sim \text{iid}(0, \sigma_v^2)$	$v_{it} \sim \text{iid}(0, \sigma_v^2)$	$\varepsilon_{it} = v_{it} - u_{it}$ $v_{it} \sim N(0, \delta_v^2)$ $u_{it} \sim N^+(0, \delta_u^2)$
Estimated inefficiency $\hat{u}_i$ and $\hat{u}_{it}$	$\hat{u}_i = \max\{\hat{\beta}_{0i}\} - \hat{\beta}_{0i}$	$\hat{u}_i = \max\{\hat{u}_i^*\} - \hat{u}_i^*$ $*1$	$\hat{u}_{it} = \text{E}(u_{it} \mid \varepsilon_{it})$

Note: *1 $u_i^* = u_i - E(u_i) = u_i - \mu$, where $\mu > 0$

However, those models have two drawbacks. First, the inefficiency term is assumed to be time-invariant. The assumption of time-invariant inefficiency seems to be unrealistic, specifically for long panel-data sets. This is applicable in our case in which more than 60 percent of the firms in our data set were observed for more than five years. Second, the time-invariant inefficiency term may capture time-invariant unobservable factors, unrelated to the production process but affecting the output. The time-invariant attributes of the firms may include some unobserved characteristics such as firm-specific innate ability, which may not vary over time. The effect of these factors may be confounded with the inefficiency term, producing biased results, that is, higher estimates of inefficiency (and hence, lower estimates of efficiency).

[9] Pitt and Lee (1981) examined a RE maximum likelihood method to estimate the parameters of the SF model, assuming a truncated normal distribution for the inefficiency term.

In an attempt to overcome this problem, Greene (2005a, b) proposed an extension of the RE model, called the "true" random-effects (TRE) model, which treats firm-specific time-invariant heterogeneity and time-varying inefficiency separately.[10] Greene's model deals with time variation in inefficiency, while allowing disentanglement of the time-varying inefficiency term from time-invariant unobserved heterogeneity.[11] The TRE model can be expressed as follows:

$$y_{it} = \beta_0 + x_{it}'\beta + \alpha_i + v_{it} - u_{it} \tag{4.2}$$

Note that α_i represents firm-specific time-invariant heterogeneity and u_{it} is a time-varying inefficiency term. Greene's model assumes a two-sided normal error v_{it} and a half-normal random term u_{it} that represents a one-sided non-negative inefficiency term ($u_{it} \geq 0$). This model can be estimated by the maximum likelihood method. Model 3 in Table 4.1 illustrates the specification of Greene's TRE model. However, it may be argued that one obstacle to these approaches is that the firm-specific term may capture possible time-invariant structural inefficiency. Thus, if there is a possibility of a time-invariant structural element in inefficiency in addition to a time-varying element, Greene's models may underestimate overall inefficiency, as noted by Kumbhakar et al. (2012).

In this study, we focus on the TRE model to exploit its unique advantage. We also apply two time-invariant SF models (conventional FE and RE models) used by Schmidt

[10] Greene (2005a, b) also proposed an extension of the FE model, which he called a "true" fixed-effects (TFE) model.

[11] Relaxing the time-invariant restriction of the inefficiency term, several SF models with time-varying inefficiency have been introduced in the literature (for instance, Cornwell et al., 1990; Kumbakhar, 1990; Battese and Coelli, 1992; 1995). However, these models do not disentangle time-varying inefficiency from time-invariant firm-specific factors (i.e., heterogeneity).

and Sickles (1984) in order to compare the efficiency estimates of time-varying and time-invariant models and determine the effect of controlling for the specification of firm-specific unobserved heterogeneity on efficiency estimates. Specifically, we use the translog functional form to represent the production technology for the manufacturing firms in Ethiopia.[12] Equation (4.3) shows the details of the TRE model that we use in the analysis:

$$\begin{aligned}\ln y_{it} = \beta_0 + \beta_l \ln L_{it} + \beta_k \ln K_{it} + \beta_m \ln M_{it} + {}^1\!/_2\, \beta_{ll} (\ln L_{it})^2 + {}^1\!/_2\, \beta_{kk} (\ln K_{it})^2 \\ + {}^1\!/_2\, \beta_{mm} (\ln M_{it})^2 + \beta_{lk} (\ln L_{it})(\ln K_{it}) + \beta_{lm} (\ln L_{it})(\ln M_{it}) \\ + \beta_{km} (\ln K_{it})(\ln M_{it}) + \beta_t T + {}^1\!/_2\, \beta_{tt} T^2 + \boldsymbol{\alpha_i} + v_{it} \\ - \boldsymbol{u_{it}} \end{aligned} \tag{4.3}$$

where
y_{it} = Gross output of firm i at time t,

L_{it} = Number of permanent and temporary employees of firm i at time t,

K_{it} = Net productive fixed assets of firm i at time t,

M_{it} = Intermediate inputs of firm i at time t,

T = Time trend, a proxy for technological change,

βs = Unknown parameters to be estimated,

α_i = Firm-specific time-invariant heterogeneity,

v_{it} = Two-sided normal error, and

u_{it} = One-sided non-negative inefficiency term.

[12] Cobb-Douglas and translog functions are commonly used in the literature. These two functional forms have different features. The main advantage of the Cobb-Douglas functional form is its simplicity of application, whereas the disadvantage is that it is not second-order flexible. Moreover, it has restrictive properties since its elasticity of substitution is equal to unity. On the other hand, the translog functional form is more flexible than the Cobb-Douglas production function. This functional form is a second-order Taylor approximation of any arbitrary production function requiring no *a priori* restrictions on the elasticity of substitution.

Firm size, age and technical efficiency

In addition to estimating the technical efficiency level of firms, this study also further investigates the relationship between firm size, age, and technical efficiency. To do so, we pursue a two-stage estimation procedure. In the first stage, we estimate the efficiency levels of each firms using Equation 4.3. In the second stage, we run a regression of the estimated technical efficiency level of firms on the above variables. One major concern of the two-stage approach is that since efficiency scores are bounded by 0 and 1, the normality assumption of any standard econometric regression is not consistent with the bounded nature of the efficiency scores. To address the boundary problem, we convert the TE scores into a continuous variable using logistic regression calculated as $\ln(TE/(1-TE))$. This approach has been used in several studies (Agrey et al., 2010; Kieschnick & McCullough, 2003; Lesaffre et al., 2007; Ramanath, 1992; van Dijk & Szrimsi, 2006;). The model to be estimated can be represented as follows:

$$TE_{it} = \beta_0 + \beta_1 lnsize_{it} + \beta_2 (lnsize)^2{}_{it} + \beta_3 lnage_{it} + \beta_4 (lnage)^2{}_{it} + \beta_5 ownership_{it} + v_i + \varepsilon_{it} \qquad (4.4)$$

where TE is the technical efficiency score for firm i at time t, $lnsize_{it}$ is the size of firm i at time t measured by the natural logarithm of the total number of employees, $lnage_{it}$ is the age of firm i at time t as measured by the natural logarithm of the number of years of operation of the firm, $ownership_{it}$ represents ownership structure of the firm (a dummy variable =1 if the firm is privately owned, 0 if state owned), $\beta's$ are unknown parameters to be estimated, v_i are time-invariant firm-specific unobserved factors affecting technical efficiency, and ε_{it} is a time-varying error term assumed to be normally and identically distributed.

Firm size: The size variable is used to test if the size of a firm as measured by the natural logarithm of the number of employees affects its technical efficiency. The theoretical literature on the relationship between firm size and efficiency suggests that firm size influences efficiency positively because larger firms may enjoy economies of scale and operate at lower average costs of production. We, therefore, expect that firm size is positively associated with technical efficiency. However, the relationship may not always be linear. Since it becomes difficult for large firms to manage all the departments when they get larger (a problems leading to diseconomies of scale), it can be argued that there is an optimal level of firm size in production beyond which large firms become inefficient size. Hence, the relationship between firm size and technical efficiency is nonlinear. The squared term for the firm size variable is included in the regression in order to test this relationship.

Firm age: Firm age is measured by the actual years the firm has been operating. According to the literature on *learning-by-doing*, as firms accumulate experience in management and market, they tend to be more efficient. Moreover, selection theory also predicts that there is a positive relationship between firm age and technical efficiency. Since new firms lack awareness of their own ability, they need to take time to establish their optimal size. Thus, we expect a positive association between firm age and technical efficiency.

Ownership structure: It is argued that private ownership of enterprises enhances their efficiency for the reason that privatization changes the incentive structure of the enterprises. Private firms motivate their workers by providing reward associated with higher level of performance (Chirwa, 2001). As discussed in Chapter 2, one of the key institutional reforms in Ethiopia has been the transfer of state-owned enterprises to private owners. Accordingly, a number of manufacturing enterprises have been privatized. Hence, we expect privatization in Ethiopian manufacturing to positively affect technical efficiency. We use state owned enterprises as a reference group.

Two problems arise related to the estimation of Equation 4.4 with OLS. The first is concerned with time-invariant unobservable firm-specific heterogeneity such as managerial ability that may affect efficiency. If such heterogeneity is left unaccounted for, results could be biased. We address this problem by applying the FE model which captures the firm-specific unobserved heterogeneity. The second issue is associated with the potential endogeneity problem of the size variable. The common approach to tackle this problem is to use the first lag of the variable as an instrument for its current value. Size squared and age squared are introduced into the model in order to check whether there is non-linear relationship between the variables and efficiency.

4.4. Empirical results

This section presents the estimation results of the SF models.[13] We begin by presenting the summary statistics of the variables (outputs and inputs) used in the translog production function in Appendix Table A.1. Given the fewer number of observations in the machinery and equipment, basic iron and steel, and motor vehicle industries, we exclude them from the estimation for individual industry groups. Prior to being changed into logarithmic form, all the variables in the model were normalized. Hence, the first-order coefficients in the model can be interpreted as elasticities of output evaluated at the sample mean. This approach has been used by many authors such as Coelli et al. (2005) and Kumbhakar et al. (2012). The technical efficiency scores for individual firms are recovered from the post-estimation routines of the *sfpanel* STATA program.[14]

4.4.1. Aggregate technical efficiency estimates

Table 4.2 shows the parameter estimates of the full (aggregate) sample. All the estimated first-order coefficients are positive and significant at the 1 percent significance level across the three models. The monotonicity condition in production indicates that an increase in input must not result in a decrease in output. Consistent with this principle, as the first-order coefficients of all the three inputs are positive, it is possible to claim that the monotonicity condition is globally fulfilled at the sample mean in the Ethiopian

[13] The STATA command *sfpanel* is used; this command is designed for the estimation of parametric stochastic frontier models using panel data.

[14] Each firm's efficiency score is estimated using the conditional mean of the efficiency, $\exp[-E(u_{it}|\varepsilon_{it})]$, as discussed in Jondrow et al. (1982).

manufacturing sector. Since the output and the regressors are logarithms and scaled by their means, the first-order coefficients are interpretable as elasticities of output evaluated at the sample mean, as mentioned above. If a firm increases labor input by one percent, the output will increase by 0.161 percent (FE), 0.191 percent (RE), and 0.135 percent (TRE), respectively; if a firm increases capital input by one percent, the output will increase by 0.0334 percent (FE), 0.0612 percent (RE), and 0.0558 percent (TRE); and if a firm increases intermediate inputs by one percent, the output will increase by 0.779 percent (FE), 0.816 percent (RE), and 0.769 percent (TRE).

Production elasticity with respect to intermediate inputs is considerably larger while those with respect to capital are relatively small across the three models. This indicates that the main source of production of Ethiopian manufacturing at the aggregate level comes from intermediate inputs. Amornkitvikai & Harvie (2010) and Lundvall & Battese (2000) also found high production elasticity of intermediate inputs for Thailand manufacturing and for Kenyan manufacturing, respectively.

Returns-to-scale (RS) is an important concept in production. It shows by how much output increases when all inputs proportionally increase. The concept of RS signifies more economic meaning, showing the scale of operation (increasing if $RS > 1$, decreasing if $RS < 1$ or constant if $RS = 1$) of firms in the manufacturing sector. If the production technology exhibits increasing returns to scale, output will increase by more than proportional increase of the aggregate input. If the production technology exhibits decreasing returns to scale, output will increase by less than proportional increase of the aggregate input. If the production technology has constant returns to scale, output increases by the same proportional increase in the aggregate input.

In our case, RS can be obtained as the sum of all elasticities with respect to labor, capital, and intermediate inputs. The estimated returns to scale for FE, RE, and TRE are, respectively, 0.97 percent, 1.07 percent, and 1.06 percent at the sample mean for the aggregate manufacturing sector. As discussed above, increasing returns to scale shows a proportionate increase in all inputs that leads to a more than proportionate increase in the output. Considering the TRE model, for instance, if a firm increases all inputs by 100 percent (doubling all inputs), output will usually increase by about 106 percent. This implies that the total factor productivity of the firm will also increase because the relative increase of output is greater than the relative increase of the aggregate inputs. However, since the estimated values of the returns to scale are close to 1 for all models, this may imply that the Ethiopian manufacturing sector exhibits almost constant returns to scale at the aggregate level.

As discussed in Coelli et al. (2005, p. 213), we take into account technological change by including a time trend in the specification. By doing so, we are able to capture industry-specific knowledge of technological development. Technological change (technical progress) indicates a shift in the production frontier determining the change in production over time. The derivative of the dependent variable (log of gross output) with

Table 4.2: Estimated Parameters of the Stochastic Frontier Production Function at Full Sample

Parameters	FE	RE	TRE
β_l	0.161***	0.191***	0.187***
	(0.0336)	(0.0201)	(0.0221)
β_k	0.0334***	0.0612***	0.0740***
	(0.0174)	(0.0134)	(0.0125)
β_m	0.779***	0.816***	0.797***
	(0.0270)	(0.0178)	(0.0170)
β_{ll}	0.0602*	0.0457*	0.0751***
	(0.0326)	(0.0246)	(0.0279)
β_{kk}	0.00129	0.00738	0.0140**
	(0.00730)	(0.00610)	(0.00576)
β_{mm}	0.0298*	0.0375**	0.0516***
	(0.0171)	(0.0149)	(0.0131)
β_{lk}	0.00883	0.00736	0.00649
	(0.00990)	(0.00870)	(0.00786)
β_{lm}	-0.0358*	-0.0344**	-0.0495***
	(0.0198)	(0.0164)	(0.0151)
β_{km}	-0.00316	-0.00656	-0.0128*
	(0.00895)	(0.00815)	(0.00741)
β_t	-0.0133	-0.0145*	-0.0157*
	(0.00915)	(0.00856)	(0.00827)
β_{tt}	0.0100***	0.00982***	0.0102***
	(0.00152)	(0.00142)	(0.00136)
β_0	-0.510***	-0.366***	-0.0645*
	(0.0485)	(0.0328)	(0.0384)
σ_u	0.2978	0.3991	0.4516***
			(0.19614)
σ_v	0.3745	0.3745	0.19614***
			(0.0325)
λ			2.3023***
			(0.0824)
LogL			-2395.9011
Observations	8,080	8,080	8,080
Number of firms	1,639	1,639	1,639

Note. Robust standard errors in parentheses,
*** significant at 1 percent significance level, ** significant at 5 percent significance level, * significant at 10 percent significance level

respect to time T yields $\beta_t + \beta_{tt}T$[15], which shows the effect of technological change. Thus, the rates of technological change evaluated at the sample mean are 4.87 percent, 4.55 percent, and 4.81 percent per annum in the FE, RE, and TRE models, respectively. Thus, we find positive technological change effects in all models. This indicates that firms in the Ethiopian manufacturing have been involving in some innovation activities which resulted in upward shift of the frontier.

Table 4.3 presents the aggregate efficiency estimates of the Ethiopian manufacturing sector obtained from the three models. Note that in the FE and RE models, efficiency is assumed to be constant over time with one firm being 100 percent efficient, while in the TRE model, efficiency is assumed to vary over time. We observe notable differences in the estimated efficiency levels between the models. The efficiency estimates of the FE and RE models are much lower (20.5 percent and 30.3 percent, respectively) than those of the TRE model (74.0 percent). The relatively low efficiency levels of these two models might partially be attributed to the fact that these models capture unobserved firm-specific time-invariant effects that are not necessarily related to inefficiency. The inefficiency estimates obtained by the FE and RE models are most likely overestimated, and will thus underestimate the efficiency estimates. Relatively higher efficiency estimates are expected from the TRE model since it has the ability to differentiate unobserved firm-specific fixed effects from the inefficiency term and is able to treat the two effects separately. This result is consistent with, for example, Kumbhakar et al. (2012), which

[15] While the Cobb-Douglas model exhibits constant technological change, the effect of technological change in the translog model can either decrease or increase with time depending on whether the coefficient β_{tt} is positive or negative.

found higher technical efficiency scores using the TRE model in a study of Norwegian grain farming. Nevertheless, since the model treats potential persistent inefficiency as a firm-specific effect, it is likely that the model overstates the efficiency estimates.

Table 4.3: Aggregate Technical Efficiency Estimates

Models	Mean	Std. Dev.	Min	Max
FE	0.205	0.099	0.011	1.000
RE	0.303	0.092	0.027	1.000
TRE	0.740	0.127	0.034	0.976

4.4.2. Technical efficiency estimates by industrial group

So far we have been discussing technical efficiency of the Ethiopian Manufacturing sector at the aggregate level. We now turn to our analysis of technical efficiency by industrial group. The parameter estimates by industrial group obtained using the TRE model are presented in Table 4.4 (for the FE and RE models, see Appendix Table A.2 and Appendix Table A.3, respectively.

The estimated parameters show that there exist noticeable differences in the significance and sign of the coefficients across the models. More negative signs of the first-order coefficients of labor and capital inputs are observed in the FE and RE models, which implies that the monotonicity condition is not fulfilled at the sample mean in some of the industrial groups. The contrasting disparity in the coefficient estimates suggests the sensitivity of the specification of the firm-specific effects in the models. With regard to the negative signs of the inputs, unlike the Cobb-Douglus frontier model, it is common to see a negative sign of the input coefficients in a translog production function due to the common problem of a high degree of collinearity. We can see similar findings in other studies (for instance, Abegaz, 2013 for Ethiopian manufacturing, Amornkitvikai & Harvie, 2010, for Thailand manufacturing, and Lundvall & Battese, 2003, for Kenyan manufacturing).

Table 4.4: Estimated Parameters of the Stochastic Frontier Production Function by Industrial Group (TRE model)

Parameters	Food & Beverage	Textile	Wearing apparel	Tanning, leather &footwear	Wood	Paper & printing	Chemicals	Rubber & Plastics	Non-metals	Fabricated Metals	Furniture
β_l	0.0973*	0.0693	0.0688	0.193***	0.229	0.385***	0.142*	0.0942***	0.0140	0.170	0.157**
	(0.0513)	(0.0448)	(0.0933)	(0.0348)	(0.170)	(0.0840)	(0.0737)	(0.0276)	(0.0839)	(0.129)	(0.0791)
β_k	0.0793***	0.0154	0.0453	0.0860**	0.150	0.0420	0.0957**	0.0303	0.150***	-0.00284	0.109***
	(0.0233)	(0.0354)	(0.0699)	(0.0342)	(0.132)	(0.0608)	(0.0400)	(0.0325)	(0.0459)	(0.0439)	(0.0327)
β_m	0.864***	0.920***	0.848***	0.787***	0.748***	0.692***	0.773***	0.871***	0.805***	0.761***	0.736***
	(0.0271)	(0.0393)	(0.0746)	(0.0259)	(0.161)	(0.0425)	(0.0536)	(0.0364)	(0.0705)	(0.117)	(0.0664)
β_{ll}	0.0937*	0.0745*	-0.0410	-0.0202	0.0105	0.0236	0.122	-0.00108	0.186**	0.0289	0.173**
	(0.0512)	(0.0425)	(0.0683)	(0.0468)	(0.0571)	(0.0877)	(0.132)	(0.0502)	(0.0725)	(0.171)	(0.0827)
β_{kk}	0.00165	-0.0239*	0.00792	0.00936	0.0463*	-0.0170	0.0448*	-0.0111	0.0346**	0.0269	0.0210**
	(0.00894)	(0.0130)	(0.0206)	(0.0233)	(0.0264)	(0.0370)	(0.0260)	(0.0170)	(0.0137)	(0.0263)	(0.0104)
β_{mm}	0.0118	0.0611	0.0240	0.0737***	-0.00345	0.0609	0.0979***	0.129**	0.0764**	0.157	0.0760***
	(0.0190)	(0.0398)	(0.0557)	(0.0212)	(0.0816)	(0.0383)	(0.0366)	(0.0512)	(0.0300)	(0.107)	(0.0256)
β_{lk}	0.00263	-0.00707	0.00269	0.0637**	-0.0220	0.0673	-0.00732	0.0510	-0.0128	0.0278	0.00491
	(0.0143)	(0.0226)	(0.0274)	(0.0310)	(0.0496)	(0.0553)	(0.0420)	(0.0374)	(0.0199)	(0.0548)	(0.0216)
β_{lm}	-0.0353	-0.0379	-0.0200	-0.0328	0.00475	-0.0731*	-0.0629	-0.0937**	-0.127***	-0.0813	-0.109***
	(0.0279)	(0.0285)	(0.0469)	(0.0335)	(0.0383)	(0.0412)	(0.0394)	(0.0450)	(0.0391)	(0.116)	(0.0352)
β_{km}	0.0118	0.0183	-0.0154	-0.0380**	-0.0169	-0.00798	-0.0515**	-0.0149	-0.00810	-0.0837	-0.0148
	(0.0107)	(0.0171)	(0.0303)	(0.0186)	(0.0436)	(0.0260)	(0.0257)	(0.0306)	(0.0174)	(0.0554)	(0.00968)
β_t	-0.0313***	-0.0523	0.0200	-0.0416	-0.0813	-0.0202	0.0179	-0.0498	-0.0401*	0.0493	0.0386*
	(0.0109)	(0.0437)	(0.0493)	(0.0255)	(0.0914)	(0.0261)	(0.0302)	(0.0369)	(0.0242)	(0.0456)	(0.0202)
β_{tt}	0.0127***	0.0153**	0.00552	0.0148***	0.0164	0.00962**	0.00627	0.0136**	0.0151***	0.00285	0.000589
	(0.00190)	(0.00739)	(0.00850)	(0.00436)	(0.0152)	(0.00379)	(0.00490)	(0.00568)	(0.00414)	(0.00828)	(0.00341)
β_0	-0.181**	-0.214	-0.218	-0.215***	0.473	0.0718	-0.201**	-0.00735	-0.101	-0.288**	-0.340***
	(0.0897)	(0.194)	(0.183)	(0.0785)	(0.507)	(0.129)	(0.0992)	(0.130)	(0.121)	(0.113)	(0.0978)
σ_u	0.2471	0.1262	0.1636	0.1981	0.1279	0.4885	0.3387	0.2208	0 .2149	0.5337	0.2021
σ_v	0.2089	0.2859	0.3175	0.2703	0 .3744	0.2261	0.2675	0.3041	0 .3002	0.2016	0 .2683
λ	1.1827	0.4413	0.5155	0.7329	0 .3415	2.1599	1.2661	0.7262	0 .7160	2.6471	0.7533
LogL	-1124.7666	-99.4881	-94.6974	-194.2895	-85.6428	-364.3132	-291.4754	-245.2114	-648.3493	-209.8673	-453.5635
Observ.	2,380	289	228	514	160	721	463	473	1,100	356	1,079
No. firms	482	46	40	89	35	111	74	87	285	88	246

Note: Robust standard errors in parentheses. *** significant at 1 percent significance level, ** significant at 5 percent significance level, * significant at 10 percent significance level.
To ensure convergence, an exponential distribution is assumed for the inefficiency term in individual sectors (except for fabricated metals industry where a half-normal distribution is assumed).

Similar to the aggregate level efficiency estimation, parameter estimates of the intermediate input for all the industrial groups were found to be positive and statistically significant at the 1 percent level of significance for all models. The coefficients for labor are relatively high and statistically significant in the paper and printing industry and the tanning, leather, and footwear industry. In contrast, the coefficients for capital are relatively high and significant in the non-metals industry.

Output elasticities, returns to scale and technological change

The output elasticities of each industrial group are given by the first-order coefficients of all three inputs in obtained using the three models. Considering the TRE model, since the first-order coefficients of all the three inputs are positive, the monotonicity condition is globally fulfilled at the sample mean in all the industrial groups except in the fabricated metals industrial group where the elasticity of capital is negative. Since the frontier variables were scaled by their mean, the first-order coefficients are interpretable as output elasticities. Taking the food and beverage industrial group as an example, if firms in this sector increase labor input by one percent, output will increase by 0.0973 percent; if firms increase capital input by one percent, output will increase by 0.0793 percent; and if firms increase intermediate inputs by one percent, output will increase by 0.864 percent. Similar interpretation can be made about the rest of the industries. As in Subsection 4.4.1, the coefficients (i.e., the elasticities of output with respect to intermediate inputs) are considerably greater than those with respect to capital across the industrial groups, which imply that the production of the Ethiopian manufacturing sector mainly relies on intermediate inputs followed by labor inputs, whereas capital seems to be the least important input. The lower output elasticity with respect to capital input indicates that the manufacturing sector is less responsive to changes in capital input. Indeed, due to the fact that the sector is still underdeveloped, the unresponsiveness to changes in capital indicates that many of the firms in the sector use older techniques of production (outdated machinery).

Returns to scale as measured by elasticity of scale of the technology and technological changes in each of the manufacturing industries are reported in Table 4.5. Considering the TRE model, from the table, we observe that food and beverage, tanning, leather and footwear, wood, chemicals, basic iron and steel industries exhibit increasing returns to scale with the majority of firms having elasticities of scale greater than 1.04. This indicates that the size of most firms in the Ethiopian manufacturing sector seems to be small, meaning that these firms can further enhance their efficiency by expanding their scale of operation. For example, the returns to scale (1.13 percent) in the wood industry indicates that if a firm doubles (100 percent) all input quantities, output will increase by 113 percent. This implies that most firms have increasing returns to scale and hence, the firms could increase productivity by increasing all input quantities. Wearing apparel, rubber and plastics, non-metals, and fabricated metals industries appear to operate with decreasing returns to scale in which the scale elasticity of majority of firms ranges from 0.928 to 0.996. For example, the 0.9621 returns to scale in the wearing apparel industry implies that if firms increase all input quantities by twofold (100 percent), output will increase by about 96 percent, which shows that most firms in this particular industry are operating under decreasing returns to scale. The majority of firms in the textile and furniture industries seem to operate under constant returns to scale for the study period.

Regarding technological change, we see that most firms in their respective industries have, on average, experienced positive technical progress in the study period indicating an upward shift of the production frontier. The technical progress ranges from a minimum of 2.4 percent in the wood industry to a maximum of 6.6 percent in the fabricated metals industry. This shows that technical progress might have played an important role for firms to increase their efficiency performance. Firms have been involved in some invention and innovation activities. With the increasing number of FDI companies in manufacturing, there could have been an opportunity for firms to learn new technology from FDI and other international experience.

Table 4.5: Estimated Elasticities of Scale and Technological Change by Industrial Group

	Elasticity of scale			Technological change		
Industry	FE	RE	TRE	FE	RE	TRE
Food & beverage	0.9513	1.1394	1.0406	0.0452	0.0441	0.0474
Textile	1.0854	1.0111	1.0047	0.0285	0.0295	0.0309
Wearing apparel	0.8529	0.956	0.9621	0.059	0.0558	0.0515
Tanning, leather & footwear	0.998	1.0753	1.066	0.043	0.0461	0.0439
Wood	1.524	1.131	1.127	0.0048	0.0226	0.0242
Paper & printing	0.9217	1.1298	1.119	0.0425	0.0381	0.0382
Chemicals	0.957	1.0673	1.0107	0.0545	0.0508	0.0551
Rubber & Plastics	1.072	0.988	0.9955	0.0591	0.0359	0.0378
Non-metals	0.7849	0.9791	0.969	0.0709	0.0594	0.0642
Fabricated Metals	0.7764	0.9262	0.92816	0.057	0.0391	0.0664
Furniture	0.7533	0.952	1.002	0.0488	0.0468	0.039

In Table 4.6, we summarize the estimated technical efficiency using the different models for each industrial group. In the FE model, the average technical efficiency estimates range from 17.6 percent in the food and beverage industry to 70.2 percent in the tanning, leather and footwear industry. Efficiency estimates also vary in the RE model, ranging from 26.5 percent in the food and beverage industry to 86.8 percent in the wood industry. In contrast, efficiency estimates for the TRE model have a narrower range, between 68.4 in the fabricated metal industry to 88.2 percent in the textile industry. Moreover, efficiency estimates in the TRE model are greater than those in the FE and RE models. As discussed in Subsection 4.4.1, the lower estimates in the FE and RE models emerge because firm-specific heterogeneity is contaminated with the inefficiency term in those models.

To measure the gap in efficiency estimates among models, we calculate the ratio of the TRE estimate to the FE estimate. The greatest is 4.3 (=0.751/0.176) in the food and beverages industry, followed by 3.5 (=0.813/0.232) in the non-metals industry and 2.5 (0.821/0.322) in the furniture industry. These industries are the three largest groups in terms of the number of firms in the Ethiopian manufacturing sector. The order of the ratio turns out to correspond to the order of the number of firms: the largest is 482 firms in the food and beverages industry, followed by 285 firms in the non-metals industry and 246 firms in the furniture industry. When the size of the industrial group becomes larger, the extent of diversity of the firms (in terms of the unobserved heterogeneity) may also become more significant. Thus, the TRE model would be more suitable for estimation because it takes account of firm-specific unobserved heterogeneity. However, since each model has its own advantages and disadvantages, it might be difficult to strongly conclude that the TRE model is better than the other models. The extended version of the results focusing on the TRE model is provided in Appendix Table A.4, where technical efficiency estimates by industrial group and year are presented.

Table 4.6: Technical Efficiency Estimates by Industrial Group

Industry	Models	Mean	Median	Std. Dev.	Min	Max
	FE	0.176	0.143	0.122	0.011	1.000
Food and beverages	RE	0.265	0.235	0.114	0.021	1.000
	TRE	0.751	0.769	0.139	0.054	0.983
	FE	0.555	0.503	0.165	0.308	1.000
Textiles	RE	0.740	0.730	0.114	0.512	1.000
	TRE	0.882	0.892	0.049	0.484	0.956
	FE	0.534	0.497	0.156	0.287	1.000
Wearing apparel	RE	0.851	0.853	0.081	0.669	1.000
	TRE	0.852	0.867	0.065	0.470	0.943
	FE	0.702	0.746	0.181	0.244	1.000
Tanning, leather &	RE	0.750	0.774	0.096	0.460	1.000
footwear	TRE	0.827	0.851	0.093	0.186	0.954
	FE	0.544	0.547	0.216	0.173	1.000
Wood	RE	0.868	0.864	0.083	0.673	1.000
	TRE	0.881	0.889	0.038	0.593	0.936
	FE	0.375	0.336	0.174	0.094	1.000
Paper and printing	RE	0.643	0.636	0.135	0.265	1.000
	TRE	0.704	0.732	0.139	0.019	0.939
	FE	0.488	0.453	0.220	0.056	1.000
Chemicals	RE	0.614	0.616	0.172	0.172	1.000
	TRE	0.741	0.788	0.153	0.025	0.946
	FE	0.415	0.379	0.168	0.154	1.000
Rubber and plastics	RE	0.742	0.730	0.097	0.534	1.000

	TRE	0.815	0.836	0.093	0.039	0.943
Non-metals	FE	0.232	0.194	0.135	0.023	1.000
	RE	0.366	0.314	0.153	0.076	1.000
	TRE	0.813	0.834	0.091	0.083	0.950
Fabricated metal	FE	0.523	0.493	0.201	0.054	1.000
	RE	0.576	0.559	0.153	0.158	1.000
	TRE	0.684	0.717	0.147	0.094	0.926
Furniture	FE	0.322	0.303	0.113	0.063	1.000
	RE	0.599	0.597	0.099	0.257	1.000
	TRE	0.821	0.844	0.110	0.003	0.957

Note: We have also run a regression using real wages and salaries as inputs instead of the labor input. The efficiency estimates are quite similar across the industries except in one industry where we found a bit higher efficiency estimates. The results are can be obtained upon request from the author.

Relatively higher efficiency estimates as estimated by the TRE model are observed in the textile, wearing, tanning, leather and footwear industries. As discussed in Chapter 2, these industries have already been selected by the government as priority sectors to emerge as exporters in the global market and have relatively longer histories of export experience. The theory of *learning by exporting* states that export-oriented firms tend to be more technically efficient than non-export-oriented firms. Hence, the participation of firms in these sectors in the global market might have contributed towards improving their efficiency. Given that Ethiopia is a poor country and the destinations of the exports are countries with advanced technology, exporting firms can learn to improve their technological capabilities. Moreover, stiff competition in the global market forces firms to improve the quality and choice of their products to meet international standards, thereby improving their efficiency and productivity. The government has also been exerting concerted efforts to provide incentives to attract export-oriented FDI in these sectors. The presence of FDI companies with rich international experience in factory management might have also contributed to the improved efficiency. The relatively higher efficiency levels in these sectors might also indicate the success of the government's preferential treatment towards these sectors.

The variation of the efficiency scores in the manufacturing sector can also be visualized for each industrial group, as illustrated in Figure 4.1 for the TRE model.

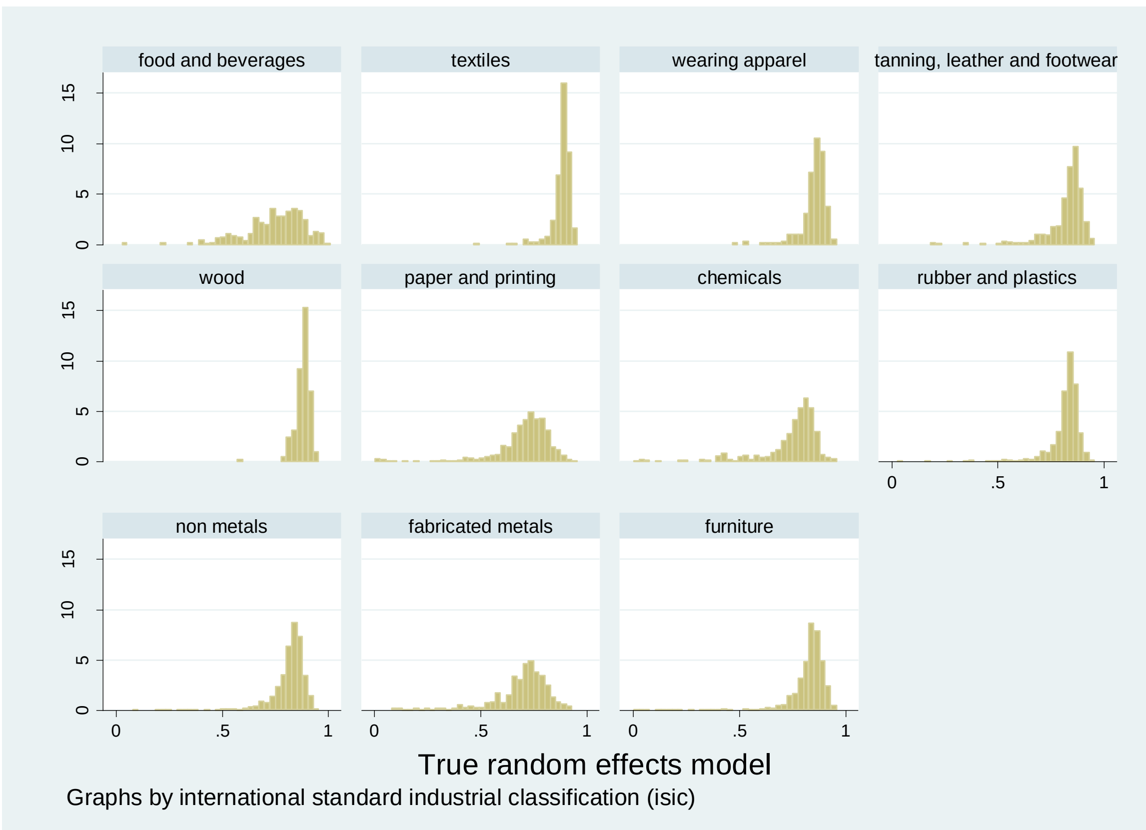


Figure 4.1: Technical efficiency distribution by industrial group (TRE model)

The graphs show that the efficiency distribution is negatively skewed, having longer tails to the left. [16] Indeed, this emanates from the implicit assumption of negatively skewed distribution of the technical efficiency of the stochastic frontier model. We observe in Figure 4.1 that there exists substantial variation in the technical efficiency distribution among the different industrial groups.

To give a better picture of the technical efficiency performance of manufacturing firms in Ethiopia, it would be helpful to compare our results with recent previous studies. One such study is Abegaz (2013). The author found that the technical efficiency for the entire manufacturing sector was 56 percent, compared to our estimate of 74 percent. Although the overall average efficiency seems to be higher in our estimation (based on the TRE model), both studies found not only similar efficiency estimates for the priority sectors (textile, leather and leather products, and wearing apparel industries), but also the efficiency is higher in these sectors compared to other sectors. This may reinforce our argument that the government's preferential treatment for these sectors might have put them to a position of better competitive advantage. However, since the two studies use different methodological approaches, it may be difficult to strongly claim that the comparison is useful. Indeed, the model used in this study (TRE) was designed to overcome the problems surrounding the model used by Abegaz (2013).

[16] If the distribution is positively skewed, the longer tail is to the right side with values above the median.

4.4.3. Efficiency rankings

It is common to see in the literature that after efficiency score are estimated, observations are ranked according to their efficiency scores. However, the rankings from different model specifications are likely to differ. Hence, it is imperative to examine the intensity of rank correlations implied by different models (Wang, 2002). To examine the consistency of the efficiency rankings between the different models, we calculate Spearman's rank correlation coefficients. The rankings of efficiency estimates from different model specifications are likely to differ. The pair-wise correlation coefficients between the efficiency estimates obtained from the three models are provided in Table 4.7. The results indicate that the FE and RE models show correlations of relatively higher ranks. However, the correlation coefficients between the FE and TRE models and between the RE and TRE models are low, suggesting substantial differences in the efficiency estimates. As already discussed, this would be due to the fact that the TRE model can treat firm-specific fixed effects separately from the inefficiency term and that it deals with time variation in inefficiency.

Table 4.7: Spearman's Rank Correlation Coefficients between Efficiency Scores

Models	FE	RE	TRE
FE	1.00		
RE	0.89	1.00	
TRE	0.34	0.33	1.00

Figures 4.2 to 4.4 illustrate the correlations of efficiency estimates from the different models using scatter plots. These figures verify the results of the Spearman's rank correlation coefficients shown in Table 4.7.

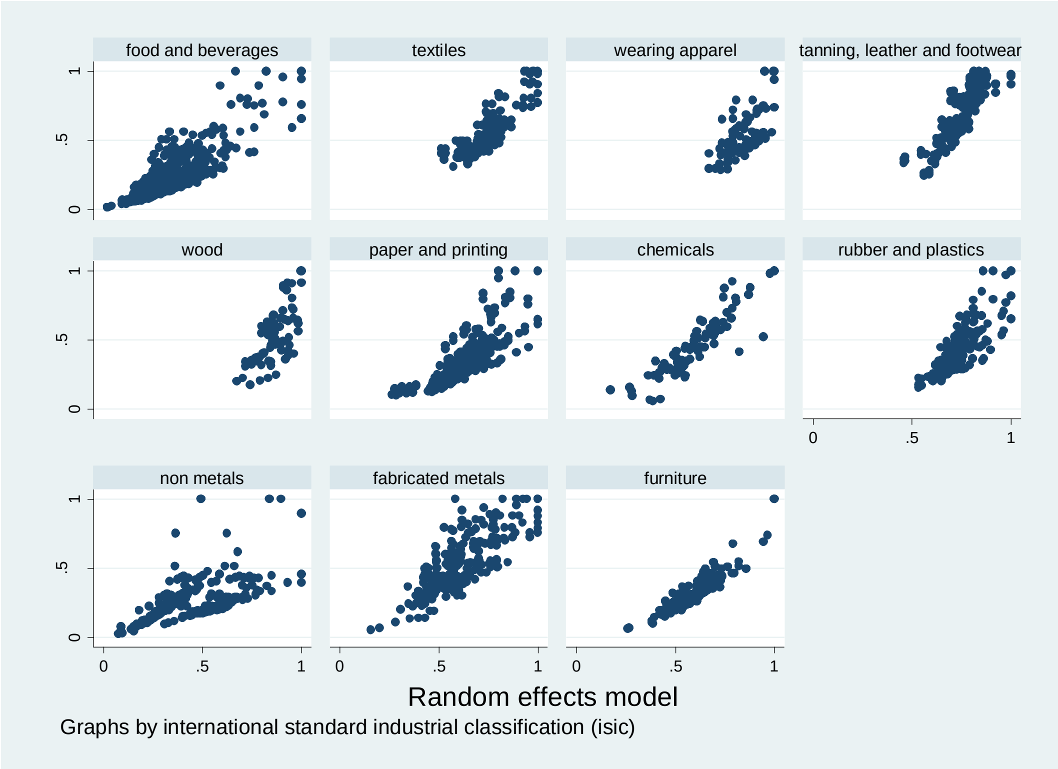


Figure 4.2: Correlation of the efficiency estimates between FE and RE models

Figure 4.3: Correlation of the efficiency estimates between FE and TRE models

Figure 4.4: Correlation of the efficiency estimates between RE and TRE models

4.4.4. Firm size, age and technical efficiency

In order to get first impression on the relationship between firm size, age and technical efficiency, we classify firms, based on the literature, into certain size and age categories. The resulting efficiency distribution is given in Table 4.8. While, we use total number of employees as a proxy for firm size, age is measured by the number of years the firm has been in operation.

From the table, we observe that overall (i.e., for all firms), the relationship between firm size and technical efficiency tends to be positive. However, the result differs by industrial group. For example, in the food and beverages, tanning, leather and footwear, paper and printing and fabricated metals industries, technical efficiency increases with firm size, indicating that larger firms are more efficient than small ones. On the other hand, wearing apparel, chemicals, rubber and plastics and fabricated metals industries exhibit a negative association between firm size and technical efficiency, suggesting that small firms are more efficient than large firms. The remaining industries do not show any regular trend.

Turning to age groups, wearing apparel, tanning, leather and footwear, paper and printing, chemicals and non-metals industries indicate that age has a favorable effect on technical efficiency, which suggests that older firms are more efficient than younger ones. In the food and beverages, rubber and plastics, fabricated metals and furniture industries, however, age affects technical efficiency negatively, implying that small firms are more efficient than larger ones. In both cases, we observe that the effect on technical efficiency seems be inconclusive. Moreover, generally, the increase or decrease in efficiency in absolute value is rather small. There is not a huge gap in efficiency between the groups.

Table 4.8: Technical Efficiency Distribution by Firm Size and Age

Group	All firms	Food and beverages	Textile	Wearing apparel	Tanning, leather& footwear	Wood	Paper &printing	Chemicals	Rubber &plastics	Non-metals	Fabricated metals	Furniture
Employees group												
10 to 19	0.727	0.738	0.872	0.857	0.834	0.882	0.705	0.764	0.824	0.814	0.683	0.826
20 to 49	0.74	0.748	0.879	0.852	0.811	0.873	0.687	0.715	0.81	0.808	0.669	0.814
50 to 99	0.751	0.746	0.877	0.853	0.835	0.888	0.706	0.768	0.816	0.826	0.695	0.804
100 +	0.753	0.775	0.885	0.846	0.835	0.882	0.728	0.733	0.814	0.811	0.703	0.82
Age group												
Age ≤ 5	0.725	0.77	0.889	0.835	0.823	0.886	0.687	0.737	0.795	0.809	0.679	0.826
5< Age≤10	0.738	0.736	0.882	0.861	0.813	0.883	0.715	0.733	0.833	0.812	0.695	0.813
10<Age≤20	0.731	0.727	0.887	0.85	0.828	0.882	0.655	0.727	0.823	0.816	0.673	0.819
20< Age≤40	0.767	0.745	0.876	0.854	0.847	0.876	0.736	0.766	0.834	0.823	0.691	0.826
Age > 40	0.766	0.775	0.881	0.864	0.844	0.887	0.722	0.772	0.802	0.817	0.65	0.813

The above analysis can only give us a general impression of the size-efficiency and age-efficiency relationship. Further statistical tests should be carried out in order to arrive at conclusive evidence. For this purpose, we run an econometric regression based on Equation 4.4. Our estimation begins with the simple OLS model reported in Appendix Table A.5 and the estimation results of the FE model (main model) are presented in Table 4.9. We base our analysis on the preferred model (FE model). Nevertheless, we also observe some similarities of results between the two models.

Table 4.9 shows that only five industries have a positive relationship between technical efficiency and firm size as measured by employment. Of those five, only in the wearing apparel and paper and printing industries is the relationship statistically significant at the 1 percent and 10 percent significance level, respectively. The positive effect of firm size on efficiency implies that larger firms are more technically efficient than small firms in these industries. As mentioned before, larger firms may enjoy economies of scale and operate at lower average cost of production. On the other hand, the coefficient of size is negative in the remaining six industries. Out of the six industries, a significant negative association of firm size with technical efficiency is observed only in the furniture industry. This result is possible if firms encounter size-related management problems leading to diseconomies of scale.

Age of the firm seems to have no significant relationship with technical efficiency in most industries under question except in the food and beverages and textiles industries where the effect of age is positively and negatively significant, respectively. However, the relationship is positive in most of the industries. It is common to see in the literature that age is insignificantly related to efficiency. For example, Lundvall & Battesse (2000) for Kenyan manufacturing firms in the food, wood, textile and metal industries, Aggrey et al. (2010) for Kenyan, Tanzanian and Ugandan manufacturing have found a non-significant relationship between age and technical efficiency. The significant positive association of age and efficiency in the food and beverages industry is consistent with the *learning-by-doing* argument that firms become more efficient since they accumulate management and market experience over time. However, the positive effect of age would be negative if depreciation of capital outweighs the accumulated experience of the particular firm. Such a relationship is reflected in some of the industries in our study.

Similarly, the relationship between ownership structure and technical efficiency is not significant in most industries with the direction of the relationship differing from industry to industry. For instance, in the wearing apparel industry, we find the effect of ownership structure to be significant at the 10 percent level of significance, which implies that privately-owned firms are more efficient than state-owned ones. However, in the food and beverages and tanning, leather and footwear industries the effect of ownership is negative, which suggests that state-owned firms tend to be more efficient than privately-owned ones. This result is consistent with the claim that although the government has been pursuing a privatization policy, the private sector in Ethiopia has been constrained by limited access to important resources which include credit and land.

Table 4.9: Parameter Estimates of the Relationship between Firm size, Age and Technical Efficiency (FE model)

Variables	All firms	Food & beverages	Textiles	Wearing apparel	Tanning, leather & footwear	wood	Paper & printing	Chemicals	Rubber & plastics	Nonmetals	Fabricated metals	Furniture
lnsize_{t-1}	0.0219	0.0201	-0.148	0.886***	-0.0391	0.131	1.132*	-1.043	-0.0312	0.209	-0.724	-0.565*
	(0.117)	(0.118)	(0.485)	(0.217)	(0.384)	(0.804)	(0.666)	(0.909)	(0.625)	(0.327)	(0.584)	(0.324)
$(\mathrm{lnsize})^2_{t-1}$	0.000286	0.000193	0.00831	0.095***	-0.00237	0.0600	-0.169*	0.133	0.0204	-0.0283	0.0965	0.0738*
	(0.0147)	(0.0131)	(0.0438)	(0.0224)	(0.0453)	(0.120)	(0.0987)	(0.113)	(0.0806)	(0.0429)	(0.0753)	(0.0423)
lnage	0.229	0.401**	-3.510**	-0.498	0.235	2.161	0.707	-1.227	0.381	0.424	-0.978	0.746
	(0.211)	(0.194)	(1.724)	(1.209)	(0.469)	(3.119)	(0.620)	(0.964)	(0.681)	(0.992)	(2.242)	(0.726)
$(\mathrm{lnage})^2$	-0.0505	-0.162**	1.124**	0.368	-0.0454	-0.525	-0.241	0.531	-0.0485	-0.0952	0.404	-0.406
	(0.0792)	(0.0763)	(0.480)	(0.486)	(0.206)	(0.929)	(0.227)	(0.368)	(0.272)	(0.356)	(0.797)	(0.335)
ownership	-0.0346	-0.119**	-0.0327	0.646*	-0.257*	-0.0520	0.0211	-0.0842	0.283	0.0322	-0.188	0.0799
	(0.0514)	(0.0600)	(0.118)	(0.360)	(0.136)	(0.330)	(0.112)	(0.203)	(0.192)	(0.255)	(0.441)	(0.0525)
Constant	0.837***	1.130***	1.735	-2.505**	1.233	-1.133	-0.746	2.859*	0.284	0.378	2.499	2.542***
	(0.263)	(0.280)	(1.991)	(1.083)	(0.839)	(2.835)	(1.032)	(1.668)	(1.184)	(0.968)	(1.528)	(0.762)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observ.	5,770	1,763	228	185	420	109	592	376	360	662	259	721
R-squared	0.021	0.027	0.106	0.179	0.056	0.336	0.116	0.050	0.050	0.041	0.110	0.043
No. firms	1,527	471	46	40	88	32	111	72	86	244	86	232

Note. Robust standard errors in parentheses, *** significant at 1 percent significance level, ** significant at 5 percent significance level, * significant at 10 percent significance level

Overall, our analysis shows that the relationship of the three variables with technical efficiency is non-significant. This suggests that there could be other factors, not included in our model, that affect technical efficiency in the Ethiopian manufacturing sector. In the next section, we qualitatively explain other factors that might have contributed to the efficiency variations among firms in the sector.

4.4.5. Explaining other factors affecting efficiency: As reported by firms in the sector

In this section, we look into the efficiency results of the TRE model from the perspective of other observable factors affecting efficiency. As mentioned before, non-negligible variations in efficiency exist among firms within the industrial group, indicating that there is room for improving efficiency levels if firms use their resources in a more efficient manner. Efficiency variations among firms may be explained by internal and external factors. In what follows, we discuss some of the factors that might have contributed to efficiency variations among firms during the study period. In particular, we highlight the tanning, leather and footwear industry and the textile industry because these industries are the top priority for the government in developing the export sector.

As discussed in Chapter 2, the Ethiopian manufacturing sector is still at a nascent stage. It is generally dominated by simple agro-processing activities, and the technological capabilities vary among firms. Despite Ethiopia's abundant human resources, the quality of the labor force involved in the sector is generally poor and not uniform across firms. There is a lack of systematic and mission-oriented worker training programs that could improve productivity in each company. Firms in the sector vary significantly in terms of modern management practice, product lines, and exposure to international markets. All these factors would lead to efficiency variations in the manufacturing sector.

The major problem, common to all the manufacturing industries, would be the inability of firms to operate at their full production capacity. A firm's ability to work at full capacity has been mainly hampered by shortages of raw materials. Other problems also include erratic electric power supply and unfavourable government rules and regulations. Our data indeed show that firms did not utilize their full capacity. While firms' potential average production at full capacity is estimated to be about ETB 25.3 million per annum, the average actual production stands at about ETB 14.8 million per annum in the period under study. This implies that firms, on average, operated at about 60 percent of their full capacity. Industry-wise capacity utilization ranges from 49 to 64 percent.[17]

Take, for example, the tanning, leather and footwear industry with its average efficiency of 83 percent. Notwithstanding the relatively high average efficiency, the variation among firms remains significant, ranging from 19 to 96 percent, which indicates the existence of poorly performing firms. Despite the availability of ample resources, some firms in this industry often face acute shortages of hides and skins. Weldegiorgis (2012) reported three possible causes of shortages, the first of which is that while the industry has remained operating at less than full capacity for a long period of time, raw hides and skins

[17] Despite the fact that a number of FDI companies are currently entering Ethiopia, there are also other FDI companies that are reluctant to do so. Prior to committing resources, foreign investors may want to see that such problems are resolved. The flow of FDI will benefit Ethiopian local firms that do not have international exposure and experience. Local firms can learn new technologies and management practice from the FDI companies, thereby leading to improved efficiency.

had been exported until the practice was banned in 2010. For instance, Ethiopia exported more than 3 million kg of hides and skins to foreign countries in 2008 alone. Second, the exports of live animals have grown rapidly, soaring from 16,137 in 1998 to about 540,000 heads in 2010. Third, a substantial amount of both live animals and raw hides and skins illegally leave Ethiopia every year to neighboring countries through border routes. Contraband trade undermines the supply of hides and skins to the domestic leather industry. The combined effects of the above-mentioned problems led to an increase in domestic prices of finished leather, thereby weakening the competitiveness of this industry. In fact, about 51 percent of the firms in this industry reported that they faced problems because they were not able to compete with foreign products in price.

Turning to the textile industry, the relatively high efficiency level (88 percent on average) may be attributed to the fact that the government has given high priority to this industry in developing the export sector. However, efficiency variations among firms still remain substantial, ranging from 48 to 96 percent. Ethiopia has the potential to grow medium- and long-fiber cotton that can be used as inputs in the textile industry. The length of the fiber is a major quality indicator of cotton. Although the problem of shortages of fiber is still a concern, the main problem here is the inconsistency of fiber length, which affects the quality of fabrics and knitted products. Cotton farms export their high quality (clean long-fiber) cotton to foreign countries and supply the remaining low-quality to the domestic textile industry. Thus, in the garment industry the major constraint is a shortage in the supply of quality fabrics. Significant shortages of supplies in raw materials prevent some firms from operating at full capacity, which in turn would lead to efficiency variations across firms.

Lack of access to credit is also another serious problem facing the manufacturing sector. The old type of loan system and a 100 percent collateral requirement by banks limit the ability of enterprises to obtain loans. Indeed, World Bank *Ease of Doing Business* 2014 report reveals that Ethiopia ranked 109th in terms of ease of getting credit. Although this rank is slightly better than the Sub-Saharan Africa (SSA) average (113th), it is much worse than Kenya (13th), Uganda (42th), and Rwanda (13th). Constrained by the unavailability of credit, some manufacturing firms are forced to operate in an inefficient way, thereby magnifying efficiency variations.

Technically speaking, the level of data aggregation may also affect efficiency levels; that is, firms may become more heterogeneous in their size and the type of products they produce when more aggregated data are used. Our study involves efficiency analysis at the 2-digit level of industry classification. Efficiency level in the industry with relatively homogeneous products may be more similar than those in industries with heterogeneous products. This can be observed particularly in the food and beverages industry, where the number and size of the firms and the variety of products are indeed highly diversified. Even after controlling for firm-specific heterogeneity in the TRE model, significant variation in efficiency distribution is observed in this industry.

4.5. Conclusions and policy implications

This study has measured the technical efficiency of the Ethiopian manufacturing sector using an establishment-level census panel data set over the period from 2000 to 2009. We have applied stochastic frontier models, specifically, conventional fixed effects (FE), random effects (RE), and recently proposed "true" random effect (TRE) models. The results indicate that efficiency estimates are sensitive to model specifications of firm-specific unobserved heterogeneity. A significant difference in efficiency estimates has been found between the TRE model and the FE and RE models, which would imply considerable heterogeneity of manufacturing firms in Ethiopia. The conventional FE and RE models appear to underestimate the efficiency estimates since the firm-specific unobserved heterogeneity is confounded with the inefficiency term. Given the diversity of the firms in the food and beverages, non-metals, and furniture industries, the firm-specific heterogeneity seems to be more pronounced in these industries. We have also shown that the production of the Ethiopian manufacturing sector is largely responsive to changes in intermediate inputs compared to labor and capital inputs.

Efficiency estimates vary considerably among firms in any given industry, with some firms achieving very low efficiency and others achieving high levels of efficiency. Perhaps the major problem, common to all the manufacturing industries, which might have greatly contributed to inefficiency and efficiency variations among firms in an industry is the inability of firms to work at full production capacity (only about 60 percent of their capacity was utilized). This was mainly caused by shortages of raw materials. Other problems also include erratic electric power supply, government rules and regulations, and a lack of demand for products. Hence, any policy reforms should address the underlying factors contributing to the underutilization of production capacity. A case in point is the need to reform the input market in the manufacturing sector. The establishment of an efficient marketing mechanism that reduces the involvement of many parties in the supply chain and hence high transaction costs may reduce the problem. In addition, efficiency variation may also be explained by other factors such as the use of obsolete technologies, poor product design, lack of management skill, lack of exposure to international markets, and products that are not competitive. Indeed, these are characteristics of Ethiopian manufacturing. Thus, to enhance their efficiency performance in the face of increasing globalization, firms need to adjust to the changing environment, for example by acquiring required management skills, learning experience from best practices (which could be domestic, international, or both), and adopting new technologies. Finally, the role of the government in providing advisory support regarding training, market information, and technology choice is also recommended.

The relationship between firm size, age, and technical efficiency is one of the widely-studied areas in the literature. In the case of the Ethiopian manufacturing sector, these variables are found not to have a significant relationship with technical efficiency in most industries. However, the direction of their effect markedly differs from industry to industry. The coefficients of size and age are positive in some industries and negative in other industries. This suggests that policies that seek to address inefficiency problems in the sector should be industry specific. For instance, in industries where the coefficient for size is negative, industrial policy should be geared towards promoting small firms, while for positive coefficients, the reverse is true. Similarly, in industries where age is negatively correlated with efficiency, government policy should focus on encouraging young entrepreneurs in creating business. Policies that focus on encouraging small and young firms will play an important role in creating job opportunities and addressing problems associated with income distribution.

It should be noted that one criticism of the TRE model is that the firm-specific heterogeneity term may capture possible time-invariant structural inefficiency. Thus, if there is a possibility of a time-invariant element in inefficiency in addition to a time-varying element, the TRE model may underestimate overall inefficiency and in turn overestimate technical efficiency. One direction for future research is to incorporate persistent inefficiency in the TRE model in order to examine the impact of possible time-invariant structural inefficiency. We have shown the effect of firm-specific unobserved heterogeneity on efficiency estimates. Future research should also look into the effect of observable heterogeneity of firms on efficiency estimates. In particular, we are puzzled by the finding that firm size and age do not have significant effect in most of the industries. This suggests there are other variables that explain technical efficiency of the sector. Thus, future research into the determinants of technical efficiency in the sector should include other variable that are specific and external to the firm. Such variables may include market structure, domestic and international competitiveness, and policy variables related to industrial reforms.

Chapter 5

Setting handicaps to industrial sectors in DEA illustrated by Ethiopian manufacturing industries

5.1. Introduction

In the ordinary macro-economic input-output tables, the industrial sector consists of several dozen industries and each industry in a certain sector is an aggregate of many companies in the sector. The sectoral statistics are the sum of statistics of companies in the respective sector. Usually, all sectors have the same set of inputs for producing outputs. For example, they have labor, capital and intermediate inputs as input and amount of production as output. We can apply the traditional DEA models for evaluation of efficiency regarding all sectors by means of these common input and output factors. However, there remain concerns about comparing all sectors as a *scratch* race. Some sectors are in fields with matured technologies, while others are in emerging fields. Some are labor intensive, while others are capital intensive. These differences lead us to compare sectors under a *handicap* race. In this paper, we propose a new DEA model based on the non-convex frontiers that all associated sectors may exhibit and from which handicaps are derived. Most DEA models assume convex set frontiers. However, there are non-convex frontiers as indicated by the S-shaped curves in production. Tone and Tsutsui (2013) proposed a new DEA model that can cope with non-convex frontiers. They classify all DMUs (decision-making units) into several clusters and define a new efficiency score, called the *SAS* (scale and cluster adjusted score), that can take into account non-convex frontiers. In this paper, we define the handicap for each industrial sector using the SAS model. We modify inputs (outputs) by the handicaps and re-evaluate the efficiency scores. We apply this model to Ethiopian industry.

Several authors have discussed handicap-related topics in DEA. Yang and Paradi (2006) proposed a "Handicapped" Data Envelopment Analysis to Adjust for Corporate Strategic Effects for Canadian banks. They applied the index number originally proposed by Fixler and Zieschang (1993). Their index number is based on the tactical and strategic heterogeneity between banks. Olsen and Petersen (2009) discussed target and technical efficiency in DEA controlling for environmental characteristics. They extended Banker & Morey (1986) and incorporated allowable handicap values into the model along the same lines as specifications of assurance regions in standard DEA.

Our problem and approach differ from the preceding ones as follows. (1) We deal with industrial sectors which have a two-layered structure, i.e., each sector consists of many companies in the sectoral category and its inputs/outputs are the sum of these companies. (2) Although we wish to evaluate the technical efficiency of sectors, there are handicaps among sectors, as mentioned above, which should be identified and be accounted for in efficiency measurement. (3) For this purpose, we first find the variable returns-to-scale (VRS) frontiers of each sector and project companies in the sector to their frontiers. (4) Then, we find the VRS meta-frontiers for the projected companies in all sectors. (5) If the best performer (company) in a sector is positioned on the meta-frontiers, then we classify the sector as having *no-handicap.* Otherwise, if the best performer is off the meta-frontiers, we classify the sector as *with-handicap*. This indicates that this sector is in either emerging fields or unfavourable environments. (6) In order to gauge the degree of handicaps, we apply a non-convex frontier model developed by Tone and Tsutsui (2013) and decide the handicaps of *with-handicap* sectors. (7) Using handicaps, we adjust inputs (input-oriented case) and outputs (output-oriented case), and apply the constant returns-to-scale (CRS) model to obtain the final sectoral efficiency score.

It should be noted that we are comparing sectoral efficiency as measured by the ratio input vs. output. For example, three sectors (food, textiles and motor) have the respective input (manpower) and output (profit) exhibited in Table 5.1. From this table, we see that the virtual (dual) value of input for Food is one tenth of that for Motor, but we do not intend to say that Food should reduce its input to 1, because the environments of the three sectors are quite different. However, this kind of comparison is necessary for understanding national and international economics.

Table 5.1: Three Sectors

Sector	Input (Manpower)	Output (Profit)	Output/Input
Food	10	1	0.1
Textiles	5	1	0.2
Motor	1	1	1

This chapter unfolds as follows: In Section 5.2, we introduce the basic framework and classify sectors into *no-handicap* and *with-handicap* groups. In Section 5.3, we set handicaps for *with-handicap* sectors. Then, we redefine sectoral inputs and outputs using the handicaps and obtain the final efficiency scores which take account of the sectoral handicaps in Section 5.4. In Section 5.5, we apply this model to Ethiopian industry. Section 5.6 concludes this chapter.

5.2. Basic framework

In this section, we describe the basic materials in the chapter. Suppose that there are K sectors in the industry and each sector k (=1,…,K) has n_k DMUs with m inputs and s outputs. Let us denote a DMU in the sector k by $\left(\mathbf{x}_j^k, \mathbf{y}_j^k\right)$ where $\mathbf{x}_j^k \in R_+^m$ ($\mathbf{y}_j^k \in R_+^s$) is the input (output) vector of the DMU. We define the set of DMUs in the sector k by $\left(\mathbf{X}^k, \mathbf{Y}^k\right)$ with $\mathbf{X}^k = \left(\mathbf{x}_1^k, \ldots, \mathbf{x}_{n_k}^k\right)^T$ and $\mathbf{Y}^k = \left(\mathbf{y}_1^k, \ldots, \mathbf{y}_{n_k}^k\right)^T$.

5.2.1. Evaluation of DMU within each sector and its projection onto frontiers of the sector

We evaluate each DMU in its belonging sector by using the variable returns-to-scale (VRS) model. In this paper, we use the input oriented SBM (slacks-based measure (Tone 2001)). However other models, e.g. radial models, can be applied as well. This can be attained as below.

For each DMU $\left(\mathbf{x}_o^k, \mathbf{y}_o^k\right)(o = 1, \ldots, n_k)$ we solve the following LP:

$$
\begin{aligned}
&\min_{\boldsymbol{\lambda}, \mathbf{s}_o^-, \mathbf{s}_o^+} 1 - \frac{1}{m} \sum\nolimits_{i=1}^{m} \frac{s_{io}^-}{x_{io}^k} \\
&\text{subject to} \\
&\mathbf{X}^k \boldsymbol{\lambda} + \mathbf{s}_o^- = \mathbf{x}_o^k \\
&\mathbf{Y}^k \boldsymbol{\lambda} - \mathbf{s}_o^+ = \mathbf{y}_o^k \\
&\mathbf{e}\boldsymbol{\lambda} = 1 \\
&\boldsymbol{\lambda} \geq \mathbf{0}, \mathbf{s}_o^- \geq \mathbf{0}, \mathbf{s}_o^+ \geq \mathbf{0},
\end{aligned}
\tag{5.1}
$$

where λ is the intensity vector, and $\mathbf{s}_o^-$ and $\mathbf{s}_o^+$ are respectively input and output slacks.

Let an optimal solution to (5.1) be $(\boldsymbol{\lambda}^*, \mathbf{s}_o^{-*}, \mathbf{s}_o^{+*})$. We project $(\mathbf{x}_o^k, \mathbf{y}_o^k)$ onto the efficient frontiers of sector k as follows:

$$\overline{\mathbf{x}}_o^k = \mathbf{x}_o^k - \mathbf{s}_o^{-*}, \ \overline{\mathbf{y}}_o^k = \mathbf{y}_o^k + \mathbf{s}_o^{+*}. \tag{5.2}$$

Thus, we obtain the set of DMUs $\left(\overline{\mathbf{X}}^k, \overline{\mathbf{Y}}^k\right) (k = 1, \ldots, K)$ which are VRS-efficient with respect to the frontiers of sector k as shown in Figure 5.1.

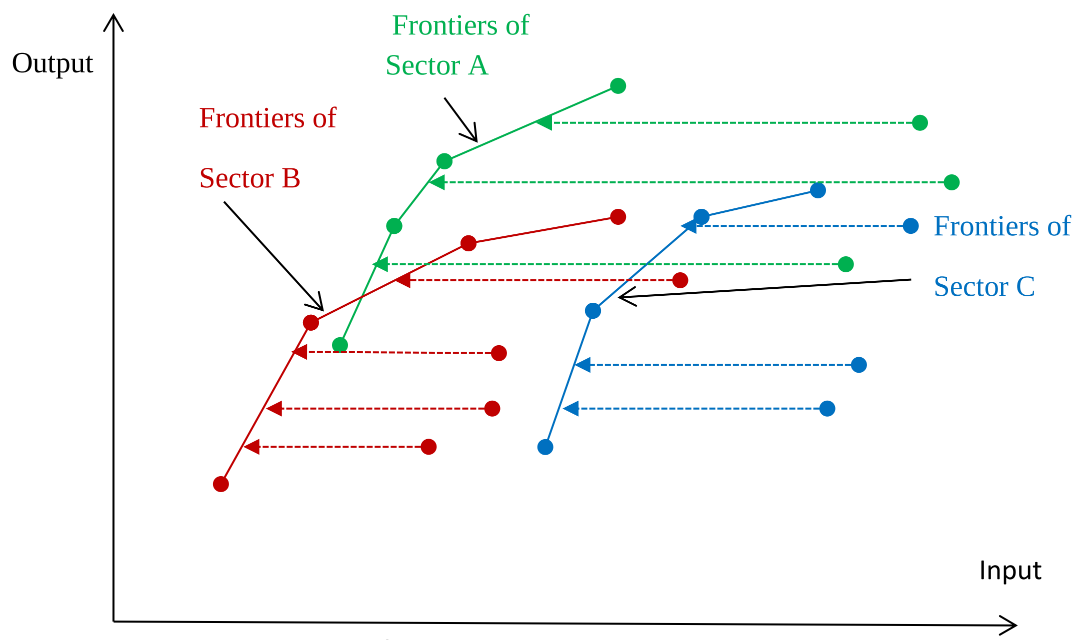


Figure 5.1: Sectoral frontiers and projections

5.2.2. Global evaluation of the projected DMUs

We merge the set $\left(\overline{\mathbf{X}}^k, \overline{\mathbf{Y}}^k\right) (k = 1, \ldots, K)$ and denote it by $\left(\overline{\mathbf{X}}, \overline{\mathbf{Y}}\right)$ which consists of $n_1 + \cdots + n_K$ DMUs. We evaluate the VRS efficiency of $\left(\overline{\mathbf{x}}_o^k, \overline{\mathbf{y}}_o^k\right)$ with respect to $\left(\overline{\mathbf{X}}, \overline{\mathbf{Y}}\right)$ and denote its VRS score by $\overline{\theta}_o^k$. Further, we define the maximum of $\overline{\theta}_o^k$ among sector k as,

$$\overline{\overline{\theta}}^{k} = \max_{o=1,\ldots,n_k} \left\{ \overline{\theta}_o^{k} \right\}. \tag{5.3}$$

If $\overline{\overline{\theta}}^{k} = 1$, the best performer of sector k is located on the global VRS frontiers (*meta-frontiers*) of $\left(\overline{\mathbf{X}}, \overline{\mathbf{Y}}\right)$. We judge that this sector k has no handicap and classify k to the *no-handicap* group. However, if $\overline{\overline{\theta}}^{k} < 1$, the best performer of sector k is inferior to the best performers in the *no-handicap* group, we classify k to the *with-handicap* group as illustrated in Figure 5.2 where Sectors A and B belong to the *no-handicap* group and Sector C to the *with-handicap* group.

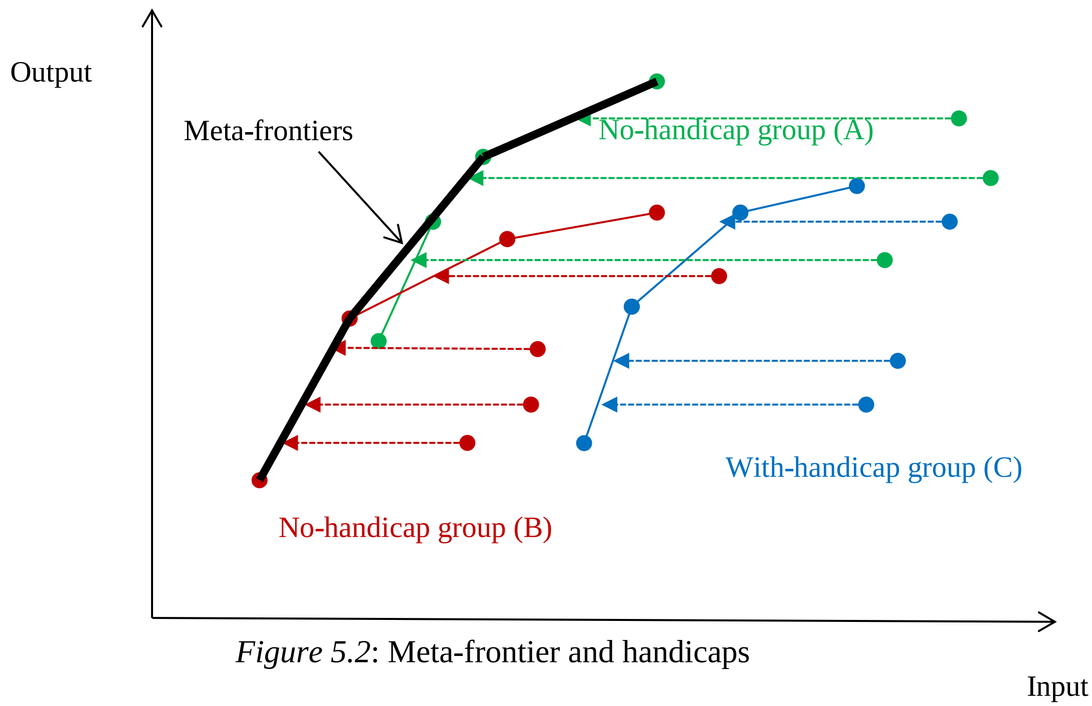


Figure 5.2: Meta-frontier and handicaps

5.3. Handicaps

In this section we describe how to set handicap for the *with-handicap* group.

5.3.1. Sectoral inputs and outputs

Sectoral inputs and outputs can be defined as the aggregates of VRS-projected DMUs in the sector as follows:

$$
\begin{aligned}
&\text{Input to Sector } k: \quad x_i^k = \sum_{j=1}^{n_k} \bar{x}_{ij}^k \quad (i = 1,\dots,m; k = 1,\dots,K) \\
&\text{Output from Sector } k: \quad y_l^k = \sum_{j=1}^{n_k} \bar{y}_{lj}^k \quad (l = 1,\dots,s; k = 1,\dots,K)
\end{aligned}
\tag{5.4}
$$

Input/output vectors of sector k are defined by

$$
\mathbf{x}^k = \left(x_1^k,\dots,x_m^k\right)^T \text{ and } \mathbf{y}^k = \left(y_1^k,\dots,y_s^k\right)^T \tag{5.5}
$$

We deal with K DMUs defined by $\left(\mathbf{x}^k,\mathbf{y}^k\right) \quad (k = 1,\dots,K)$.

5.3.2. Clustering

We classify K sectors in several clusters. First, sectors belonging to the *no-handicap* group go to cluster "NHD", while a sectors *with-handicap* hold its sector name as the cluster name. For example, if a sector "Machinery and equipment" belongs to the *with-handicap* group, its cluster name is "Machinery and equipment".

The characteristics of industrial sectors are diverse. Some are in mature fields while others are in emerging fields. This suggests the existence of S-shaped (non-convex) frontiers as exhibited in Figure 5.3. Tone & Tsutsui (2013) proposed a method for solving non-convex frontiers based on clusters.

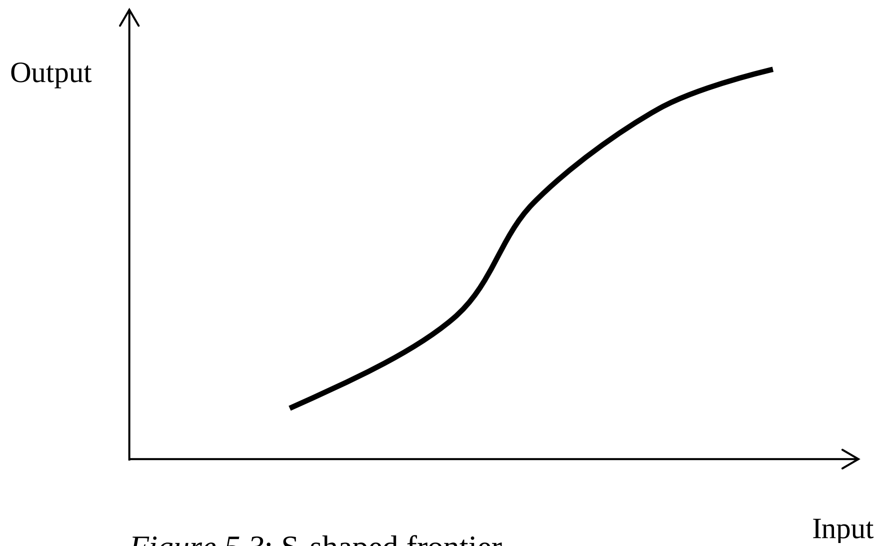


Figure 5.3: S-shaped frontier

5.3.3. Solving with the non-convex model

We solve the dataset $\left(\mathbf{x}^k, \mathbf{y}^k\right)$ $(k=1,\ldots,K)$ with cluster name using the above non-convex model and obtain the scale and cluster adjusted efficiency score, *SAS*, which takes into account the effect of non-convex frontiers.

5.3.4. Handicap

We define the handicap h_k of sector *k* as follows:

$h_k = 1$, if the sector belongs to the *no-handicap* group. (5.6)

$h_k = \text{SAS score}$, if the sector belongs to the *with-handicap* group. (5.7)

5.4. Global issues

In this section, we redefine sectoral inputs and outputs using the above defined handicap and obtain the overall efficiency score for industries.

5.4.1. Input (Output) under handicap

In the input-oriented case, we define sectoral inputs and outputs as follows:

$$\begin{aligned}&\text{Sectorial input } \xi_i^k = h_k \sum\nolimits_{j=1}^{n_k} x_{ij}^k \quad (i=1,\ldots,m : k=1,\ldots,K)\\&\text{Sectorial output } \eta_l^k = \sum\nolimits_{j=1}^{n_k} y_{lj}^k \quad (l=1,\ldots,s : k=1,\ldots,K)\end{aligned} \tag{5.8}$$

Further we define input/output vectors for each sector as follows:

$$\boldsymbol{\xi}_k = \left(\xi_1^k,\ldots,\xi_m^k\right)^T \text{ and } \boldsymbol{\eta}_k = \left(\eta_1^k,\ldots,\eta_s^k\right)^T \quad (k=1,\ldots,K) \tag{5.9}$$

See Figure 5.4 for an example.

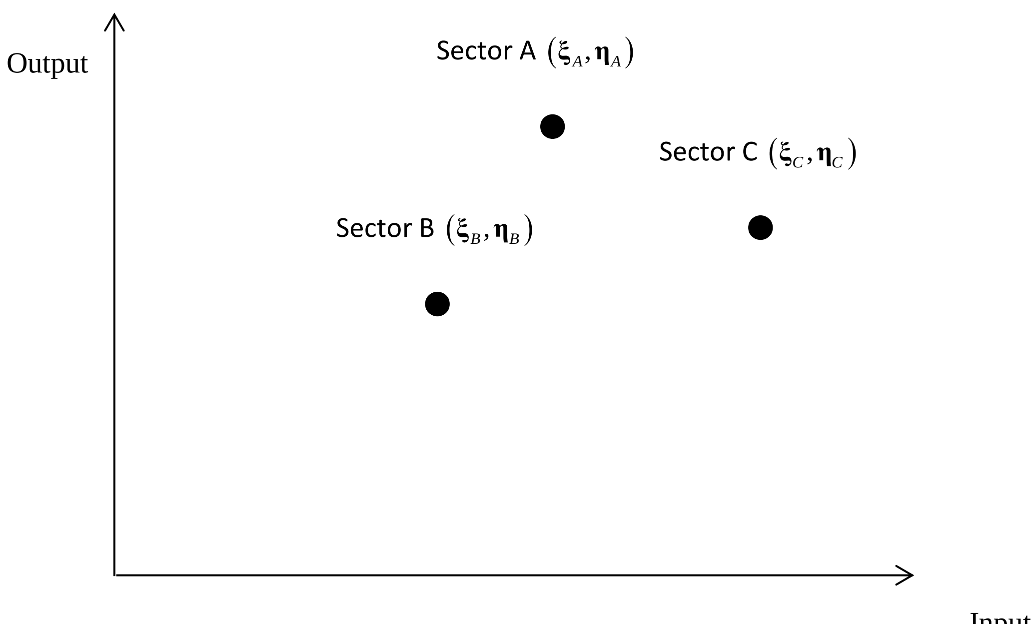


Figure 5.4: Handicapped input and output

5.4.2. Solving with the CRS model

In the non-radial SBM model case, we solve the following LP and obtain the sector-specific efficiency score $\theta_o^*(o=1,\ldots,K)$ under handicap.

$$
\begin{aligned}
&\theta_o^* = \min_{\boldsymbol{\lambda},\mathbf{s}^-,\mathbf{s}^+} 1 - \frac{1}{m}\sum\nolimits_{i=1}^{m} \frac{s_{io}^-}{\xi_i^o} \\
&st. \\
&\sum\nolimits_{k=1}^{K} \boldsymbol{\xi}_k \lambda_k + \mathbf{s}_o^- = \boldsymbol{\xi}_o \\
&\sum\nolimits_{k=1}^{K} \boldsymbol{\eta}_k \lambda_k - \mathbf{s}_o^+ = \boldsymbol{\eta}_o \\
&\boldsymbol{\lambda} \geq \mathbf{0}, \mathbf{s}_o^- \geq \mathbf{0}, \mathbf{s}_o^+ \geq \mathbf{0}
\end{aligned}
\tag{5.10}
$$

Let an optimal solution to (5.10) be $\left(\boldsymbol{\lambda}^*, \mathbf{s}_o^{-*}, \mathbf{s}_o^{+*}\right)$. Then we have the projection to the SAS efficient frontiers as follows:

$$
\begin{aligned}
&\text{Projected input: } \boldsymbol{\xi}_o^* = \boldsymbol{\xi}_o - \mathbf{s}_o^{-*} \\
&\text{Projected output: } \boldsymbol{\eta}_o^* = \boldsymbol{\eta}_o + \mathbf{s}_o^{+*}.
\end{aligned}
\tag{5.11}
$$

5.5. Application to Ethiopian manufacturing industries

The characteristics of the Ethiopian manufacturing sector are already described in chapter 2. In this section, we describe our data, and apply our model to 14 industrial groups which largely dominate this sector.

5.5.1. Data description

The data used in this application was extracted from the CSA data described in chapter 1. For the purpose of this chapter, we use data from the 2008 census that comprises relevant outputs and inputs. The inputs and output used in this chapter are the same as those used in chapter 4 (a single-output and 3-input production technology). For the purpose of this application, the firm level data were aggregated to 2-digit level industries and hence analysis is made at industry level. Prior to data aggregation, we have made super-efficiency procedures to detect outliers in the data. According to the findings, three firms with super-efficiency greater than or equal to three were found as outliers and we deleted them from the data leaving the total of firms from which data was aggregated to industry level 1,213. Finally, to avoid data fluctuations, we also smooth the data using a four-year moving average[18].

5.5.2. Main statistics[19]

We begin by presenting the original (non-handicapped) dataset in Table 5.2. The summary statistics of this dataset is exhibited in Table 5.3. The summary statistics in Table 5.3 represent the Min/Max inputs and output of the industry.

Table 5.2: Original Dataset for the Year 2008

Industry	Companies	(I)Labour	(I)Capital	(I)Intermediate	(O)Production
Food and beverage	349	35391.1458	1788168221	1495232246	4068003497
Textiles	21	18363.7916	381057469	395188377	692187774
Wearing apparel	26	4815.79165	104353732	65318032.1	129750825
Tanning, leather &footwear	62	7887.5625	363361747	561064968	890647967
wood	28	1959.81248	6871141.31	20176600.1	56729660.1
Paper and printing	96	7967.64585	180550018	320157164	638558017
Chemicals	61	6426.50001	286834161	482231522	818780598
Rubber and plastics	75	7083.16665	361385672	417657829	727078679
Non-metals	243	10300.75	677356667	576183151	1377392696
Basic iron and steel	14	1821.60418	212223001	633340164	1002609408
Fabricated metals	49	2482.89584	88309646.7	189549991	342615766

[18] We used data for 2008. The 2008 data is part of the big dataset described in chapter 1. We first made a four-year moving average adjustment using the 2000 to 2009 dataset and then extracted the 2008 data for the purpose of this application.

[19] "I" and "O" stand for input and output, respectively. The value of capital, intermediate inputs and output are measured in Ethiopian Birr (ETB), Ethiopia's currency. The current exchange rate of ETB against USD is about Birr 19.41 to 1 USD. Labour is measured by the number of annual temporary and permanent workers. Moreover, to consider price changes in our study, inputs (except labour) and output were deflated by their respective implicit sectoral GDP deflator at 2000 price.

Machinery and equipment	9	1303.5	92018536.2	67075028.3	116429874
Motor vehicles	10	1214.41666	60968765.8	233431786	327031850
Furniture	170	4529.18749	93204031.8	87966624.3	189933023

Table 5.3: Industry level summary statistics (non-handicapped data)

Statistics	(I)Labour	(I)Capital	(I)Intermediate	(O)Production
Minimum	1214.417	6871141.31	20176600.1	56729660.1
Average	7967.698	335475915	396040963	812696402
St. Dev.	9133.455	454726832	378329529	1014420298
Maximum	35391.15	1788168221	1495232246	4068003497

5.5.3. Evaluation of DMU within each sector and projection

Utilising the scheme described in Sub-section (5.2.1), we evaluate each DMU in their respective industry to obtain sectoral frontiers and projections. To this end, we use the VRS input oriented SBM. The development of the handicap model begins with the utilisation of the projected inputs and output where all the DMUs are on their efficient frontier in their respective industry. In Table 5.4, we provide the industry level summary statistics of the projected inputs and output.

Table 5.4: Industry Level Summary Statistics of the projected Data

Statistics	(I)Labour	(I)Capital	(I)Intermediate	(O)Production
Minimum	942.0572	3140337.5	18952775	57420822.6
Average	4461.147	158798402	285544233	871889484
St. Dev.	4508.271	226084166	219213081	1150917694
Maximum	18689.76	870850327	821789723	4544356485

5.5.4. Global evaluation of the projected DMUs

The efficiency scores in Table 5.5 were calculated according to the procedure outlined in Sub-section (5.2.2). After merging the projected inputs and output, we evaluated

DMUs with the VRS model from which the maximum score $\overline{\overline{\theta}}^{k}$ of DMUs in their respective sector was defined to judge whether the industry belongs to the *no-handicap* or *with-handicap* group. Accordingly, we see in Table 5.5 that *Wearing apparel, Tanning, Leather and footwear, Paper and printing,* and *Machinery and equipment* industries are in the *with-handicap* group while the remaining industries are in the *no-handicap* group. We also exhibit inputs and output of a sample company with the maximum score $\overline{\overline{\theta}}^{k}$ for each industry. An industry with $\overline{\overline{\theta}}^{k} = 1$ belongs to the meta-frontiers.

Table 5.5: No-handicap and with-handicap Group before Non-convex Adjustment

Industry	$\overline{\overline{\theta}}^{k} = \max_{o=1,\dots,n_k} \left\{ \overline{\theta}_o^{k} \right\}$	A sample company with max θ (I)Labor	(I)Capital	(I)Intermediate	(O)Output	Meta-frontier(Y/N)[20]
Food and beverage	1	12.35922	140318.8	177992.6516	8041129	Y
Textiles	1	1725	32069.7	21700000	37900000	Y
Wearing apparel	0.343418	13.16667	4321.956	66919.76	87352.65	N
Tanning, leather and footwear	0.909345	10.5	1823.441	12303.54	60075.27	N
Wood	1	40	2111.534	205487.8	1042979	Y
Paper and printing	0.488351	12	3216.459	43311.45	97698.5	N
Chemicals	1	21.23822	435970.9	2246884.544	6319859	Y
Rubber and plastics	1	62	6717595	1254564	74600000	Y
Not-metals	1	91.58334	170206.5	6084128	18100000	Y
Fabricated metals	1	19	832519.9	26876.57	2437786	Y
Basic iron and steel	1	290	2863552	102000000	182000000	Y
Machinery and equipment	0.447216	177.0833	3709670	27800000	48100000	N
Motor vehicle	1	148	6583011	177000000	217000000	Y
Furniture	1	12.33333	36995.28	2078167	5568806	Y

5.5.5. Handicaps

5.5.5.1. Sectoral inputs and outputs

[20] While "Y" indicates the sector is on the Meta-frontier (belonging to the *no-handicap* group), "N" implies the sector is off the Meta-frontier (belonging to the *with-handicap* group).

Table 5.6 presents sectoral inputs and outputs aggregated from the VRS-projected DMUs in the sector according to Sub-section (5.3.1).

Table 5.6: Aggregates of Inputs (output) of VRS-projected DMUs in the Sector

Industry	(I)Labour	(I)Capital	(I)Intermediate	(O)Production
Food and beverage	18689.76	870850327	821789723	4544356485
Textiles	5477.866	37291624	191300303	363220956
Wearing apparel	5713.199	139074482	112307222	220631685
Tanning, leather and footwear	5005.315	186313400	469860107	800649505
Wood	2325.809	3140337.5	18952775	57420822.6
Paper and printing	5693.758	88431187	267162146	614123385
Chemicals	2788.107	82517926	442951464	1028226007
Rubber and plastics	2374.122	174408612	174512573	956744221
Not-metals	6230.622	379273000	490968503	1782276024
Fabricated metals	2052.191	74160812	223054964	460355315
Basic iron and steel	942.0572	46086368	392698767	659006974
Machinery and equipment	1046.282	60668080	59152487	114955660
Motor vehicle	1313.834	50655770	262797476	397401292
Furniture	2803.14	30305709	70110758	207084441

5.5.5.2. Solving non-convex models

Here, we solve the non-convex nature of the data using the data in Table 5.6 and classify the scale adjusted scores (SAS) of each sector. In Table 5.7 an “a” in the ‘cluster’ column represents the *non-handicapped* group. We found that all *with-handicap* sectors belong to non-convex (S-shaped) frontiers.

Table 5.7: No-handicap and with-handicap Groups after Non-convex Adjustment

Industry	(I)Labour	(I)Capital	(I)Intermediate	(O)Production	Cluster	SAS
Food and beverage	18689.8	870850327	821789723	4544356485	a	1
Textiles	5477.87	37291624	191300303	363220956	a	0.5931
Wearing apparel	5713.2	139074482	112307222	220631685	Wearing apparel	0.768
Tanning, leather and footwear	5005.31	186313400	469860107	800649505	Tanning, leather and footwear	0.9923
Wood	2325.81	3140337.5	18952775	57420822.6	a	1
Paper and printing	5693.76	88431187	267162146	614123385	Paper and printing	0.9715
Chemicals	2788.11	82517926	442951464	1028226007	a	1
Rubber and plastics	2374.12	174408612	174512573	956744221	a	1
Not-metals	6230.62	379273000	490968503	1782276024	a	0.7429
Fabricated metals	2052.19	74160812	223054964	460355315	a	0.664
Basic iron and steel	942.057	46086368	392698767	659006974	a	1
Machinery and equipment	1046.28	60668080	59152487	114955660	Machinery and equipment	0.5433
Motor vehicle	1313.83	50655770	262797476	397401292	a	0.6274
Furniture	2803.14	30305709	70110758	207084441	a	0.6622

5.5.5.3. Handicap

The final (after non-convex adjustment) handicap scores are reported in Table 5.8.

Table 5.8: Handicap Score after Non-convex Adjustment

Industry	Handicap
Food and beverage	1
Textiles	1
Wearing apparel	0.768
Tanning, leather and footwear	0.9923
Wood	1
Paper and printing	0.9715
Chemicals	1

Rubber and plastics	1
Non-metals	1
Fabricated metals	1
Basic iron and steel	1
Machinery and equipment	0.5433
Motor vehicle	1
Furniture	1

5.5.6. Global issue

5.5.6.1. Input (output) under handicap

In this section, we apply the scheme outlined in Sub-section (5.4.1) to obtain the handicapped data. Since we are using the input-oriented model, the inputs of the original dataset of each sector were multiplied by the handicap scores given in Table 5.8 to arrive at the data in Table 5.9.

Table 5.9: Handicapped Inputs and Outputs

Industry	(I)Labour	(I)Capital	(I)Intermediate	(O)Production
Food and beverage	35391.15	1788168221	1495232246	4068003497
Textiles	18363.79	381057469	395188377	692187774
Wearing apparel	3698.528	80143666.2	50164248.7	129750825
Tanning, leather and footwear	7826.828	360563862	556744768	890647967
Wood	1959.812	6871141.31	20176600.1	56729660.1
Paper and printing	7740.568	175404343	311032684	638558017
Chemicals	6426.5	286834161	482231522	818780598
Rubber and plastics	7083.167	361385672	417657829	727078679
Not-metals	10300.75	677356667	576183151	1377392696
Fabricated metals	1821.604	212223001	633340164	1002609408

Basic iron and steel	2482.896	88309646.7	189549991	342615766
Machinery and equipment	708.1915	49993670.7	36441862.9	116429874
Motor vehicle	1214.417	60968765.8	233431786	327031850
Furniture	4529.187	93204031.8	87966624.3	189933023

5.5.6.2. Solving the CRS model

So far, we have been adjusting the original data in order to account for the handicap industry. In Table 5.10, we report the efficiency scores of each industry obtained after making handicap adjustments. To obtain the efficiency scores reported in Table 5.10, we used the dataset given in Table 5.9.

Table 5.10: Efficiency Score with-handicap Model

Industry	Score	Rank
Food and beverage	0.8357	6
Textiles	0.5192	14
Wearing apparel	0.5727	13
Tanning, leather and footwear	0.5836	12
Wood	1	1
Paper and printing	0.8722	5
Chemicals	0.6640	9
Rubber and plastics	0.5899	11
Non-metals	0.7839	8
Fabricated metals	1	1
Basic iron and steel	0.834	7
Machinery and equipment	1	1
Motor vehicle	1	1
Furniture	0.6019	10

5.5.6.3. Comparisons with the *no-handicap* model

The scores in Table 5.11 were obtained using the original (*non-handicapped*) dataset reported in Table 5.2. Figure 5.5 compares the scores from the *no-handicap* and *with-handicap* models where the heading (H) indicates the *with-handicap* sector.

Table 5.11: Efficiency Sore with no-handicap model

Industry	Score	Rank
Food and beverage	1	1
Textiles	0.5359	13
Wearing apparel	0.5037	14
Tanning, leather and footwear	0.5776	11
Wood	1	1
Paper and printing	0.8918	7
Chemicals	0.6943	8
Rubber and plastics	0.6216	10
Non-metals	0.9304	5
Fabricated metals	1	1
Basic iron and steel	0.9215	6
Machinery and equipment	0.5401	12
Motor vehicle	1	1
Furniture	0.6627	9

5.5.7. Observations

In Figure 5.5, we see that of the 3 handicapped industries, *Wearing apparel*, *Tanning*, and *Machinery and equipment* have seen improvements in efficiency after the handicap adjustment was made, with *Machinery and equipment* industry becoming efficient. There is a slight decline in the efficiency score in the *Paper and printing* industry (handicapped) and the *no-handicap* industries as compared to *no-handicap* model. The decrease of efficiency scores in *Paper and printing* and other sectors might have been caused by the increase in the *Machinery and equipment* score (it has the smallest handicap and is now efficient). The emergence of this efficient sector affects all other sectors.

In this application, we tried to standardize different industries of different nature which use different inputs to produce different outputs. However, we believe that the model can also be applied to sectors (DMUs) in the same industry such as banks and electric power industry. Given that these industries provide similar services to their respective customers, the only difference remains the environment in which they operate. Some of the DMUs may enjoy advantages such as location and infrastructure while others do not. Unlike the traditional DEA which assumes DMUs enjoy similar environment, our model takes these environmental differences into account.

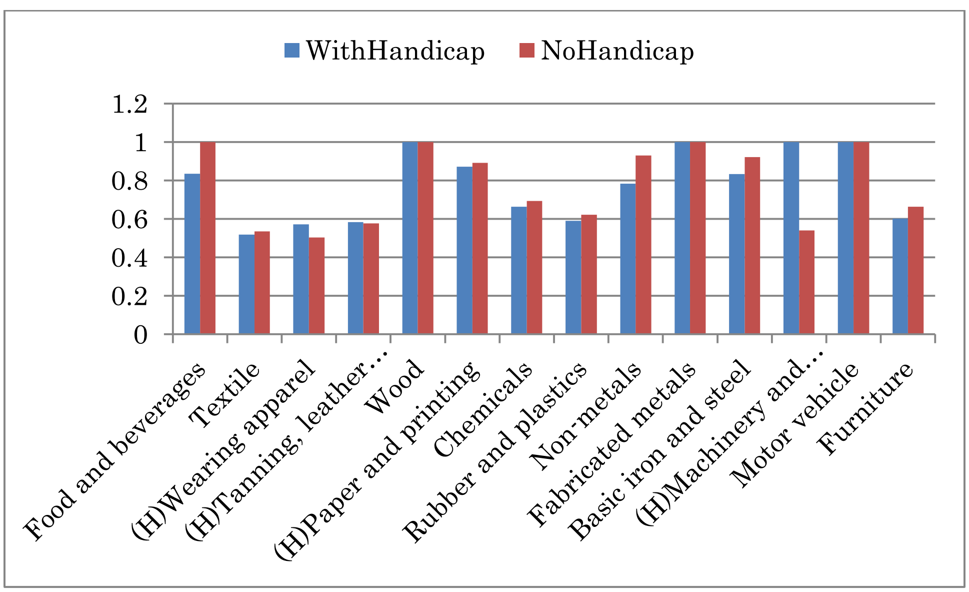


Figure 5.5: Comparison of handicap and *no-handicap* models

5.6. Conclusions

In this paper, we proposed a handicap setting method for fair evaluation of industrial sectors and applied it to Ethiopian manufacturing industries. The manufacturing industry comprises many sectors which include many companies in the category. Thus, there is a "two-layered" structure. The statistics of a sector is the sum of those of its member companies. In order to evaluate the relative efficiency of industrial sectors, we need to take account of performance of their membership companies. For this purpose, we evaluated sectoral frontiers and projected member companies to their respective frontiers. We then merged the projected companies and found the meta-frontiers of all projected companies in the industry. If a member of a certain sector is on the meta-frontiers, we classified this sector to the *no-handicap* group, whereas if all members of a sector are off the meta-frontier, we classified the sector to the *with-handicap* group. Then we applied the non-convex model proposed by Tone and Tsutsui (2013) for deciding handicaps of *with-handicap* sectors. Most of them beloned to no-convex (S-shaped) frontiers. We modify inputs (in the input-oriented case) or outputs (in the output-oriented case) using the handicaps and re-evaluate the sectoral efficiency. With respect to the developing industry of Ethiopia, several sectors are in emerging fields. We found four sectors belonged to the *with-handicap* group; (1) *Wearing apparel* (handicap=0.768), (2) *Tanning, leather and footwear* (handicap=0.9923), (3) *Paper and printing* (handicap=0.9715), and (4) *Machinery and equipment* (handicap=0.5433). The most handicapped sector is the *Machinery and equipment*. If this sector could be improved by innovation, it would become the top sector, while the other three handicapped sectors remain inefficient even after taking account of handicaps. The sectors in the *no-handicap* group could not increase the relative efficiency. This might be caused by the emergence of the *Machinery and equipment* sector as the most efficient sector.

Further areas for research include cost, revenue and profit-related extensions of this approach.

Chapter 6

Efficiency in the presence of measurement error in Ethiopian manufacturing: An application to resampling in DEA

6.1. Introduction

In Chapter 4, we estimated technical efficiency using SFA and in chapter 5 we developed a handicap model that takes environmental difference into consideration to estimate efficiency. The purpose of this chapter is to measure technical efficiency in the Ethiopian manufacturing sector applying resampling in DEA method. We also apply the handicap model developed in chapter 5.

As mentioned in Chapter 4, DEA is a nonparametric approach that does not require any functional form specification. However, a growing concern about DEA is that it does not account for measurement error and other statistical noise. In the presence of measurement error and other statistical noise, efficiency estimates from DEA may be biased (Coelli et al., 2005). This has led scholars of DEA to engage in developing statistical methodologies which account for statistical noise. One such an attempt can be found in the seminal paper of Simar & Wilson (2000) in which the authors try to account for statistical noise by applying bootstrapping technique. In the words of Tone (2013), the idea behind bootstrapping is to test the sensitivity of the efficiency score obtained from DEA by repeatedly sampling from the original samples. A sampling distribution of the efficiency score is then calculated from which confidence intervals and may be and statistical tests of significance are derived. Despite the remarkable contribution of the bootstrap method in the

DEA literature, its underlying assumptions and properties have been questioned. For instance, Barnum et al. (2012) argued that bootstrapping methods developed thus far do not consider the stochastic variation of input/output performance of individual decision making units (DMU) resulting in incorrect computation of the confidence intervals for each DMU.

More recently, Tone (2013) proposed new resampling method in DEA. The author argued that since the input/output values of each DMU are subject to change for several reasons, such as measurement errors, hysteretic factors, and arbitrariness, DEA efficiency scores need to be examined by taking these factors into account. Unlike the preceding bootstrapping methods, this resampling method considers the changing nature of inputs and outputs of each DMU. In particular, this method deals with measurement errors in inputs and outputs and then resamples data depending on the empirical distribution of the errors, and estimates confidence intervals within which the estimated efficiency score of individual DMU occurs. To do so, the author develops three resampling models: triangular distribution, historical data, and future forecasts. Another important difference between Tone's resampling method and that of Simar & Wilson is that while the former uses different production possibility set in the resampling procedure, the later uses the same production possibility set.

In this chapter, we exploit the unique advantages of the new resampling models by Tone (2013) that consider measurement errors in inputs and outputs to measure the efficiency of Ethiopian manufacturing industries. Based on the observed historical data of the industries, we further forecast the future efficiency scores of each industry in the sector.

To measure the efficiency of the industries, we adopt a slacks-based efficiency measure (SBM) proposed by Tone (2002). For comparison of results, we also apply the radial measure of efficiency (Radial). The difference between the two models is that while the former can account for slacks in inputs and outputs, the later neglects the slacks (Tone, 2001, 2002). Since, efficiency models under the assumption of variable returns to scale (VRS) suffer from an infeasibility problem, we employ input-oriented efficiency measures under the assumption of constant returns to scale to avoid the potential infeasibility problem.[21]

This chapter contributes to the literature in different aspects. First, it is the first empirical application of the recently proposed resampling method in DEA (Tone, 2013) that accounts for measurement errors in inputs and outputs. Studies that estimate technical efficiency in DEA in the presence of measurement error are rare in the literature. Second, we estimate the future forecast of the technical efficiency of the Ethiopian manufacturing industries. Previous studies try to estimate past and present efficiency of a DMU with available data. The importance of forecasting future performance of firms has been noted by Chang et al. (2013). The authors argued that past and present performance evaluations of a firm are not sufficient for decision making. In order to have a complete performance evaluation, the evaluator must also assess the future potential of the DMU since it may take quite some time to convert inputs into outputs. Thus, unlike previous studies, this paper tries to forecast the future performance of the Ethiopian manufacturing industries using

[21] Under constant returns to scale the output- and input-oriented technical efficiency measures are the same.

historical data. Forecasting future efficiencies can be helpful for the DMUs to allocate their resources in an efficient and productive way.

The rest of the chapter is structured as follows. In section 6.2, we describe the data used in this chapter. Section 6.3 discusses the resampling methods used to calculate efficiency scores. After discussing the empirical results in Section 6.4, we conclude the chapter in Section 6.5.

6.2. Data description

The data used in this chapter are part of the data set described in Chapter 1. Although they differ according to the resampling methods employed, generally the data used in this chapter cover the period from 2000 to 2008. Similar to Chapter 4, we use a single-output and 3-input production technology in this chapter, too. Output is measured by the gross value of all outputs produced by the firm. The inputs include capital, labor, and intermediate inputs. For the purpose of this chapter, the firm-level data were aggregated to 2-digit level industries for 8-year balanced panel data. Data conversion into panel data by aggregating to 2-digit level industry was an unavoidable step because the DEA used could not accommodate unbalance panel data.

Since the resampling method used in this chapter is sensitive to data fluctuations, data cleaning procedures were necessary in order to prepare data suitable for the models. Initially, to avoid data fluctuations, we employed a data smoothing procedure using a four-year moving average. We then adjusted the data depending on the particular resampling method used. In the triangular distribution method, the whole data set (2004 to 2008), as historical data, was used to estimate the percentage of error rates for each input and output. We use these error rates to estimate efficiency scores for each industry for the present period (2008). In the historical data method of resampling, the data (2004 to 2008) were used to estimate the weights used to calculate efficiency for the present period (2008). Finally, in the forecast method of resampling, we used 2004 to 2008 as past-present data to forecast future data (2009) from which efficiency scores are obtained.

6.3. Resampling in DEA

In this section, we introduce the resampling models of Tone (2013) used in this paper. The author proposes three resampling models. The first model assumes that there exist upside and downside measurement errors in the data and uses triangular distribution for resampling., The second model uses historical data for estimating data variations, while the third model deals with forecasting future efficiency scores for individual DMUs. In the following sections, we briefly describe each of the three models.

6.3.1. The common upside and downside measurement errors case

A) Triangular distribution approach

The underlying assumption in this approach is that the data are bounded by upside and downside limits with a single mode. As shown in Figure 6.1, the downside limit, the mode and the upside limit are denoted by *a*, *m* and *b,* respectively. The observed input and output values represent the mode *m*.

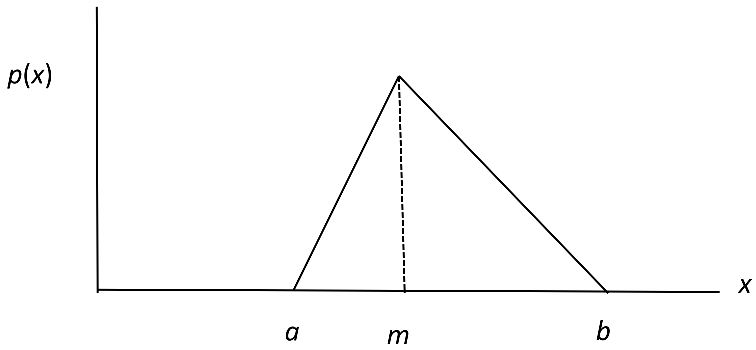


Figure 6.1: Triangular distribution

The choice of the triangular distribution over others is for computational simplicity given the three parameters *a*, *m* and *b* to be estimated. It is further assumed that *a* and *b* can be represented by the error rates α and β as follows:[22]

$$\begin{aligned} a &= (1-\alpha)m \quad (0 \le \alpha \le 1) \\ b &= (1+\beta)m \quad (\beta \ge 0). \end{aligned} \tag{6.1}$$

Under the triangular distribution, the error rates, α and β are not generated by the data generation process. They are externally generated and can differ in their input and output factors, but are common to all DMUs.

B) Estimating α and β

The author suggests two types of techniques for estimating α and β.

1. Expert knowledge: In some instances, data can be intentionally underestimated or overestimated, for example, in accounting statements. From experience, experts in the concerned areas can estimate them. Companies may underreport their data for

[22] See Tone (2013) for the details of the data generation process for the triangular distribution.

tax purposes or fraudulently report higher data to enjoy favourable policies such as bank loans. Indeed, we believe that such practices are widespread in Ethiopia.

2. Use of historical data: The availability of historical data can make it easier to determine the error rates by applying the following procedure. Let the past T periods data for a certain input (output) i be $z_t (t = 1, \ldots, T)$ where T is the current (latest) period. Comparing this with z_T, we evaluate downside (upside) error variation rates α_i^t (β_i^t) for the period t. From the distribution of $\{\alpha_i^t\}$ and $\{\beta_i^t\}$ for all DMUs, we can decide their median or average as α_i and β_i.

Estimating α and β by applying the expert knowledge could rather be challenging since the method is prone to subjective judgement. Thus, exploiting the panel nature of our data, we estimate α and β using the historical data approach.

6.3.2. Use of historical data for estimating data variations

In this section we introduce how to use historical data to simulate measurement errors.

Historical data and weights

Let the historical set of input and output matrix be $(\mathbf{X}^t, \mathbf{Y}^t)$ $(t = 1, \ldots, T)$ where $t = 1$ is the first period and $t = T$ is the last period with $\mathbf{X}^t = (\mathbf{x}_1^t, \cdots, \mathbf{x}_n^t)$ and $\mathbf{Y}^t = (\mathbf{y}_1^t, \cdots, \mathbf{y}_n^t)$. The number of the DMUs is n and, $\mathbf{x}_j^t \in R^m$ and $\mathbf{y}_j^t \in R^s$ are respectively input and output vectors of DMU_j.

Efficiency scores of $(\mathbf{X}^T, \mathbf{Y}^T)$

First we evaluate the efficiency scores of the last period's DMUs. Then we gauge their confidence interval using replicas from $(\mathbf{X}^t, \mathbf{Y}^t)\ (t = 1, \ldots, T)$ as follows.

Lucas weight

We set the weight w_t to period *t* and assume the weights are increasing in *t*. For this purpose, the following Lucas number series $(l_1, \ldots, l_T)$ (a variant of Fibonacci series) is a candidate where we have

$$l_{t+2} = l_t + l_{t+1}\ (t = 1, \ldots, T-2; l_1 = 1, l_2 = 2). \tag{5.2}$$

Let the sum be $L = \sum_{t=1}^{T} l_t$ and the weight w_t be defined as

$$w_t = l_t / L \quad (t = 1, \ldots, T). \tag{5.3}$$

6.3.3. Resampling with future forecast

Tone's innovative approach here enables us to forecast future efficiency of a DMU (industry in our case). The idea here is that given the "past-present" data $(\mathbf{X}^t, \mathbf{Y}^t)\ (t = 1, \ldots, T)$, we can forecast "future" input/output $(\mathbf{X}^{T+1}, \mathbf{Y}^{T+1})$ of each industry from which future efficiency scores of individual industries with their confidence intervals can be recovered.

6.4. Empirical Results

In this section we analyse our results obtained using the three resampling models. To compute the technical efficiency scores, the DEA-Solver Pro version 11.0 computer program proposed by Tone (2013) is used. We evaluate each industry by the input-oriented slacks-based measure of efficiency (SBM) and the radial measure models[23] (Tone, 2001, 2002) under the assumption of constant-returns-to-scale. The three resampling techniques are applied to these models to recover the efficiency scores of each industry. The resampling techniques we use are sensitive to data variations. Indeed, our preliminary analysis shows that there exists a huge variation in the data. To minimize this problem, we smooth the data using a moving average over the four years prior to estimation. Moreover, we define past period data for the years before 2008 and present period data as year 2008. Thus, while we use the past and present data to calculate the Lucas Weight to be used in the data generating process and externally estimate the downside and upside errors, efficiency scores are estimated for the present period (2008) in the triangular and historical approaches. In the future forecast model, we use the 2008 data as present data and forecast efficiency score for the period 2009. We apply the handicap model developed in chapter 5 in order to control for the difference in environmental settings in which the industries operate.

---

[23] Efficiency estimates and hence the rank of the industries may differ between SMB and Radial models. This may be attributed to the basic assumptions on which the models depend. While the former assumes non-proportional change inputs and outputs, the later assumes proportional change in inputs and outputs

Here, we would like to note that since we are using a one-time data to calculate efficiency in this chapter, the efficiency estimates in chapter may not be directly compared with the results in this chapter. Thus, results should be interpreted with this difference in mind.

6. 4.1. Results from triangular distribution approach

The summary statistics of the inputs and output for the year under consideration are reported in Table 6.1.[24] Prior to estimating efficiency scores, error rates for the inputs and outputs were calculated following the method described in Section (B) of (6.3.1). We use historical data and estimate the percentage of error rates for each input and output. The resulting estimates of α_i and β_i are reported in Table 6.2 where the subscript i represents inputs/output. In principle, it is possible to use either the mean or the median of the error rates. Nevertheless, since the value of mean may be influenced by some extreme values, we opt to use the median values of the error rates.

Table 6.1: Summary Statistics of Inputs and Output Data

Statistics	Inputs			Output
	Labor	Capital	Intermediate inputs	Total production
Maximum	35391.1	1788168221	1495232246	4068003497
Minimum	1027.81	6871141.31	20176600.1	56729660.1
Average	7926.64	333561243	394430893	812696402
Standard Dev.	8820.96	439174439	365635170	977519859

[24] The value of capital, intermediate inputs and output are measured in Ethiopian birr (ETB), Ethiopian currency, the current exchange rate of which against USD is about Birr 19.41 for 1 USD. Labor is measured by the number of annual temporary and permanent workers.

Table 6.2: Downside and Upside Error Rates in Percentage

Variables	Downside error rate α	Upside error rate β
Labor	17.6	10.9
Capital	15.1	21.2
Intermediate inputs	16.5	4.8
Output	23.3	13.7

The average efficiency scores from the radial and SBM models are summarised in Table 6.3 (see Appendix Table A.6 and Appendix Table A.7 for details of the 95%, 80%, and 60% confidence intervals efficiency scores). We observe from Table 6.3 that the only efficient industries (efficiency equal to 1) in the Ethiopian manufacturing sector are wood and basic iron and steel industries as evaluated by the radial and SBM models. The results reveal that the most inefficient industry in the Ethiopian manufacturing sector is the wearing apparel industry. The overall efficiency performance of the sector as measured by the SBM model is 77.27 percent in the year under consideration.

Table 6.3: Average Efficiency Scores from Radial and SBM Models

Industry	Average (SBM)	Average (Radial)	Rank (SBM)	Rank (Radial)
Food and beverages	0.9762	0.9894	3	3
Textiles	0.5151	0.6401	13	14
Wearing apparel	0.5038	0.7239	14	13
Tanning, leather and footwear	0.6016	0.7578	12	11
Wood	1	1	1	1
Paper and printing	0.8471	0.9228	6	7
Chemicals	0.6882	0.8296	9	9
Rubber and plastics	0.6104	0.746	11	12
Non-metals	0.9034	0.9514	5	5
Basic iron and steel	1	1	1	1
Fabricated metals	0.8422	0.9371	7	6
Machinery and equipment	0.7546	0.8576	8	8
motor vehicles	0.9339	0.9799	4	4
Furniture	0.6412	0.7752	10	10
Overall efficiency	0.7727	0.8651	-	-

In Figure 6.2, we present the upper boundary (UB) and lower boundary (LB) of the 95% confidence interval as well as the original DEA efficiency scores. The idea here is that the confidence interval should encompass the original DEA efficiency scores in order for the estimation process to be reliable. That is exactly what we see in Figure 6.2 where the original DEA scores are, as expected, included in the 95% confidence interval. The width of the confidence interval varies from industry to industry, ranging from 0 in the wood and basic iron and steel industries to 0.32 in the furniture industry. As can be seen from Figure 6.2, the UB, LB and DEA efficiency scores in the wood and basic iron and steel industries are the same implying that these industries are perfectly efficient. The average width of the 95% confidence interval for all the industries is 0.22.

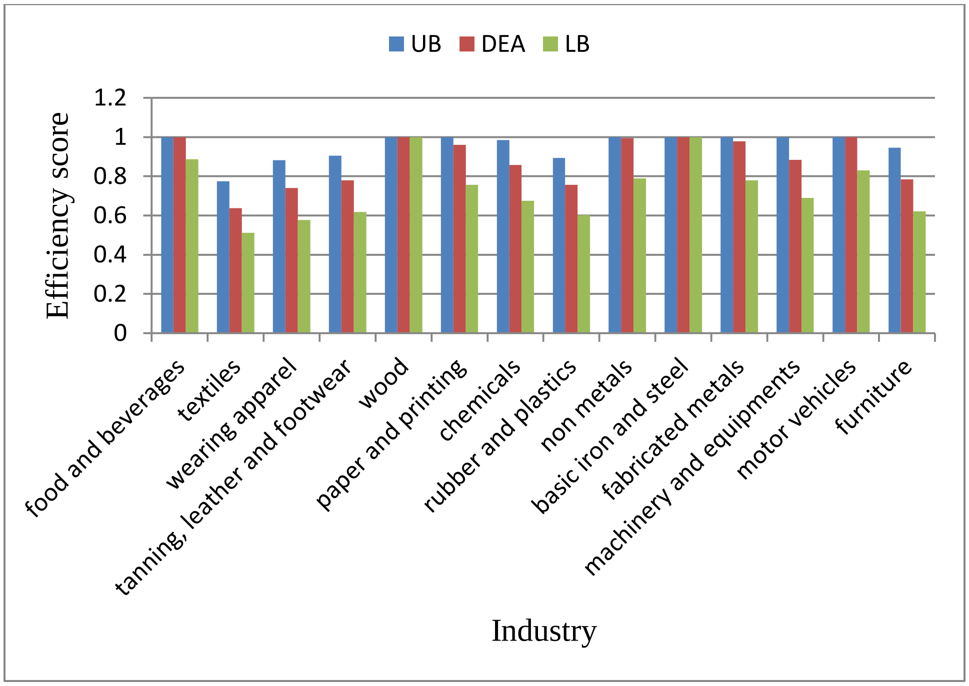


Figure 6.2: 95% confidence interval and DEA efficiency scores: radial model

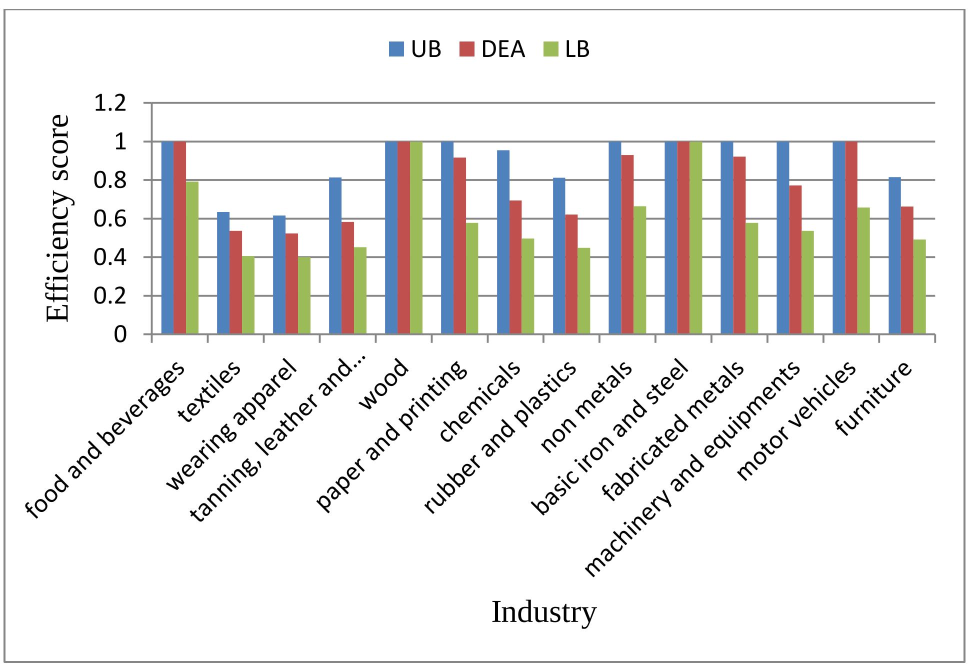


Figure 6.3: 95% confidence interval and DEA efficiency scores (SBM model)

We have also calculated the efficiency scores using different levels of confidence intervals as reported in the Appendix tables, which generally resulted in smaller widths compared to those of the 95% confidence interval[25]. For instance, on average, the width of the 80% and 60% confidence intervals were 0.21 and 0.15, respectively. Tone (2013) noted that, in the triangular distribution approach, the width of the confidence interval depends on the downside and upside error rates. If the error rates are small, the confidence interval will also be small and vice versa.

Figure 6.3 reports the 95% confidence interval for the SBM model. As compared to Figure 5.2 (radial model), the width of the confidence intervals in Figure 6.3 (SBM model) seem to be relatively wider, the widest (0.46) being observed in the chemical and machinery and equipment industries. The overall average 95% confidence interval (0.30) for SBM is larger than that of the radial model (0.22). These differences may emanate from the fact that while the SBM model takes account of the proportionate changes in inputs, the radial model does not. However, wood and basic iron and steel industries still remain perfectly efficient industries as can be observed in Figure 6.3. It is observed in the figure that original DEA efficiency scores in all the industries are contained in the 95% confidence interval. The average confidence intervals of 80% and 60% for all industries are also found to be 0.38 and 0.30, respectively.

[25] In order to conserve space and avoid repetitions, the histograms for the 80% and 60% confidence intervals are not reported in the analysis. Results are available up on request.

6. 4.2 Results from historical data method for estimating data variations

In this section we resample the data using the historical data technique as outlined in Sub-section (6.3.2) to estimate the efficiency score of individual industries. Similar to the previous section, we estimate the efficiency of the industries using the radial and SBM approaches. The summary statistics of the data used in this section are exhibited in Table 6.4.

Table 6.4: Summary Statistics of Inputs and Output Data

Statistics	Inputs			Output
	Labor	Capital	Intermediate inputs	Total production
Maximum	35391.1	1788168221	1495232246	4068003497
Minimum	1027.81	6871141.31	20176600.1	56729660.1
Average	7926.64	333561243	394430893	812696402
Standard Dv.	8820.96	439174439	365635170	977519859

The efficiency estimates obtained from the radial and SBM models are reported in Appendix Tables A.8 and Appendix Table A.9, respectively. Results are obtained by repeated resampling of the data (5000 replicas) at 95%, 80% and 60% confidence intervals. Table 6.5 compares the average efficiency score from both models. The table indicates that, on average, there is no fully efficient industry as measured by both models. Nevertheless, on average, the wood industry was the most efficient (99.95 percent) followed by basic iron and steel industry (98.81 percent) as measured by the SBM model. The poorest performance was observed in the textile industry followed by the tanning, leather and footwear industry. The average performance of the entire sector during the period under study (2008) stands at 71.51 percent and 81.33 percent as evaluated by the SBM and radial models, respectively.

Figure 6.4 shows the UB and LB of the 95% confidence interval in addition to the original DEA efficiency scores of the 2008 data estimated using the Radial model. We observe from Figure 6.4 that although the actual DEA score is contained in the 95% confidence interval, the confidence intervals are wider in most of the industries. The average of the 95% confidence interval for all the industries is 0.42 which is, double of the average confidence interval shown in Figure 6.2 (the radial triangular method). The overall average width of the 80% and 60% confidence intervals in this model are 0.30 and 0.22, respectively.

Table 6.5: Average Efficiency Scores from the Radial and SBM Models

Industry	Average (SBM)	Average (Radial)	Rank (SBM)	Rank (Radial)
Food and beverages	0.9024	0.9564	3	3
Textiles	0.4533	0.599	14	14
Wearing apparel	0.5679	0.7012	11	12
Tanning, leather & footwear	0.5541	0.6834	12	13
Wood	0.9995	0.9999	1	1
Paper and printing	0.7676	0.8615	5	4
Chemicals	0.6746	0.7897	8	9
Rubber and plastics	0.599	0.7226	10	10
Non-metals	0.7408	0.8569	7	6
Basic iron and steel	0.9881	0.9962	2	2
Fabricated metals	0.7631	0.8289	6	7
Machinery and equipment	0.6549	0.8179	9	8
Motor vehicles	0.7938	0.8615	4	4
Furniture	0.5524	0.711	13	11
Overall efficiency	0.7151	0.8133	-	-

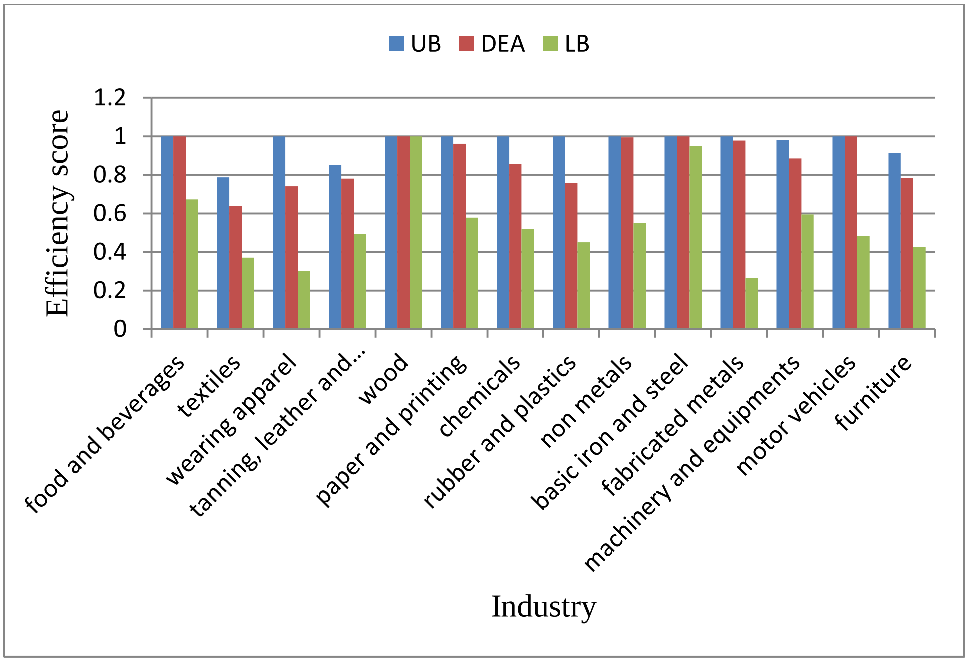


Figure 6.4: 95% confidence interval and DEA efficiency scores: radial model

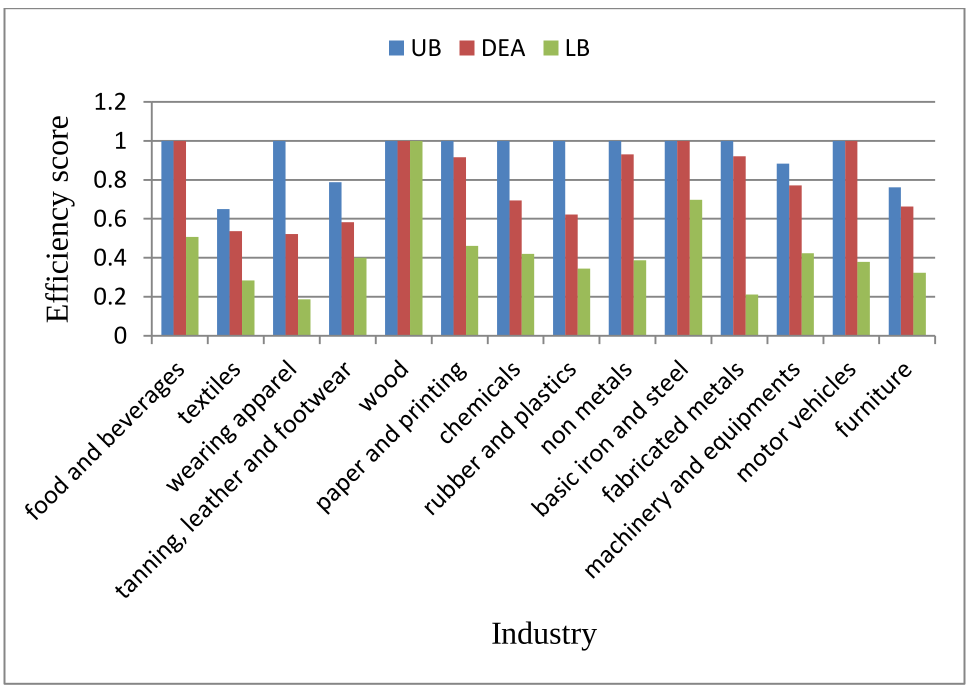


Figure 6.5: 95% confidence interval and DEA efficiency scores (SBM model)

In Figure 6.5, the 95% confidence interval and actual DEA score obtained from the SBM model are shown. Although the Original DEA score is still in the feasible range, the confidence interval appears to be more volatile. The average confidence interval for the industries is 0.50 which is much higher than the average confidence interval Figure 6.3 (SBM triangular method). Tone (2013) observed that in the historical data method, such a difference could be the result of large variations in the data which is a characteristic of our dataset.

6.4.3 Forecasting future efficiency scores

In this section, we utilize a forecasting model to evaluate the future efficiency scores of each industry given the past-present data. To do so, we first forecast the future inputs and output of the individual industries from the observed data. Following Tone (2013), we employ trend analysis and weighted average (weight by Lucas number) to obtain the forecast input and output. We regard 2004 to 2007 data as past data and 2008 data as present and then forecast the future data for 2009, upon the basis of which the future efficiency of the industries is estimated. In the interest of space we present results obtained from the SBM model. Readers can refer to the results from the radial model in Appendix Tables A.10 and A.11.

i) Forecasting efficiency by trend

Table 6.6 reports the summary statistics of the forecast inputs and output data using trend and Lucas weight approaches.

Table 6.6: Summary Statistics of the Forecast 2009 Data

Forecast by	Statistics	Inputs			Output
		Labor	Capital	Intermediate	Total production
Trend	Average	8257.41	310747504	420073505	876124473
	Maximum	37515.5	1540732183	1546068634	4285685863
	Minimum	1063.35	7656945.44	21226181.8	62556102.9
	Standard Dev	9624.32	399182617	398879501	1072629397
Lucas weight	Average	7523.06	354440581	376452762	744187703
	Maximum	32911.9	1878889258	1450262191	3807883986
	Minimum	1040.02	6440520.31	19739420.9	54167006
	Standard Dev	8829.81	483663123	370806322	950400990

In Table 6.7, we present the forecast original DEA scores and different confidence intervals for the forecast 2009 data. Data were resampled 5000 in order to gauge the confidence intervals. We observe in Table 6.7 that, on average, the wood and the basic iron and steel industries are the best-performing industries in the sector. The worst-performing industry is the textile industry whose forecast efficiency score in the year under study stands at about 48 percent. In terms of rank, the wood industry remains the most efficient industry in the sector. This shows that assuming the present situation in the manufacturing sector remains the same, the wood industry will remain the most efficient industry in the future. However, since the Ethiopian manufacturing sector is currently in its infant stage, various changes are taking place to boost the sector. As a policy direction, the government is focusing its attention on the textile and leather industries. Hence, we expect changes in the future efficiency performance in the sector.

Table 6.7: Forecast Efficiency Score and Confidence Intervals - SBM Model: Forecast by Trend

Industrial group	DEA	97.50%	90%	75%	50%	25%	10%	2.50%	Average
Food and beverages	1	1	1	1	1	0.8091	0.6183	0.4942	0.8991
Textiles	0.6078	0.6746	0.6054	0.5428	0.478	0.4159	0.3594	0.3011	0.4808
Wearing apparel	0.4995	1	1	0.6425	0.4832	0.3424	0.2321	0.1842	0.5359
Tanning, leather and footwear	0.6337	0.7801	0.7141	0.6341	0.5547	0.4975	0.4436	0.3886	0.5676
Wood	1	1	1	1	1	1	1	1	0.9974
Paper and printing	0.8684	1	1	0.9344	0.739	0.6047	0.516	0.4398	0.7526
Chemicals	0.7617	1	0.9764	0.8048	0.6584	0.557	0.4815	0.4009	0.6864
Rubber and plastics	0.5823	1	0.8063	0.6765	0.5536	0.4605	0.3866	0.3214	0.5797
non metals	0.8798	1	1	1	0.7801	0.575	0.4572	0.3691	0.7627
Basic iron and steel	1	1	1	1	1	1	1	1	0.9895
Fabricated metals	0.9161	1	1	1	0.9264	0.5766	0.3778	0.2279	0.7805
Machinery and equipment	0.8005	0.9447	0.8399	0.77	0.6815	0.5757	0.4871	0.4095	0.6732
Motor vehicles	1	1	1	1	1	0.6815	0.4863	0.3755	0.85
Furniture	0.6809	0.8204	0.7394	0.6738	0.5755	0.4738	0.3943	0.3244	0.5745

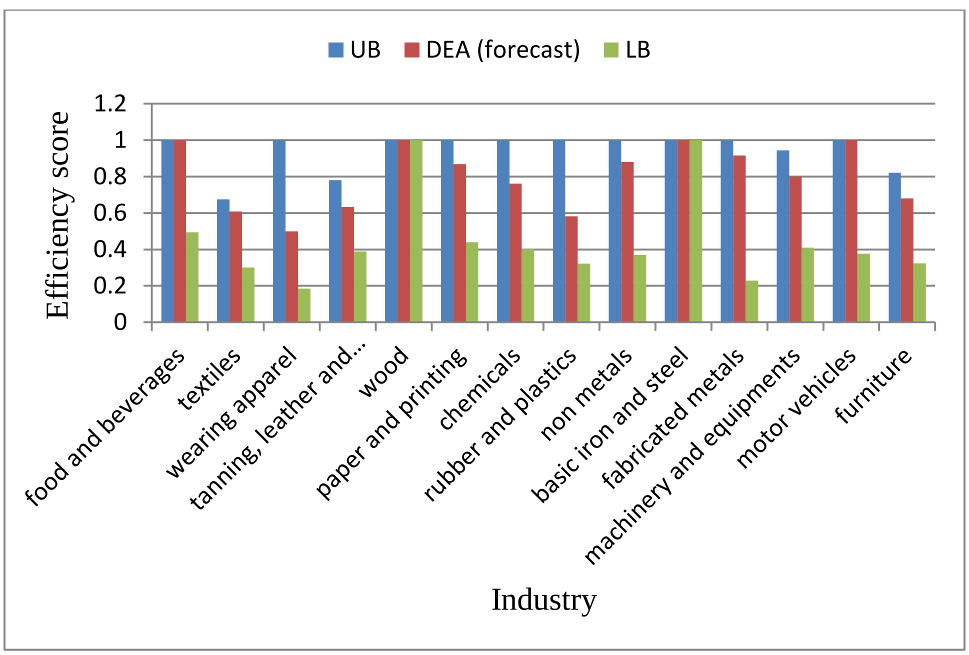


Figure 6.6: 95% confidence interval and forecast efficiency score-SBM model: Forecast by trend

We see from Figure 6.6 that the forecast efficiency scores of all the industries are included in the 95% confidence interval. However, we observe wider confidence intervals in industries such as wearing apparel and wood. The confidence interval of each industry seems more volatile ranging from 0 in the wood and basic iron and steel industries to 0.82 in the wearing apparel industry. The average 95% confidence interval for all the industries is relatively higher (0.50) than that of the triangular and historical data methods.

ii) Forecast by Lucas weight

In this section we forecast the data by the Lucas weight instead of the trend approach. We then gauge the confidence interval at different levels after resampling the data 5000 times. Table 6.8 exhibits the different levels of confidence intervals and the forecast efficiency score of each industry.

Table 6.8: Forecast Efficiency Score and Confidence Intervals - SBM Model: By Lucas weight

Industrial group	DEA	97.50%	90%	75%	50%	25%	10%	2.50%	Average
Food and beverages	1	1	1	1	1	1	0.7634	0.5822	0.9524
Textiles	0.5267	0.6311	0.5799	0.5293	0.4744	0.4246	0.379	0.3277	0.4773
Wearing apparel	0.5514	1	1	0.7042	0.499	0.393	0.2965	0.2336	0.569
Tanning, leather and footwear	0.5899	0.7847	0.6853	0.6212	0.5678	0.523	0.4841	0.4358	0.5776
Wood	1	1	1	1	1	1	1	1	1
Paper and printing	0.9674	1	1	0.9946	0.843	0.6941	0.5968	0.5172	0.822
Chemicals	0.7593	1	0.9038	0.7957	0.6926	0.602	0.5336	0.462	0.7044
Rubber and plastics	0.6621	0.993	0.8285	0.7206	0.5999	0.5152	0.4517	0.3901	0.6239
non metals	0.8486	1	1	1	0.7983	0.6533	0.5288	0.4426	0.7856
Basic iron and steel	1	1	1	1	1	1	1	1	0.9951
Fabricated metals	0.9034	1	1	1	0.838	0.636	0.4728	0.2723	0.7911
Machinery and equipment	0.7649	0.8735	0.8101	0.7676	0.7162	0.6427	0.5397	0.4634	0.6985
Motor vehicles	0.7853	1	1	1	0.8368	0.6697	0.4865	0.412	0.8125
Furniture	0.6644	0.7554	0.7122	0.6625	0.6041	0.5132	0.4481	0.3773	0.5879

The results seem to be comparable with that of the trend approach. In terms of rank, the wood industry is still the best performer in the sector followed by basic iron and steel industry.

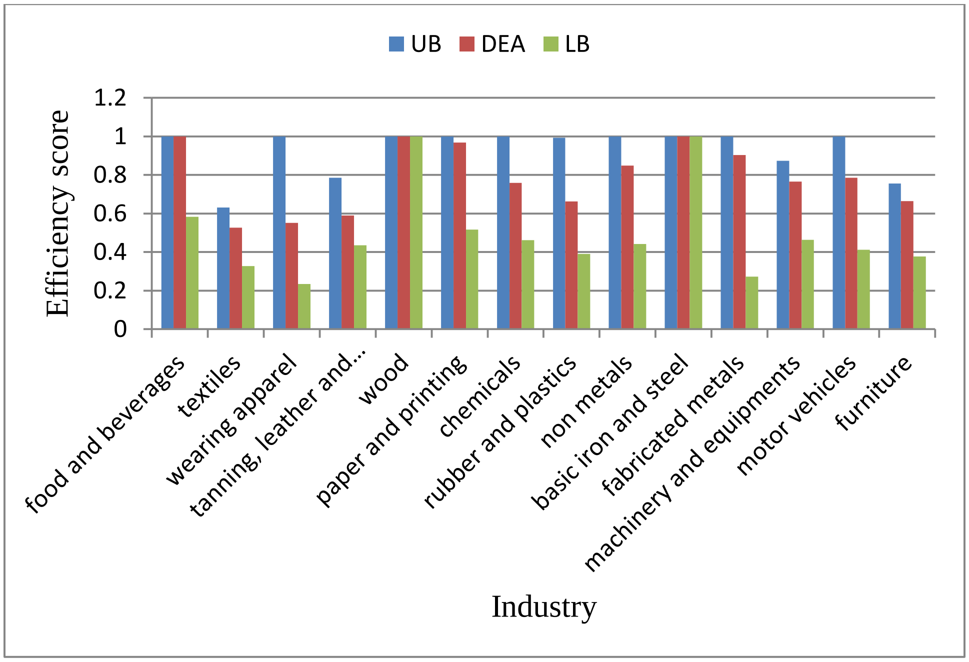


Figure 6.7: 95% confidence interval and forecast efficiency score: by Lucas weight

The 95% confidence interval and forecast efficiency score are shown in Figure 6.7. We observe that the forecast efficiency scores are included in the confidence interval for all the industries. It can also be seen from the figure that the confidence interval seems to be less volatile in this case. The average of the 95% confidence interval for all industries in this case is 0.44 as compared to 0.50 in the trend case.

As a final remark, the results obtained from the three types of resampling techniques show that the wood and basic iron and steel industries consistently appear to be the best performing industries in the Ethiopian manufacturing sector. The textile industry on the other hand experiences the worst performance in the year under study. The consistency of the results may indicate the robustness of the results. Overall, the average efficiency of the Ethiopian manufacturing sector remains fairly stable across the three resampling techniques ranging from 71.5 percent in the historical data method to 77. 3 percent in the triangular distribution approach as evaluated by the SBM model. This result indicates that there is a room for the firms in the sector to improve their efficiency

Another point is that the 95% confidence intervals, although differ from model to model, are generally wider. It should be noted that the width of the confidence interval can be affected by the variability of the data under consideration. The more dispersed the data are, the wider the confidence intervals are. In this regard, our preliminary assessment of the data shows the existence of data variations in the sample in general and within an industry (year-wise). Since the industrial sector in Ethiopia is at its infant stage, data fluctuations maybe expected due to the frequent internal (firm-specific) and external (government policies) changes taking place in the sector. Our aggregation of the data to industry level could have also contributed to the data variation.

The width of the confidence interval also depends on the level of confidence interval we are using. The smaller the confidence interval, the smaller is the width of the confidence interval. Our analysis is based on the 95% confidence interval which resulted in a relatively wider confidence interval. However, we also estimated efficiency score of the industries at 80%, 60% and 50% confidence intervals (see tables in Appendices). Indeed, the width of the confidence intervals decreases as we go down from the 95% to 50%.

6.5. Conclusions

This chapter examines the efficiency of Ethiopian manufacturing industries at the 2-digit level using census data from CSA of Ethiopia that covers the period from 2000 to 2009. We used three recently proposed resampling methods in DEA to construct confidence intervals for the actual DEA efficiency scores. While we use the panel nature of our data to estimate the measurement errors in the data, efficiency score are calculated for the year 2008 only in the triangular and historical data models. In the future forecast model, we forecast efficiency scores for the year 2009. Hence, it is worth noting that the results in this chapter may not be compared with that of chapter 4.

The results obtained from the three types of resampling techniques indicated that the wood and basic iron and steel and industries consistently appear to be the best performing industries in the Ethiopian manufacturing sector. The consistency of the results may indicate the robustness of the results. Another point is that the 95% confidence intervals, although differing from model to model, are generally wider. Again, the width of the confidence interval can be affected by the variability of the data under consideration which, indeed, could be observed in our data.

Chapter 7

An enquiry into the firm size distribution, firm growth rate distribution, and firm growth persistence: Evidence from Ethiopian manufacturing

7.1. Introduction

In the previous chapters, we evaluated firm performance in terms of technical efficiency. In this chapter, we study the evolution of the Ethiopian manufacturing sector by looking into firm size and growth rate distribution and the growth process.

Studying firm size and firm growth rate distributions is a natural starting point to understand the market structure and the evolution of an industry. As a result, firm size and growth rate distributions have long been a matter of considerable interest in the study of industrial dynamics. In the empirical industrial organization literature, perhaps the first attempt to explain firm size dynamics and their relationship with firm growth is that of Gibrat (1931). Gibrat investigated the size distribution of French firms and concluded that firm size distribution can be approximated by a log-normal distribution; moreover, he proposed a model of firm growth independent of firm size that came to be called Gibrat's law (also known as the law of proportionate effect) in the literature.[26] Precisely speaking, Gibrat's law may be summarized by the following three propositions: (1) firm size and growth rate can be represented by a normal distribution, (2) firm growth rate is independent

[26] See Coad (2009) for a detailed survey of Gibrat's law.

of its size, and (3) firm growth rates in two consecutive periods are independent of each other. Together these propositions imply that the firm growth rate follows a random walk.

A number of empirical studies have been undertaken to test the validity of Gibrat's law, yet the findings were inconclusive. Among the earlier studies in favor of Gibrat's law were Hart & Prais (1956) and Simon & Bonini (1958), who independently confirmed that firm grow rates were independent of size and that firm size distribution could be represented by a log-normal distribution. More recently, consistent with the earlier studies, Reichstein & Jensen (2005) found that the firm size distribution in the Danish manufacturing seems to be approximated by the log-normal distribution. However, several other studies did not find support for Gibrat's law (see for example, Kumar, 1985; Evans, 1987; Yasuda, 2005; Oliveira and Fortunato, 2005). These studies suggest that firm growth is somewhat negatively associated with firm size. Similarly, Hymer & Pashigian (1962) observed an inverse correlation between the variance of growth rates and firm size for the 1000 largest US manufacturing firms.

Wagner (1992) emphasized the industrial policy implications of such a result. The author argued that if the finding reveals small firms grow faster than larger ones, it would help policy makers to design policies that promote the entry and growth of small firms in the market, thereby reducing unemployment. If, on the contrary, large firms appear to grow faster than small ones, industrial policy makers could design policies that encourage the expansion and growth of large firms in the market.

As a natural extension of testing the dependence of firm growth rate on size, several studies have investigated the distributional characteristics of firm growth rates. Looking at Danish manufacturing firms, Reichstein and Jensen (2005) observed that firm growth rate seems to be inconsistent with Gibrat's proposition that firm growth rates are purely random draws from independent and identical distributions. Instead, the authors found that firm growth rates are leptokurtic, depicting fat tails which resemble a tent-shaped Laplace (double exponential) distribution. Moreover, we can also find a fat-tailed Laplace distribution of firm growth rate in the following studies: Bottazzi et al. (2002) for Italian manufacturing firms, Bottazzi and Secchi (2003) for US manufacturing, Bottazzi and Secchi (2005) for the worldwide pharmaceutical industry, Reichstein et al. (2010) for Danish manufacturing, service, and construction sectors, and Coad & Holzl (2009) for Australian service industries.

In order to have a complete picture of firm growth trajectories, a rigorous empirical study should also go beyond analyzing the distributional properties of firm size and growth rates. One such study could look further into the autocorrelation of growth rate (i.e., the persistence of firm growth over time, which is Proposition 3 above). According to Gibrat's law of proportionate effect, firm growth rate is independently and identically distributed, which implies that growth rates at time t are not affected by the previous period's growth rates. Empirical studies on this subject have also come up with contradictory findings. Chesher (1979) for UK quoted firms, Wagner (1992) for Germany manufacturing firms, and Bottazzi et al. (2001) for the world's top 150 pharmaceutical firms found positive autocorrelation in firm growth. Using value-added as an indicator of size, Bottazi et al. (2007) found negative autocorrelation for Italian manufacturing firms.

Looking at the above results, one might ask why these conflicting results are emerging. Coad (2009) tried to explain the emergence of the difference in autocorrelation coefficients. Coad argued that one possible reason was the aggregation of firms of different sizes in a given dataset. This can be substantiated by the findings from Coad (2007), which show that while small firms experience negative autocorrelation, larger firms display positive autocorrelation of growth in French manufacturing. Similarly, Coad & Holzl (2009) found that the patterns of autocorrelation in micro firms are different from those of small, medium and large firms in the Australian service industry.

This chapter has four specific objectives: (1) to determine whether firm size distribution can be approximated by the log-normal distribution, (2) to determine the shape of firm growth rate distribution, (3) to test whether firm growth rate is independent of its size, and (4) to investigate the persistence of firm growth over time for the Ethiopian manufacturing sector. To the best of our knowledge, firm growth dynamics in the context of persistence of growth have not yet been addressed for Ethiopian manufacturing. The only reported studies testing the relationship between firm growth rate and size that we can find about Ethiopian manufacturing are those of Admasu (2006) and Bigsten & Gebreeyesus (2007). Using older data from the same source as in the present study, the authors utilized the standard OLS-type in their estimation. However, there are concerns in using such estimation methods in analyzing firm growth. Resent developments in the firm grow literature show that firm growth rate followed a fat-tailed distribution (non-normal). In this respect, Coad (2007), Coad & Holzl (2009), and Reichstein (2010) argued that since OLS-type models are designed to summarize average effect for the average firm, they are not consistent with the fat-tailed nature of firm growth distribution. They suggested that such a problem can be circumvented by using quantile regression models, which are not limited only to regressions against averages, but also gives detailed information on the entire distribution of firm growth. In this study, we follow their suggestion and apply quantile regression approach.

This chapter makes some contributions to the literature on industrial dynamics in Ethiopia. First, it presents the first detailed account of the shape of firm size and growth rare distributions. Second, unlike previous studies, this study applies quantile regression techniques which best suit the fat-tailed nature of the firm growth rate distribution. Third, this study explicitly takes the autocorrelation of firm growth rates into account. Coad & Holzl (2009) noted that autocorrelation in the firm growth process allows us to study the persistence of chance in firm growth trajectories. This in turn helps to know whether new jobs created disappear the following year or the growth process remains healthy. Finally, unlike previous studies which focused on aggregated data, our approach is based on data classified by different firm size groups. We further disaggregate our data by sector and time. We believe this kind of approach may give a clearer picture of the growth process in the Ethiopian manufacturing sector.

The next section of this chapter describes the data used in this chapter. Section 7.3 offers estimation strategy, while Section 7.4 gives the descriptive and empirical results. Section 7.5 presents a number of robustness checks. Finally, Section 7.6 presents the conclusion of this chapter and offers some policy recommendations.

7.2. Data description

The data used in this chapter are drawn from the same CSA database described in Chapter 1. The entire cohort of manufacturing firms that employ 10 or more persons over the period 2000 to 2009 is considered in this chapter. We are aware that this data censoring (i.e., the cutoff point of 10 employees) that leaves micro and small firms underrepresented in the study may introduce some bias in the analysis of firm size and growth rate distribution. Nonetheless, as Bigsten & Gebreeyesus (2007) did with a slightly different approach, we test the sensitivity of our findings by increasing the cutoff point from 10 to 20, 50, and 100 employees.

The original dataset includes a total of 11,217 observations from a total of 3213 firms over a period of 10 years (unbalanced panel). However, for the purpose of this chapter, a number of data cleaning procedures were undertaken. Since the CSA survey is conducted for establishments that employ 10 or more persons, we removed all observations for which employment is less than 10. All observations with missing values of the variables used were also excluded from the analysis. Accordingly, at this stage, the total number of observation decreased from 11,217 to 9,781. Given the number of relevant *lags* used in the quantile regression analysis of the firm growth process, we further restrict our data to firms which appear in the data for at least three years. This further reduces the number of observations used in the final analysis.

Regarding the measure of firm size, although there are many proxy variables in the literature such as sales and value-added, this study adopts the number of employees as a proxy for firm size for two reasons (Oliveira & Fortunato, 2005). First, it allows comparisons with previous studies which were based on employment data. Second, it provides important policy implications from an employment perspective. While firm size is given by the natural logarithm of employment, $\log(SIZE)$, firm growth rate at time t is calculated by the difference between $\log(SIZE)$ in two consecutive years: $GROWTH_{i,t} = \log(SIZE)_{i,t} - \log(SIZE)_{i,t-1}$.

7.3. Methodology and estimation strategy

Standard econometric least square regression models are designed for point estimates. They summarize the average relationship between the dependent variable and the regressors based on a conditional mean function. However, since working with the average effect can only yield a partial view of the relationship, if we are interested in describing the entire conditional distribution of the dependent variable, we must be aware that some important information of the underlying firm growth trajectories might be hidden (Coad, 2009). In order to capture such important information, the quantile regression technique is preferable to the standard least square models.

First proposed by Koenker & Bassett (1978), the quantile regression model is a semi-parametric model which allows for the impact of the independent variables to vary over quantiles of a distribution, which makes it advantageous to a mean regression. Recently, many researchers have applied quantile regression in the context of firm growth (see for instance, Ribeiro, 2007; Coad, 2007; Coad & Rao, 2008; Coad & Holzl, 2009 and Reichstein, 2010). A fat-tailed firm growth rate distribution which can be represented by a Laplace distribution has recently emerged as 'stylized fact' in the industrial organization literature (Bottazzi & Secchi, 2003; Bottazzi et al., 2005; Reichstein, 2005; Stanley et al. 1996), indicating that the firm growth process consists of some quickly declining and some quickly growing firms which could be considered outliers. Indeed, such outliers (firms with high growth events) are of great interest and should be examined, not ignored as outliers. Under such circumstances, conventional regression estimators that focus on the average firm and ignore extreme events as outliers may not be robust (Coad, 2007). The author argued that the quantile regression model is characteristically robust to outliers and fat-tailed distributions. Moreover, the quantile regression model is advantageous in that it avoids the assumption that the error terms are identically distributed at all points of the conditional distribution. Finally, quantile regression also provides a richer characterization of the data, allowing us to consider the effect of the independent variables varying on the entire distribution of the dependent variable, instead of merely on its conditional mean.

In line with the above findings, our graphical illustration and statistical test of firm growth rate in Sub-section (7.4.2) also reveals that firm growth rate in Ethiopian manufacturing follows a fat-tailed Laplace distribution as opposed to a Gaussian (normal) distribution. In this chapter, exploiting its advantages, we therefore apply the quantile regression approach in our analysis.

The quantile regression model as proposed by Koenker and Bassett (1978) can be given as follows:

$$y_{it} = x_{it}'\beta_\theta + u_{\theta it} \qquad \text{with} \qquad Quant_\theta(y_{it}|x_{it}) = x_{it}'\beta_\theta \tag{7.1}$$

where y_{it} is the firm growth rate which can be measured by employment, sales, and value-added (among other variables), x_{it} is a vector of explanatory variables, β represents the vector of parameters to be estimated, and u is a vector of residuals. $Quant_\theta(y_{it}|x_{it})$ is the θ^{th} conditional quantile of y_{it} given x_{it}. The θ^{th} regression quantile $(0 < \theta < 1)$ solves the following problem:

$$min_\beta \frac{1}{n}\left\{\sum_{i,t:y_{it}\geq x_{it}'\beta_\theta} \theta|y_{it} - x_{it}'\beta_\theta| + \sum_{i,t:y_{it}<x_{it}'\beta_\theta}(1-\theta)|y_{it} - x_{it}'\beta_\theta|\right\} =$$

$$min_\beta \frac{1}{n}\sum_{i=1}^{n} \rho_\theta\, u_{\theta it} \tag{7.2}$$

where $\rho_\theta(.)$ is called a 'check function' and is defined as follows:

$$\rho_\theta(u_{\theta it}) = \begin{pmatrix} \theta u_{\theta it} & if\ u_{\theta it} \geq 0 \\ (\theta - 1u_{\theta it}) & if\ u_{\theta it} < 0 \end{pmatrix} \tag{7.3}$$

Equation (7.2) can be solved using a linear programming technique. If we increase θ continuously from 0 to 1, we can trace the whole conditional distribution of y, conditional on x (Buchinsky, 1998).

The regression model estimated in this study is represented as follows:

$$Growth_{i,t} = \beta_0 + \beta_1 \log\left(size_{i,t-1}\right) + \beta_2 Growth_{i,t-1} + \beta_3 Growth_{i,t-2} + \varepsilon_{i,t} \tag{7.4}$$

where $Growth_{i,t}$is the current growth rate computed as the logarithmic difference of size (measured by the annual number of employees) between two consecutive years, $size_{i,t-1}$ is firm size lagged one year, $Growth_{i,t-1}$ and $Growth_{i,t-2}$ are growth rates lagged one and two years, respectively, $\beta's$ are parameters to be estimated, and $\varepsilon_{i,t}$ is an error term.

Equation (6.4) can be used to test the Gibrat's propositions stated before. In particular, we are interested in testing the following two main hypotheses:

Hypothesis 1: Firm growth rate is independent of firm size.

To examine the effect of firm size on firm growth, we test the following null hypothesis:

$$H_0: \beta_1 = 0$$

If β_1 is positive, large firms grow faster than small firms, there will be a high concentration, and the distribution of firm sizes becomes highly skewed. The opposite is true if β_1 is negative.

Hypothesis 2: Firm growth rate is not persistent.

Because our model consists of the lagged values of firm growth, we test the serial correlation of growth rates in two consecutive periods. Considering the growth rate lagged one year, the persistence of firm growth can then be examined by the following hypothesis:

$$H_0: \beta_2 = 0$$

$$H_1: \beta_2 \neq 0$$

If $\beta_2 = 0$, it implies Gibrat's proposition that firm growth is independent of its past growth history. If $\beta_2 \neq 0$, firm growth persists from one period to the next.

7.4. Analysis of results

7.4.1. Size distribution

In this section we briefly describe the aggregate and sectoral-level distribution of firm size. As in many other studies, we use the logarithmic form of total employment as a measure of firm size[27]. This allows for comparison of our study with previous studies. Total employment has been obtained as the sum of annual permanent and temporary workers.

Table 7.1 exhibits the summary statistics of aggregate and sectoral firm size. Figure 7.1 presents the histogram of firm size distribution for all firms during 2000-2009. A Gaussian (normal) distribution plot has been added to the histogram for comparison. A simple comparison of the mean and median in Table 7.1 and visual inspection of Figure 7.1 confirm the 'stylized facts' documented by previous studies (Angelini & Generale, 2008; Bigsten & Gebreeyesus, 2007; Bottazzi et al., 2011; Cabral & Mata, 2003; Coad, 2007, 2009; Ribeiro, 2007) that firm size distribution is positively skewed. As indicated by Figure 7.2, this shape seems to persist over time. The corresponding kernel density estimate of the logarithmic firm size for each industry is presented in Appendix Figure B.1. Consistent with the results in Table 7.1 and Figure 7.1, the shapes of the kernel density estimates suggest that firm size

[27] We have also tried total sales as a measure of firm size. Overall, the results are similar to those obtained using number of employees as measure of firm size. However, there are two exceptions: Firm size distribution in the case of total sales approaches normal distribution more closely and in the pooled quantile regression firm size is positively correlated with firm growth only at the lower quqntile of the distribution. Results are available upon request.

Table 7.1: Summary Statistics of Firm Size for 10% and 90% Quantiles, Mean and Median

Industry	Observations	10%	Mean	Median	90%
Food and beverages	2733	2.442	3.720	3.359	5.598
Textile	344	2.890	5.273	5.305	7.505
Wearing apparel	281	2.565	4.142	3.876	6.035
Tanning, leather and footwear	580	2.746	4.138	3.948	5.875
Wood	215	2.398	3.502	3.164	5.220
Paper and printing	771	2.565	3.809	3.611	5.280
Chemicals	502	2.708	4.169	4.143	5.659
Rubber and plastics	505	2.708	4.148	4.043	5.628
Non-metals	1557	2.398	3.266	2.872	4.927
Fabricated metals	118	3.258	4.469	4.304	5.872
Basic iron and steel	501	2.335	3.350	3.091	4.860
Machinery and equipment	160	2.568	3.697	3.401	5.150
Motor vehicles	112	2.565	4.163	3.970	5.549
Furniture	1317	2.367	3.126	2.833	4.431
All firms	9706	2.413	3.705	3.367	5.587

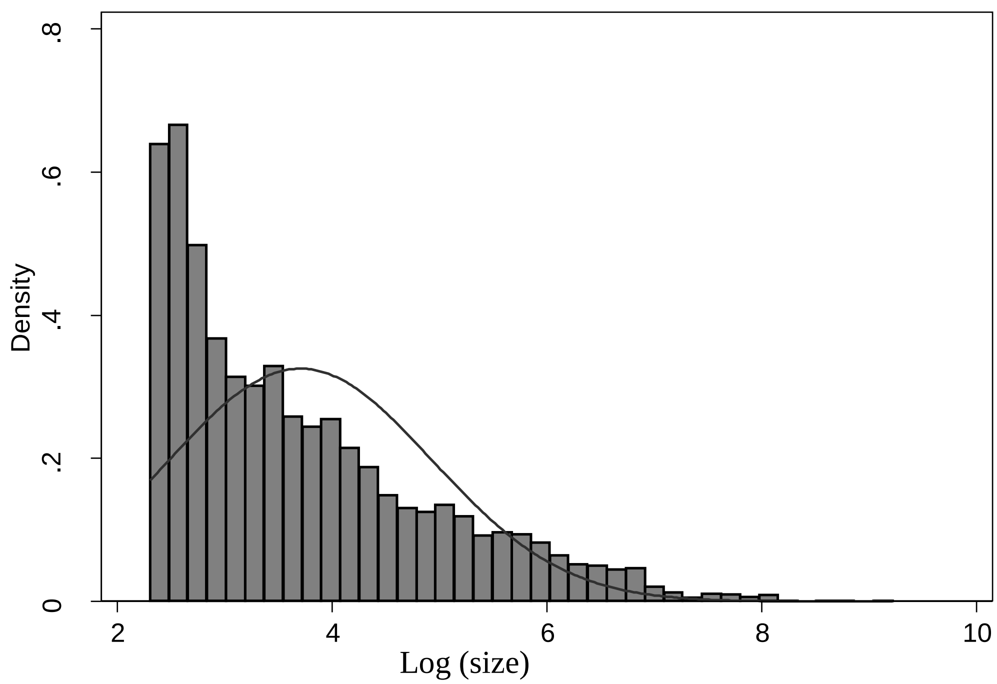


Figure 7.1: Log (size) distribution of all firms, 2001-2009

distribution in most industries is right-skewed. However, we also observe bimodality in the size distribution of firms in some industries, thus giving support to the findings in Bottazzi and Secchi (2005) in their study of the worldwide pharmaceutical industry and Demirel and Mazzucato (2010) for the quoted U.S. pharmaceutical industry.

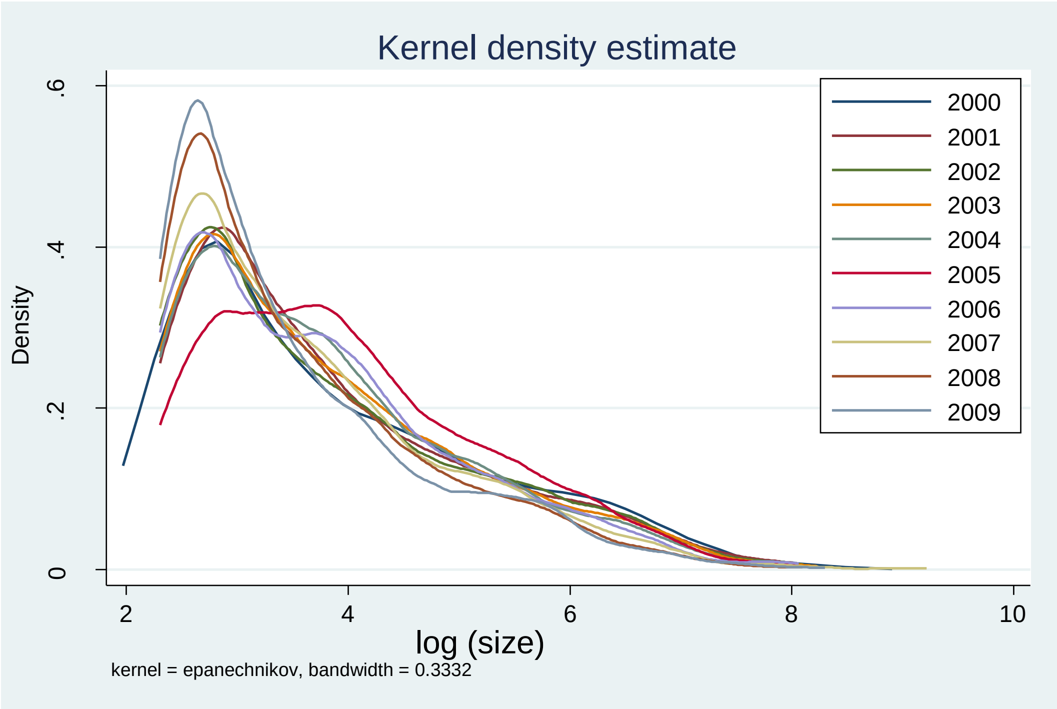


Figure 7.2: Log (size) distribution by year

The above analysis shows that firm size in the Ethiopian manufacturing sector generally exhibits asymmetric distribution instead of a log-normal distribution as suggested by Gibrat's Law. However, simple visual inspection may not be sufficient to arrive at this conclusion. Hence, we conduct further statistical tests to confirm the conclusions from the graphical representation. To do so, we first test whether the size distribution significantly departs from normality using the Kolmogorov-Smirnov normality test; thereafter we test the skewness and kurtosis of the size distribution.

Table 7.2 presents the Kolmogorov-Smirnov normality test statistics for the logarithmic firm size distribution. The *D*-statistics and their corresponding *p*-values are also given in the table. In Table 7.2, it can be observed that firm size distribution in the Ethiopian manufacturing sector is far from normal. Since the *p*-values in Table 7.2 are very low, the null hypothesis that firm size is normally distributed is rejected both within each industry and within the total manufacturing sector. It is only in the rubber and plastics and basic iron and steel industries that the *p*-values exceed the 5 percent significance level. While the *p*-value in the basic iron and steel industry is a little higher than the 5 percent significance level, it is very close to the 10 percent significance level in the rubber and plastics industry, which indicates that there is a high probability that the size distribution in this sector is drawn from a normal distribution. The Kolmogorov-Smirnov statistics for the rest of the sectors suggest a significant deviation from the normal distribution. This in turn allows rejection of Gibrat's proposition that firm size distribution is log-normally distributed.

This finding is consistent with some of the findings from Reichstein Jensen (2005), who studied firm size and growth distribution in four industries in Denmark. The authors found that firm size distribution as measured by employment was far from normal in the iron metal and machine industries. However, the authors found contrasting results in the four industries considered when size was measured by total sales. Using the Kolmogorov-Smirnov test, we have shown the departure of the firm size distribution from normality.

In order to evaluate the consistency of the results, we now conduct skewness and kurtosis tests. [28] Table 7.3 summarizes the skewness and kurtosis statistics of the size distribution as well as their associated overall *p*-values. On the basis of skewness alone, for all but one industry (the textile industry, which is left-skewed), the log (size) distribution is right-skewed. Moreover, the distribution is significantly asymmetric except for the textile, chemicals and motor vehicle industries, which are symmetrically distributed.[29] In total, the manufacturing sector can be considered to be right-skewed, which is consistent with visual proposition shown in Figure 7.1. In terms of peakedness, the wood, rubber and plastics, and fabricated metals industries reveal a mesokurtic distribution. Five of the industries, namely food and beverages, paper and printing, non-metals, machinery and equipment, and furniture industries, demonstrate a significant leptokurtic distribution. The remaining six industries (textile, wearing apparel, tanning, leather and footwear, chemicals, basic iron and steel, and motor vehicle) have a significant platykurtic shape.

The *p*-value in Table 7.3 presents the test for the normality of size distribution taking account of both skewness and kurtosis together. Accordingly, we observe that the basic iron and steel, and motor vehicle industries have significantly asymmetric distributions at the 5 percent level of significance. The remaining twelve industries are

[28] If skewness = 0, the distribution is perfectly symmetric, if skewness is negative, the distribution is left-skewed and if skewness is positive, the distribution is right-skewed. Kurtosis is a measure of how peaked a distribution is compared to a normal distribution. If the value of kurtosis = 3, the distribution is mesokurtic, if kurtosis < 3, the distribution is platykurtic, and if kurtosis > 3, the distribution is leptokurtic. A platykurtic distribution has its central peak lower and broader with its tails being shorter and thinner compared to a normal distribution. A leptokurtic distribution has its central peak higher and sharper with its tails being longer and fatter compared to a normal distribution.

[29] Since our main interest is on the overall (combined) *p*-values, the *p*-values for the skewness and kurtosis are not reported.

Table 7.2: Kolmogorov-Smirnov Normality Test of Log (size) Distribution

Industry	D-Statistics	*p*-value
Food and beverages	0.1274	0.000
Textiles	0.1125	0.000
Wearing apparel	0.1081	0.003
Tanning, leather and footwear	0.0859	0.000
Wood	0.1573	0.000
Paper and printing	0.0921	0.000
Chemicals	0.0693	0.016
Rubber and plastics	0.0552	0.092
Non-metals	0.1811	0.000
Basic iron and steel	0.1228	0.057
Fabricated metals	0.1372	0.000
Machinery and equipment	0.1398	0.004
Motor vehicles	0.2444	0.000
Furniture	0.1710	0.000
All firms	0.1263	0.000

Table 7.3: Skewness and Kurtosis tests of Log (size) Distribution

Industry	Skewness	Kurtosis	Significance (*p*-value)
Food and beverages	1.041	3.511	0.0000
Textiles	-0.093	1.690	0.0000
Wearing apparel	0.623	2.543	0.0002
Tanning, leather and footwear	0.607	2.622	0.0000
Wood	1.051	3.197	0.0000
Paper and printing	0.882	3.344	0.0000
Chemicals	0.152	1.974	0.0000
Rubber and plastics	0.448	2.704	0.0004
Non-metals	1.692	5.211	0.0000
Basic iron and steel	0.190	2.154	0.0136
Fabricated metals	0.848	2.696	0.0000
Machinery and equipment	1.128	3.891	0.0000
Motor vehicles	0.298	2.264	0.0407
Furniture	1.263	3.810	0.0000
All firms	1.027	3.439	0.0000

found to deviate significantly from the normal distribution at the 1 percent level of significance. Hence, we conclude that based on skewness and kurtosis, it is possible to reject the supposition that firm size distributions in the Ethiopian manufacturing sector were drawn from a normal distribution.

7.4.2. Growth rate distribution

Table 7.4 represents the summary of aggregate and sectoral firm growth rate in Ethiopian manufacturing. From Table 7.4, it emerges that while firms in the Ethiopian manufacturing sector, on average, experienced slight negative and positive growth rates both at the sectoral and aggregate levels, the median growth rate was zero, which indicates that firms at or around the median growth rate grow very little. Figure 7.3 shows the histogram of firm growth rate distribution for all firms during 2000-2009. A Gaussian (normal) distribution has been added to the histogram for reference. We see that overall firm growth rate distribution is highly peaked compared to the normal distribution, an indication of a Laplace as opposed to the Gaussian distribution. As indicated in Figure 7.4, this shape seems to be stable over time. The corresponding kernel density estimate of the firm growth rate distribution for each sector is presented in Appendix Figure B.2. Consistent with Figures 7.3 and 7.4, the shapes of the kernel density estimates suggest that the firm growth rate distribution in most of the industries is highly peaked with a number of observations located around zero growth rates with some firms exhibiting extreme growth rates (right tail) and some firms experiencing a decline in growth rate (left tail) of the distribution; in most cases the tails of the distribution are fatter as compared to the normal distribution. This confirms that, consistent with the aggregate manufacturing, sectoral

Table 7.4: Summary Statistics of Firm Growth Rate for 10%, 90% Quqntiles, mean and Median

Industry	Observations	10%	Mean	Median	90%
Food and beverages	1998	-0.390	0.016	0.000	0.495
Textile	265	-0.364	-0.015	0.000	0.330
Wearing apparel	206	-0.350	0.017	0.000	0.492
Tanning, leather and footwear	430	-0.346	0.029	0.000	0.450
Wood	147	-0.338	-0.018	0.000	0.377
Paper and printing	625	-0.303	0.045	0.000	0.405
Chemicals	401	-0.333	0.039	0.000	0.470
Rubber and plastics	390	-0.302	0.053	0.000	0.405
Non-metals	866	-0.446	0.013	0.000	0.492
Fabricated metals	97	-0.281	0.078	0.027	0.503
Basic iron and steel	321	-0.265	0.032	0.000	0.373
Machinery and equipment	124	-0.347	0.020	0.000	0.433
Motor vehicle	69	-0.318	-0.002	0.000	0.380
Furniture	860	-0.369	0.015	0.000	0.387
All firms	6807	-0.353	0.022	0.000	0.445

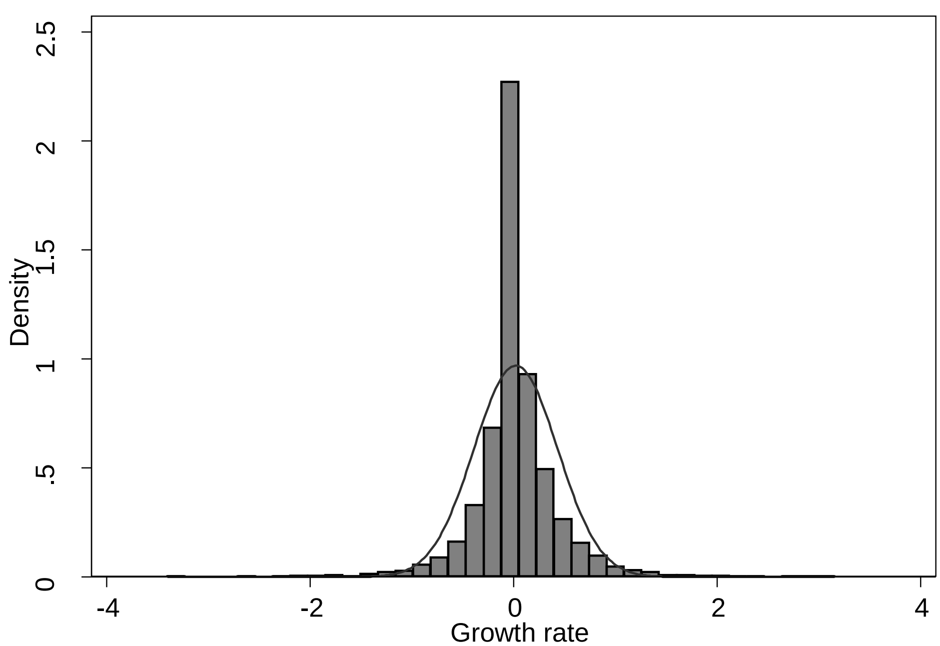


Figure 7.3: Growth rate distribution of all firms, 2001-2009

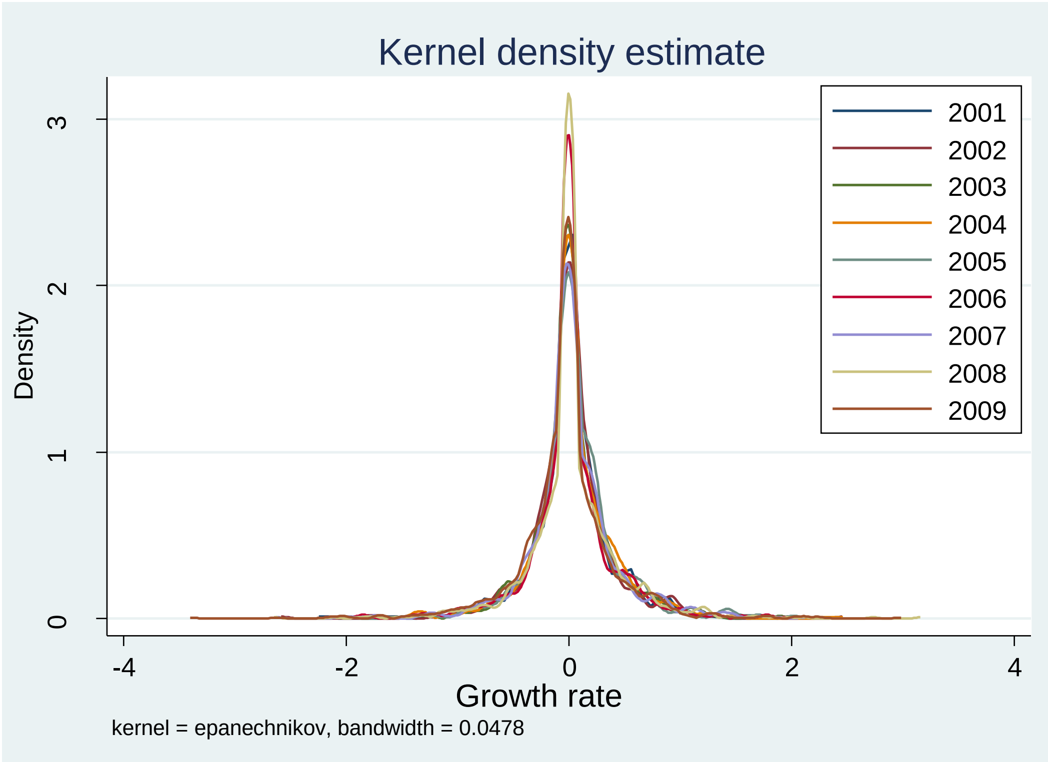


Figure 7.4: Growth rate distribution by year

analysis of firm growth rate distribution also takes the shape of a Laplace distribution rather than the normal distribution.

In order to provide a more precise account of the shape of firm growth rate in Ethiopian manufacturing, we conduct further statistical tests. In so doing, we first test whether the growth rate distribution significantly departs from normality using the Kolmogorov-Smirnov normality test and then we test the skewness and kurtosis of the growth rate distribution.

Table 7.5 presents the Kolmogorov-Smirnov normality test statistics for the firm growth rate distribution. The *D*-statistics and their corresponding *p*-vales are also given in the table. In Table 7.5, it can be observed that the firm growth rate distribution in the Ethiopian manufacturing sector is far from normal. Since the *p*-values in Table 7.5 are very low across industries, the null hypothesis that firm growth rate is normally distributed is rejected both at the individual industry and the aggregate level. The normality tests are all significant at the 1 percent significance level across the industries and at the aggregate level (with the exception of the motor and vehicles industry where the normality test is rejected at the 10 percent significance level). Hence, the growth rate distribution in the Ethiopian manufacturing sector can be characterized as having little in common with a normal distribution, at least for the period under study.

In order to evaluate the consistency of our results, we further apply the skewness and kurtosis tests to the growth rate distribution at the aggregate and sectoral levels. This test can be used to examine the normality of the growth rate distributions based on skewness, kurtosis, or both. Table 7.6 summarizes the results of the test. On the basis of skewness alone, we see in Table 7.6 that the majority of the industries have right-skewed growth rate distributions with the skewness being more pronounced in the chemicals and rubber and plastics industries. It is also clear from the table that a number of industries have left-skewed growth rate distributions with the wood industry being the most left-skewed industry in the sector. According to the kurtosis test, all the growth rate distributions are significantly leptokurtic with the central peak being higher and sharper and the tails being longer and fatter compared to the normal distribution. This indicates that all distributions are significantly asymmetric which corroborates our graphical analysis. Such considerably peaked distributions as compared to the Gaussian shape in all the sectors suggest that the Ethiopian manufacturing sector can be approximated by the Laplace distribution with fat tails. This finding is consistent with many other previous studies including Stanley et al., (1996) and Bottazzi et al., (2002). for Italian manufacturing, Bottazzi & Secchi (2003) for

Table 7.5: Kolmogorov-Smirnov Normality Tests of Growth Rate Distribution

Industrial group	*D*-Statistics	*p*-value
Food and beverages	0.1191	0.000
Textiles	0.1816	0.000
Wearing apparel	0.1474	0.000
Tanning, leather and footwear	0.1202	0.000
Wood	0.1607	0.001
Paper and printing	0.1231	0.000
Chemicals	0.1436	0.000
Rubber and plastics	0.1650	0.000
Non-metals	0.1132	0.000
Basic iron and steel	0.1767	0.005
Fabricated metals	0.1537	0.000
Machinery and equipment	0.1480	0.009
Motor vehicles	0.1620	0.053
Furniture	0.1350	0.000
All firms	1.0000	0.000

Table 7.6: Skewness and Kurtosis Tests of Growth Rate Distribution

Industrial group	Skewness	Kurtosis	Overall (*p*-value)
Food and beverages	0.111	9.216	0.0000
Textiles	0.499	15.919	0.0000
Wearing apparel	-0.222	7.829	0.0000
Tanning, leather and footwear	0.544	10.458	0.0000
Wood	-2.973	27.962	0.0000
Paper and printing	0.111	9.012	0.0000
Chemicals	1.213	11.053	0.0000
Rubber and plastics	1.318	13.199	0.0000
Non-metals	-0.385	8.449	0.0000
Basic iron and steel	0.253	12.115	0.0000
Fabricated metals	-0.047	10.081	0.0000
Machinery and equipment	0.335	10.024	0.0000
Motor vehicles	-0.085	6.659	0.0000
Furniture	-0.184	9.127	0.0000
All firms	0.088	10.722	0.0000

the U.S. manufacturing, Bottazzi and Secchi (2005) for the worldwide pharmaceutical industry, Reichstein and Jensen (2005) for Danish manufacturing, Reichstein et al. (2010) for Danish manufacturing, service, and construction sectors, and Coad & Holzl (2009) for Australian service industries.

The *p*-value in Table 7.6 shows the normality test of firm growth rate distribution based on both skewness and kurtosis. Based on the *p*-values in the table, it is clear that firm growth rate distribution is significantly far from normality at the 1 percent level of significance, which lends support to the graphical analysis and Kolmogorov-Smirnov normality test shown in Table 7.5**.** This result holds true at the aggregate level (for all firms) and with sectoral disaggregation.

Summing up our analysis so far, we draw two major conclusions. First, visual inspection and a formal test of the proposition of log-normality of size distribution as measured by employment suggest that Girat's law, which assumes log-normal firm size distribution, is far from reality in the Ethiopian manufacturing sector; this corroborates findings by Bigsten and Gebreeyesus (2007). Using the same data source as in this study, the authors found that firm size distribution was far from normal in Ethiopian manufacturing. Our finding implicitly rejects the hypothesis that the process of firm growth rates is independent of size. However, this finding needs to be verified by a direct test of the relationship between firm growth rate and size, which will be established in the subsequent sections. The results are robust over time (year-wise) and at the sectoral level. Second, our analysis regarding firm growth rate distribution also suggests significant deviation of firm growth rate from Gaussian (normal) distributions, which indicates that the supposition of Gibrat's law that firm growth rates are purely random draws from independent and identical distributions is questionable. Consistent with many previous studies **(**Bottazzi et al., 2002; Bottazzi & Secchi, 2003, 2005; Ciriaci et al., 2012; Reichstein and Jensen, 2005; Stanley et al., 1996;)**,** we find that the shape of the growth rate distribution in Ethiopian manufacturing resembles the Laplace distribution with fat tails. Viewed by sectoral disaggregation and over time, our analysis also confirms that firm growth distributions have shown no sign of convergence to normality.

7.4.3. Quantile regression analysis

In this section, we present and analyze the results from the quantile regression for the 10%, 25%, 50%, 75% and 90% quantiles for the aggregate manufacturing over the whole period (2000 to 2009). We allow two lags in autocorrelation in the regression. The results of the quantile regression are reported in Table 7.7. We can interpret the coefficients as the partial derivative of the conditional quantile of the dependent variable with respect to individual regressors.

Beginning with the coefficient of size (β_1), we can observe in Table 7.7 that the coefficient of firm size is always negative and significant across all the quantile regressions. This shows that we reject hypothesis 1 firm growth rate is independent of its size. Since firms at or around the median of growth rate do not grow (Coad & Holzl, 2008; see Table 7.4), we focus our attention on the effect of size on growth rates at the two extreme quantiles (10% and 90%) of the growth rate distribution. At the 10% quantile where declining firms are located, the negative coefficient of firm size signifies that among the declining firms, larger firms tend to decline significantly faster than smaller firms. Similarly, the coefficient of size at the upper quantile (90%) testifies that among the fast growing firms, larger firms also decline significantly faster than small firms. Although the impact of size on growth is negative across the quantiles, this impact is more pronounced for firms in the upper quantile than in the lower one. This implies that for the small firms, among the rapidly growing firms, size has contributed very much to their better growth performance.

The results imply that small firms grow faster than larger firms in Ethiopian manufacturing. This means that growth is systematically determined by firm size, a finding that contravenes Gibrat's law of proportionate effect. This finding is consistent with previous studies such as Ciriaci et al. (2012) for Spanish firms and Bigsten & Gebreeyesus (2007) for Ethiopian manufacturing.

Table 7.7: TabQuantile regression estimation of equation (7.4) for 10%, 25%, 50%, 75% and 90% quantiles (total manufacturing)a, 2000-2009[a]

Parameters	10%	25%	50%	75%	90%
β_1	-0.0433***	-0.0149***	-0.00378**	-0.0265***	-0.0619***
	(0.0103)	(0.00519)	(0.00190)	(0.00605)	(0.0104)
β_2	-0.363***	-0.278***	-0.165***	-0.221***	-0.265***
	(0.0337)	(0.0170)	(0.00622)	(0.0198)	(0.0341)
β_3	-0.145***	-0.0829***	-0.0185***	-0.0708***	-0.115***
	(0.0340)	(0.0171)	(0.00627)	(0.0200)	(0.0344)
β_0	-0.166***	-0.0698***	0.0128	0.273***	0.679***
	(0.0443)	(0.0223)	(0.00818)	(0.0260)	(0.0448)
Observations	3,815	3,815	3,815	3,815	3,815

Note. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
[a]In Sub-section 7.5.3 (robustness check by sectoral disaggregation), we find the second lag of growth is not statistically significant in almost all sectors. However, for consistency, we decided to use a model with two lags of the growth process across our analyses. In the literature, we also find that most studies have dealt with one or two lags.

With regard to autocorrelation, we see that the values of the estimated coefficients vary across the conditional growth rate distribution. To begin with the median regression, we see in Table 7.7 that there is a smaller (as compared to the rest of the quantiles) negative autocorrelation in employment growth in both the first-order (β_2) and second-order (β_3) autocorrelation coefficients. The median distribution being one part of the story, the autocorrelation coefficient estimates substantially differ across the growth rate distribution. We are more interested in the two extreme values, however. While the negative autocorrelation in employment growth for the declining firms testifies that these firms were possibly experiencing above-average growth in the previous period, for the growing firms it reflects the likelihood that the employment growth of these firms in the previous period was somewhat below average. This means that any fast growth or decline of employment growth in any one year is unlikely to be repeated in the following year. In a nutshell, this result indicates that even though there are some firms in the Ethiopian manufacturing sector that enjoy significant employment growth events in any one period, it is unlikely this growth event to be repeated the following period. Note that the magnitude of the coefficient for the first-order autocorrelation is always greater than that of the second-order, which implies that the strength of the effect of past employment growth on current employment growth fades as we go back in time.

Our findings are comparable to those of Coad (2007), who studied the autocorrelation of the firm growth process for French manufacturing. Similar to our results, the author found a persistent negative autocorrelation over the entire growth rate distribution. We can also observe similar yet not identical results in Coad & Holzl (2009), whose findings differ slightly from those of the present study in that while they find significant autocorrelation estimates for the 25%, 75% and 90% quantiles considering the first lag, the estimates for the 75% and 90% quantiles are found to be significant in the case of the second lag. Similar tour findings, the magnitude of the coefficients in their findings also fades as we move from the first lag to the second lag.

7.5. Robustness checking

A common practice in empirical studies is undertaking a series of "robustness checks" to ensure the consistency and unbiasedness of our results. In this chapter, we perform several robustness checking mechanisms to make sure that our results are not due to some data aggregation over heterogeneous industries. In particular, in the spirit of Coad

(2007), we undertake robustness checks of our previous regression of size group, time, and sectoral disaggregation.

7.5.1. Robustness by size disaggregation

The regression in Section 7.4.3 is based on data aggregated over the entire manufacturing sector which includes firms of different sizes. An important question is if the preceding results will be robust across different firm size groups when our data are disaggregated into four size categories. Our definition of size category is based on the average firm size of two consecutive years rather than using $Size_{i,t-1}$ to categorize firms into their respective sizes. Coad & Holzl (2009) maintained that doing so is advantageous in that it avoids the potential bias that could favor the smaller size category when using $Size_{i,t-1}$and the larger size category when using $Size_{i,t}$. In fact, we have experimented with our regression using size category based on the latter and the results are quite similar to that of the size category based on average firm size.

To be consistent with previous studies, we define firm size categories as follows: size category 1 (10 ≤ employees < 20), size category 2 (20 ≤ employees < 50), size category 3 (50 ≤ employees < 100), and size category 4 (employees ≥ 100). We then run quantile regression for each size category. Results are exhibited in Table 7.8.

Furthermore, such an exercise allows us to check, to some extent, if there exists some bias due to the cutoff point of 10 employees (excluding micro and small firms) in our data. Due to such exclusion of micro and small firms in the data, there are concerns in the literature that results may be biased if the model is sensitive to changes in the coverage of the data (Bigsten & Gebreeyesus, 2007). In classifying firms according to the average size, it also means that we are increasing our cutoff point from 10 to 20, 50 and 100 employees. Thus, if results remain unchanged, we may conclude that our model is not sensitive to data coverage.

As shown in Table 7.8, regardless of the size category, the sign and significance of the coefficient of size (β_1) appears to be reasonably consistent across the growth rate distributions. The negative and statistically significant coefficient of the size variable in the smallest size group (size category 1) signifies that, within the small firms group, large firm size is associated with a decrease in annual employment growth rates without any change across all the quantiles. This result also holds true in the larger firms (size category 4) except for the fact that in the latter group the size coefficient becomes insignificant but remains negative. Similar conclusions can also be drawn from the other size categories (size categories 2 and 3). Generally, this result is consistent with the previous one (see Table 7.7), in which there is a negative association between size and employment growth rate in Ethiopian manufacturing.

Our findings are similar to those of Coad & Holzl (2009). Despite the fact that the authors' dataset contains a large number of micro and small firms (1 to 10 employees), our firm size classification beyond the 10-employees cutoff point is the same as theirs. Using similar methodology (quantile regression) as in our study, the authors observed that growth rate declines with size. In extensive literature surveyed by Coad (2009) firm growth rate was found to be negatively correlated with its size.

Table 7.8: Quantile Regression Estimation of Equation 7.4 for the Four Size Categories, 2000-2009

Parameter	10%	25%	50%	75%	90%
Size category 1: 10 ≤ average employees < 20: Observations = 807					
β_1	-0.697***	-0.469***	-0.336***	-0.542***	-0.791***
	(0.0582)	(0.0544)	(0.0352)	(0.0527)	(0.0651)
β_2	-0.0995**	-0.123***	-0.142***	-0.134***	-0.196***
	(0.0455)	(0.0425)	(0.0275)	(0.0411)	(0.0509)
β_3	-0.0675*	-0.0619*	-0.0449*	-0.0445	-0.121***
	(0.0401)	(0.0375)	(0.0242)	(0.0363)	(0.0448)
β_0	1.587***	1.099***	0.873***	1.547***	2.347***
	(0.156)	(0.146)	(0.0945)	(0.141)	(0.175)
Size category 2: 20≤ average employees<50: Observations = 1,057					
β_1	-0.854***	-0.472***	-0.448***	-0.609***	-0.841***
	(0.0882)	(0.0364)	(0.0285)	(0.0369)	(0.0614)
β_2	-0.219***	-0.248***	-0.205***	-0.187***	-0.127**
	(0.0776)	(0.0320)	(0.0251)	(0.0324)	(0.0540)
β_3	0.0648	-0.0512	-0.0670***	-0.0589*	-0.0410
	(0.0760)	(0.0314)	(0.0246)	(0.0318)	(0.0529)
β_0	2.536***	1.499***	1.565***	2.316***	3.289***
	(0.302)	(0.125)	(0.0979)	(0.126)	(0.211)
Size category 3: 50 ≤ average employees<100: Observations = 705					
β_1	-1.316***	-0.962***	-0.866***	-0.895***	-1.103***
	(0.0716)	(0.0412)	(0.0404)	(0.0497)	(0.0713)
β_2	-0.144***	-0.169***	-0.165***	-0.145***	-0.0989*
	(0.0519)	(0.0299)	(0.0293)	(0.0360)	(0.0517)
β_3	0.0387	0.0336	-0.0234	-0.0512	-0.0360
	(0.0522)	(0.0300)	(0.0294)	(0.0362)	(0.0520)
β_0	5.192***	3.855***	3.646***	3.949***	5.018***
	(0.299)	(0.172)	(0.169)	(0.208)	(0.298)
Size category 4: average employees ≥ 100: Observations = 1,246					
β_1	-0.0301	-0.0330**	-0.0385***	-0.112***	-0.199***
	(0.0332)	(0.0135)	(0.00796)	(0.0173)	(0.0340)
β_2	-0.563***	-0.404***	-0.212***	-0.194***	-0.262***
	(0.0667)	(0.0271)	(0.0160)	(0.0348)	(0.0684)
β_3	-0.282***	-0.130***	-0.0109	-0.0739**	-0.123*
	(0.0700)	(0.0285)	(0.0168)	(0.0365)	(0.0717)
β_0	-0.147	0.0780	0.231***	0.818***	1.564***
	(0.189)	(0.0771)	(0.0455)	(0.0989)	(0.194)

Note. Robust standard errors in parentheses, *** significant at 1 percent significance level, ** significant at 5 percent significance level, * significant at 10 percent significance level

Moving on to autocorrelation, we observe in Table 7.8 that the first-order autocorrelation coefficient (β_2) remains negative and significant in all regressions and size categories. For the smaller firms (size category 1), this shows that both declining and growing firms experienced significant and negative first- and second-order autocorrelation growth rates. We can also see similar results for the larger firms. The results for the other size categories are also quite similar except for the fact that we see some positive non-significant second-order autocorrelation for the declining firms in the size categories 2 and 3.

From a different perspective, firm growth may bring about organizational and structural changes. However, these changes differ according to the size of the firms. While small firms are more flexible and are able to quickly adjust to the environment, large firms are less flexible to do so. These changes can partly be explained by looking into the pattern of growth rate autocorrelation for different size groups (Coad & Holzl, 2009). In light of this idea, looking at the autocorrelation coefficients, our result suggests that the pattern of change in the small and large firms is similar. This contrasts with the finding in Coad and Holzl (2009) in which they find a different structure of growth rate autocorrelation between micro and small firms and large firms. In fact, since the cutoff point is 10 employees, our dataset does not contain micro and small firms (1 to 10 employees) as in the case of Coad & Holzl (2009), thus making it difficult to directly compare with their study. However, even disregarding the micro and small firms in their study and using the 10-employee cutoff point in both studies, we still find a difference in the autocorrelation structure between small and large firms in Coad & Holzl (2009).

This implies that disruptions to growth are not only a characteristic of small firms but also of large firms in Ethiopian manufacturing. While suggesting further study that includes micro and small firms would better illuminate the issue, we are also inclined to conclude that the current results may not be ruled out on the ground that the sector is currently in an early stage and thus facing such problems as unskilled labor, poor management, frequent government policy changes, lack of experience, and competitive pressure. After all, given the results in Table 7.8 that larger firms experience negative autocorrelation, the inclusion of micro and small firms may not alter the result. The reason is our expectation that while micro and small firms experience erratic growth rates, large firms exhibit relatively stable growth rates. Due to the fact that our results are reasonably consistent across size groups, if the model is sensitive to changes in the coverage, the bias concern which arose because of the exclusion of the micro and small firms in the data can also be addressed. In conclusion, our result in Table 7.7 is robust to heterogeneity in firm size.

7.5.2. Robustness by temporal disaggregation

In the preceding discussions, the data were pooled over the entire period under consideration (2000 to 2009). Coad (2007) noted that pooling the data over the entire period may be an appropriate approach if the autocorrelation structure varies from year to year. Hence, this section provides a robustness check of the previous result by splitting the data into two time categories. In so doing, we can observe if the pattern of autocorrelation changed over the period for Ethiopian manufacturing. We split the growth rates into two categories. The first category contains the time period 2000 to 2006 and the second category is 2007 to 2009.[30] We then apply the same quantile regression techniques to the two time period categories. Table 7.9 summarizes the results of the regression. The results are generally comparable to that of the entire period. No significant differences can be observed in the coefficients in terms of sign and significance. Some difference appear in the coefficients of size of the two time period, but the changes are neither significant nor have different signs.

Table 7.9: Quantile Regression Estimation of Equation 7.4 by Year Categories

Parameter	10%	25%	50%	75%	90%
Time period: 2000-2006: Observations = 1,918					
β_1	-0.0212	-0.00521	-0.00631*	-0.0457***	-0.0951***
	(0.0134)	(0.00693)	(0.00331)	(0.00867)	(0.0128)
β_2	-0.366***	-0.255***	-0.130***	-0.181***	-0.229***
	(0.0462)	(0.0239)	(0.0114)	(0.0299)	(0.0440)
β_3	-0.122***	-0.0647***	-0.0194*	-0.0644**	-0.102**
	(0.0466)	(0.0241)	(0.0115)	(0.0301)	(0.0444)
β_0	-0.224***	-0.0965***	0.0277*	0.359***	0.825***
	(0.0589)	(0.0304)	(0.0145)	(0.0381)	(0.0560)
Time period: 2007-2009: Observations = 1,897					
β_1	-0.0623***	-0.0230***	-0.00380	-0.00293	-0.00890
	(0.0145)	(0.00737)	(0.00281)	(0.00931)	(0.0178)
β_2	-0.345***	-0.308***	-0.229***	-0.263***	-0.343***
	(0.0451)	(0.0229)	(0.00871)	(0.0289)	(0.0553)
β_3	-0.155***	-0.104***	-0.0372***	-0.113***	-0.164***
	(0.0455)	(0.0231)	(0.00878)	(0.0291)	(0.0558)
β_0	-0.117*	-0.0503	0.0108	0.170***	0.467***
	(0.0612)	(0.0310)	(0.0118)	(0.0392)	(0.0751)

Note. Robust standard errors in parentheses, *** significant at 1 percent significance level, ** significant at 5 percent significance level, * significant at 10 percent significance level

[30] Our rationale for the time break in 2007 is that in this year, inflation started to prevail in the Ethiopian economy. Thus, while the time period 2000 to 2006 saw modest levels of inflation, the latter time period was characterized by high inflation. This might have brought some changes into the manufacturing sector.

7.5.3. Robustness by sectoral disaggregation

In Sub-section 7.4.3, analysis was done by pooling data from all firms operating in different industrial sectors. However, doing so may lead to ambiguous inferences. Bottazzi & Secchi (2003) argued that considering a large collection of heterogeneous firms may introduce statistical regularities that are only the result of the aggregation procedure, and, at the same time, can hide the specific characteristics of the dynamics of firms operating in different sectors. Hence, in checking the robustness of the aggregated data to sectoral disaggregation, in this section we perform the same quantile regressions at 2-digit industries. Results are reported in Table 7.10.

Overall, the evidence in Table 7.10 reveals that the results at the sectoral level are in agreement with the results at the aggregate level. There are slight differences that need to be explained, however. In terms of growth rate and size relationship, we find that majority of the industries have seen a negative relationship between growth and size across the entire conditional growth rate distribution, which lends support to the results for the aggregated data. In five of the industries, however, we see the sign of the size coefficient varying across the conditional distribution. For instance, in the textile, fabricated metals, basic iron and steel, and tanning, leather and footwear industries, we observe that for the declining firms (lower quantile), size seems to positively correlate with growth, which implies that larger firms experience higher growth rate. On the contrary, for the growing firms (upper quantile), size does not seem to positively correlate with growth rate.

Table 7.10: Quantile Regression Estimation of Equation (7.4) by Sectoral Disaggregation for 10%, 25%, 50%, 75% and 90% Quantiles, 2000-2009

Parameters	10%	25%	50%	75%t	90%
Food and beverages: Observations = 1,112					
β_1	-0.112***	-0.0226**	-0.00168	-0.00382	-0.0460**
	(0.0250)	(0.00998)	(0.00476)	(0.0121)	(0.0224)
β_2	-0.373***	-0.305***	-0.242***	-0.309***	-0.315***
	(0.0785)	(0.0313)	(0.0149)	(0.0380)	(0.0704)
β_3	-0.146*	-0.0912***	-0.0666***	-0.153***	-0.225***
	(0.0824)	(0.0329)	(0.0157)	(0.0399)	(0.0739)
Textile: Observations = 176					
β_1	0.0279	0.0102	-0.00380	-0.0109	-0.0538
	(0.0399)	(0.0174)	(0.00562)	(0.0203)	(0.0392)
β_2	-0.301	-0.229***	-0.110***	-0.205**	-0.303
	(0.196)	(0.0857)	(0.0277)	(0.100)	(0.193)
β_3	-0.0458	0.00602	0.0216	0.0558	-0.140
	(0.159)	(0.0692)	(0.0224)	(0.0808)	(0.156)
Wearing and apparel: Observations = 131					
β_1	-0.0269	0.000972	-0.000536	-0.0300	-0.111
	(0.0680)	(0.0304)	(0.0169)	(0.0335)	(0.0978)
β_2	-0.105	-0.169*	-0.00789	0.0327	0.275
	(0.226)	(0.101)	(0.0562)	(0.111)	(0.325)
β_3	-0.258	-0.0530	0.00250	0.193	0.240
	(0.260)	(0.116)	(0.0646)	(0.128)	(0.373)
Tanning, leather and footwear; Observations =277					
β_1	0.00979	0.0108	-0.00957	-0.0447*	-0.0946*
	(0.0368)	(0.0221)	(0.0128)	(0.0261)	(0.0541)
β_2	-0.239**	-0.202***	-0.225***	-0.193**	-0.467***
	(0.113)	(0.0681)	(0.0395)	(0.0805)	(0.167)
β_3	-0.0530	-0.0703	-0.0451	-0.0645	-0.137
	(0.118)	(0.0709)	(0.0411)	(0.0838)	(0.173)
Wood: Observations = 83					
β_1	-0.0906**	-0.0719**	-0.0236	-0.00173	0.0113
	(0.0453)	(0.0290)	(0.0193)	(0.0425)	(0.0856)
β_2	-0.149	-0.207*	-0.176**	-0.0631	-0.190
	(0.162)	(0.104)	(0.0693)	(0.152)	(0.307)
β_3	-0.153	0.00851	0.00863	-0.0447	-0.201
	(0.151)	(0.0971)	(0.0646)	(0.142)	(0.286)
Paper and printing: Observations = 416					
β_1	-0.0224	-0.0203	-0.0131	-0.0586***	-0.100***
	(0.0335)	(0.0159)	(0.00935)	(0.0197)	(0.0347)
β_2	-0.344***	-0.191***	-0.127***	-0.203***	-0.214*
	(0.106)	(0.0501)	(0.0295)	(0.0620)	(0.109)
β_3	-0.172	0.0404	0.00837	-0.0558	-0.135
	(0.108)	(0.0511)	(0.0301)	(0.0633)	(0.111)
Chemicals: Observations = 260					
β_1	-0.0170	-0.0282	-0.00510	-0.00259	-0.0716
	(0.0554)	(0.0204)	(0.0114)	(0.0342)	(0.0503)
β_2	-0.406***	-0.392***	-0.183***	-0.152	-0.186
	(0.150)	(0.0552)	(0.0308)	(0.0927)	(0.136)
β_3	-0.227	-0.130**	-0.0505	-0.0854	-0.217
	(0.162)	(0.0596)	(0.0333)	(0.100)	(0.147)
Rubber and plastics; Observations = 231					
β_1	-0.00330	-0.0118	-0.00991	-0.0474*	-0.0810
	(0.0726)	(0.0263)	(0.0101)	(0.0245)	(0.0844)

β_2	-0.270	-0.0522	-0.0816***	-0.0904	-0.187
	(0.203)	(0.0736)	(0.0284)	(0.0684)	(0.236)
β_3	-0.154	-0.0631	-0.0499*	-0.0215	0.00867
	(0.207)	(0.0751)	(0.0290)	(0.0698)	(0.241)
Non-metals: observations = 375					
β_1	-0.0375	-0.0319*	-0.0116	-0.0346	-0.0855*
	(0.0420)	(0.0175)	(0.00957)	(0.0266)	(0.0499)
β_2	-0.451***	-0.262***	-0.217***	-0.323***	-0.278*
	(0.125)	(0.0521)	(0.0284)	(0.0790)	(0.148)
β_3	-0.294**	-0.112**	-0.0847***	-0.177**	-0.151
	(0.125)	(0.0521)	(0.0284)	(0.0790)	(0.148)
Basic iron and steel: Observations = 62					
β_1	0.0580	0.00376	-0.0629	-0.179**	-0.257
	(0.0602)	(0.0679)	(0.0665)	(0.0886)	(0.230)
β_2	-0.538***	-0.330**	-0.0581	0.0161	0.440
	(0.117)	(0.132)	(0.129)	(0.172)	(0.446)
β_3	-0.127	0.000840	0.0699	0.0229	0.197
	(0.0899)	(0.101)	(0.0993)	(0.132)	(0.343)
Fabricated metals: Observations = 158					
β_1	0.0423	-0.00810	0.00280	-0.0391	-0.0778
	(0.0887)	(0.0262)	(0.0189)	(0.0330)	(0.0889)
β_2	-0.353	-0.243***	-0.0919*	-0.206**	-0.356
	(0.238)	(0.0703)	(0.0507)	(0.0885)	(0.238)
β_3	-0.0604	-0.124*	0.0130	0.0210	-0.0841
	(0.232)	(0.0686)	(0.0496)	(0.0865)	(0.233)
Machinery and equipment: 76					
β_1	-0.0607	0.0151	0.0216	-0.0533	-0.0659
	(0.185)	(0.0430)	(0.0311)	(0.0529)	(0.106)
β_2	-0.637	-0.508***	-0.454***	-0.382***	-0.425
	(0.504)	(0.117)	(0.0848)	(0.144)	(0.288)
β_3	-0.0269	-0.188	-0.0134	0.0499	-0.253
	(0.575)	(0.134)	(0.0968)	(0.164)	(0.329)
Motor vehicles: Observation = 43					
β_1	-0.00369	-0.00207	-0.0318	-0.0792	-0.0744
	(0.148)	(0.0535)	(0.0549)	(0.0772)	(0.0446)
β_2	0.140	-0.226	-0.297*	-0.522**	-0.511***
	(0.476)	(0.172)	(0.176)	(0.248)	(0.143)
β_3	0.185	-0.00910	-0.00220	-0.350	-0.117
	(0.414)	(0.149)	(0.153)	(0.215)	(0.124)
Furniture: Observations = 410					
β_1	-0.0508	-0.0172	0	-0.0148	-0.0629
	(0.0352)	(0.0201)	(0.0101)	(0.0278)	(0.0541)
β_2	-0.590***	-0.355***	-0.225***	-0.211***	-0.184
	(0.0930)	(0.0532)	(0.0266)	(0.0733)	(0.143)
β_3	-0.173**	-0.125***	0	-0.0316	-0.113
	(0.0843)	(0.0482)	(0.0241)	(0.0664)	(0.129)

Note. Robust standard errors in parentheses, *** significant at 1 percent significance level, ** significant at 5 percent significance level, * significant at 10 percent significance level.

If we move to autocorrelation, the coefficients for the first-order autocorrelation remain negative and significant in most industries and across the distributions, which therefore favors analysis at the aggregate level. However, we observe changes in the signs of the coefficients in wearing apparel, basic iron and steel, and motor vehicle industries. Generally, our analysis in this sub-section indicates that some characteristics of the firms which have been concealed in the aggregated data are now uncovered, which suggests that sectoral disaggregation of the data reveals true characteristics of the dynamics of firm growth. However, since in most of the cases the coefficients are insignificant, it is difficult to draw strong conclusion.

7.6. Conclusions and policy implications

Using the entire population of Ethiopian manufacturing firms that employ 10 or more persons over the period of 2000 to 2009, this study explored various aspects of firm dynamics. We began by analyzing the distributional properties of firm size and firm growth rate using graphical and simple statistical tests at both the aggregate and 2-digit industry levels. We then examined the relationship between firm growth and firm size and further investigated the autocorrelation structure of the annual growth rate in employment using quantile regression techniques.

Overall, our findings on firm size and firm growth rate distribution seem to contradict Gibrat's law. Visual inspection and a formal test of firm size distribution suggest that the proposition of log-normality of size distribution as measured by log-employment is highly right-skewed. This finding contrasts with Girat's law of log-normal firm size distribution. Our finding is in line with that of Bigsten and Gebreeyesus (2007), who documented evidence on firm size distribution in Ethiopian manufacturing. Our finding is also consistent with several other recent findings (e.g., Angelini & Generale, 2008; Bottazzi et al., 2011; Cabral & Mata, 2003; Coad, 2007; Coad, 2009; Ribeiro, 2007). The results are robust to year-wise analysis. However, disaggregating the data at the 2-digit industry level shows that there is some heterogeneity in firm size distribution in Ethiopian manufacturing. Our analysis regarding growth rate distribution suggests that firm growth rate is highly leptokurtic, which implies significant deviations from a Gaussian distribution. Thus, the foundation of Gibrat's law that firm growth rates are purely random draws from independent and identical distributions is questionable. Consistent with many previous studies (e.g., Bottazzi et al., 2002; Bottazzi & Secchi, 2003, 2005; Ciriaci et al., 2012; Reichstein & Jensen, 2005; Stanley et al., 1996), we find that the shape of the growth rate distribution in Ethiopian manufacturing resembles the Laplace distribution with fat tails. Viewed by sectoral disaggregation and over time, our analysis also confirms that firm growth distributions have shown no sign of convergence to normality.

The above results have important implications for the use of appropriate regression models. With the firm growth rate exhibiting a fat-tailed Laplace distribution, the standard econometric models which focus on the average relationship between the dependent variable and the regressors are not useful (Coad & Holzl, 2009). For this reason, in our analysis of size-dependence and autocorrelation of growth rates, we applied quantile regression, which allows for the effect of the explanatory variables to vary over the conditional growth rate distribution. Regarding the relationship between firm growth rate and its size, our aggregate results reveal that size is always negatively and significantly associated with firm growth across all quantile regressions. Although the impact of size on growth is negative across the quantiles, this impact is more pronounced for firms in the upper quantile than in the lower one. This implies that for the small firms, among the rapidly growing firms, size has contributed significantly to their growth performance. The implication of this result is that small firms grow faster than larger firms in Ethiopian manufacturing, which means that growth is systematically determined by firm size. Our findings are comparable with the findings of such previous studies as Bigsten and Gebreeyesus (2007) for Ethiopian manufacturing and Ciriaci et al. (2012) for Spanish firms. As far as autocorrelation is concerned, our results suggest that there is a significant negative autocorrelation of firm growth rate across the entire growth rate distribution. However, autocorrelation coefficient estimates substantially differ across the quantiles with stronger effects being pronounced in declining and growing firms. While the negative autocorrelation in employment growth for the declining firms testifies that these firms were probably experiencing above average growth in the previous period, for the growing firms, it reflects that employment growth of these firms in the previous period was relatively below average. This means that any fast growth or decline of employment growth in any one year is unlikely to be repeated the following year.

We further disaggregated our data by size, time period, and sector and conducted the same quantile regression. We confirmed that, with the exception of a few industries, the results from both the aggregate data and the disaggregated data hold true. This implies that the fact that firms come from diversified sectors and are of heterogeneous size does not affect the main results. Data disaggregation into two sub-periods also confirmed results are stable over time.

Generally speaking, our results suggest that Gibtar's law is not valid for the case of Ethiopian manufacturing because (a) firm growth rate is highly leptokurtic with a fat-tailed Laplace distribution, (b) small firms grow faster than large firms, and (c) there is a high correlation of growth rates in consecutive years.

Some important policy implications can be drawn on the basis of our analysis. The analysis demonstrates that firm growth declines with size. This suggests that small firms grow faster than larger firms in terms of employment. Hence, national and regional policies that promote small firms are likely to create significant job opportunities, which may play an important role in reducing the current serious problem of unemployment in the country. In addition, the promotion of small firms can also be justified from an income distribution point of view since these firms are important sources of employment generation. Such policies may include a size-based differential tax, encouragement of innovation activities, skill-oriented training, and credit facilities to entrepreneurs in the sector. Policy measures should include effective implementation strategies that include continuous monitoring.

The outcome of growth rate autocorrelation also carries important policy implications for policymakers who want to know the continuity of jobs created in the previous period to the next period and reward firms according to their performance. We have shown that small firms have a greater ability to create jobs than larger firms. Thus, the persistence of this ability should be investigated. In this regard, our findings indicate that high growth events are not persistent either in small and larger firms. This suggests that policies that target sustain employment growth need to address possible factors such as market failures that challenge firms to sustain the jobs they create.

This study also paves the way for future research in the dynamics of firm growth trajectories in Ethiopian manufacturing. It would be interesting to further investigate why employment growth registered in the previous year could not be repeated the following year. Furthermore, since firm growth is affected by other factors, future studies on firm growth should include additional firm-specific and industry-specific variables to better explain what determines the firm growth process. The scope of this study is limited to manufacturing establishments that employ 10 or more persons. Thus, this study can be extended to include data on micro and small enterprises (firms with fewer than 10 employees) to check the consistency of the findings.

Chapter 8

Conclusions and policy implications

8.1. Conclusions

The manufacturing sector is considered to be a special driver of economic transformation because it has the potential to impact the economy through various channels. The sector is characterized by high value addition and high productivity and hence it has the potential to create job opportunities for both skilled and unskilled workforce. However, the manufacturing sector in developing countries, particularly, in Sub-Saharan Africa, has not yet fulfilled that role. The sector is characterized by low efficiency and productivity as a result of many problems: malfunctioning markets, low managerial and technological capabilities, and unfavorable policy environments.

This dissertation has evaluated the performance of Ethiopian manufacturing firms as measured by technical efficiency and firm growth dynamics using establishment-level census unbalanced panel data over the period 2000 to 2009 annually collected by the CSA of Ethiopia. While we used two competing models (SFA and DEA) in the efficiency analysis, a quantile regression model was utilized in the firm growth analysis.

We began by first describing the features of the Ethiopian manufacturing in Chapter 2. We looked into the structure of the sector. We also identified the challenges the sector has been facing which might have contributed to the poor performance of the sector. We then reviewed relevant literature in efficiency and firm growth analyses and introduced the research gap and hence the need for the present study.

Having discussed the characteristics of the Ethiopian manufacturing in Chapter 2 and identified the research gap in Chapter 3, we reported on the empirical analyses in Chapters 4 to 7. Chapter 4 provides the estimates of the technical efficiency of firms in Ethiopian manufacturing using three different stochastic frontier models. While two of the models (conventional FE and RE models) do not account for firm-specific unobserved heterogeneity, the recently proposed TRE model has the ability to explicitly disentangle firm-specific unobserved heterogeneity from inefficiency. A significant difference in efficiency estimates has been found between the TRE model and the FE and RE models, which would imply considerable heterogeneity of manufacturing firms in Ethiopia. The conventional FE and RE models appear to underestimate the efficiency estimates since the firm-specific unobserved heterogeneity is confounded with the inefficiency term. Apart from the difference in efficiency estimates among the models, we also found widespread efficiency variations among firms estimated using one particular model. On average, technical efficiency for the whole manufacturing sector is estimated to be 74 percent. Perhaps the major problem common to all the manufacturing industries, which might have greatly contributed to efficiency variations among firms in an industry, is the inability of firms to work at full production capacity (they utilized only about 60 percent of their capacity) which was mainly caused by shortages of raw materials. Other problems also include erratic electric power supply, unfavourable government rules and regulations, and lack of demand for products.

The relationship between firm size, age, and technical efficiency is one of the widely studied subjects in the literature. In Chapter 4, we also looked into this area. In the case of the Ethiopian manufacturing sector, overall, these variables are found not to have a significant relationship with technical efficiency. However, the direction of their effect markedly differs from industry to industry. The coefficients of size and age are positive in some industries and negative in other industries. This suggests that policies that seek to address inefficiency problem in the sector should be industry specific. For instance, in industries where the coefficient for size is negative, industrial policy may be geared towards promoting small firms. Similarly, in industries where age is negatively correlated with efficiency, government policy should focus on encouraging young entrepreneurs to create businesses. Policies that focus on encouraging small and young firms would play an important role in creating job opportunities and addressing problems associated with income distribution.

In Chapter 5, we proposed a handicap-setting method for fair evaluation of industrial sectors and applied it to Ethiopian manufacturing industries. The manufacturing industry comprises many sectors which include many companies. Thus, there is a "two-layered" structure. The statistics of a sector are the sum its member companies. In order to evaluate the relative efficiency of industrial sectors, we need to take account of the performance of their member companies. For this purpose, we evaluated sectoral frontiers and projected member companies to their respective frontiers. We then merged the projected companies and found the meta-frontiers of all projected companies in the industry. If a member of a certain sector is on the meta-frontier, we classified this sector into the no-handicap group, whereas if all members of a sector are off the meta-frontier, we classified the sector into the with-handicap group. Then we applied the non-convex model proposed by Tone and Tsutsui (2013) for deciding handicaps of with-handicap sectors. Since we use an input-oriented model, we modify inputs using the handicaps and re-evaluate the sectoral efficiency. We found four sectors belonging to the *with-handicap* group: (a) Wearing apparel (handicap=0.768), (b) Tanning, leather and footwear (handicap=0.9923), (c) Paper and printing (handicap=0.9715), and (d) Machinery and equipment (handicap=0.5433). The most handicapped sector is the machinery and equipment. If this industry could be improved by innovation, it would become the top industry in the manufacturing sector, while the other three handicapped sectors remain inefficient even after taking account of handicaps.

In Chapter 6, we analysed technical efficiency at the industry level using three recently proposed resampling techniques in DEA. The results obtained from the three types of resampling techniques indicated that the wood and basic iron and steel industries consistently appear to be the best performing industries in the Ethiopian manufacturing sector. The consistency of the results indicates the robustness of the results. Another point is that the 95% confidence intervals, although differing from model to model, are generally wider. It is to be noted that the width of the confidence interval can be affected by the variability of the data under consideration which, indeed, could be observed in our data. We would like to note that since this chapter is conducted at the industry level and uses 2008 cross-sectional data to calculate efficiency, the results may not be compared with the results in Chapter 4. We have used several SFA and DEA models to estimate technical efficiency in the Ethiopian manufacturing. However, it may be difficult to recommend one benchmark model. Their usage depends on the nature of the data and the assumptions from which the models are constructed. For instance, the SFA models (FE, RE, and TRE) can be applied for panel data, while the DEA models (Handicap, resampling) can be applied for cross-sectional data. The resampling method is particularly useful when there is significant measurement error in the data which is a characteristic of data in developing countries. The TRE model will be useful when we have longer panel data since it disentangles the unobserved heterogeneity from inefficiency.

In Chapter 7, we investigated the dynamics of firm growth in Ethiopian manufacturing in the context of growth persistence. The benchmark to our analysis here is Gibrat's law of proportionate effect. Our results generally suggest that Gibrat's law is rejected in the Ethiopian manufacturing, because (a) firm size distribution is far from log-normal, (b) firm growth rate is highly leptokurtic with a fat-tailed Laplace distribution, (c) small firms grow faster than large firms, and (d) there is a high correlation of growth rates in consecutive years. Our results are robust to size, sectoral disaggregation, and temporal disaggregation of the data.

8.2. Policy implications

The findings we have presented here have some policy implications. We have shown that firms in the sector operate at about 60 percent of their production capacity, which might have caused inefficiency to prevail in the sector. The main problem reported by the firms as contributing to is shortages of raw materials supply. Other problems also include erratic electric power supply, government rules and regulations, and a lack of demand for products. Hence, any policy reforms should address the underlying factors contributing to the underutilization of each firm's production capacity. A case in point is the need to reform the input market in the manufacturing sector. The establishment of an efficient marketing mechanism that reduces the involvement of many parties in the supply chain and hence high transaction costs would help ameliorate the problem. In addition, efficiency variation may also be explained by such other factors as the use of obsolete technologies, poor product design, lack of management skill, lack of exposure to international markets, and thee production of non-competitive products. Indeed, these are the characteristics of Ethiopian manufacturing. Thus, to enhance their efficiency performance in the face of increasing globalization, firms need to adjust to the changing environment, for example, by acquiring necessary management skills, learning experience from best practices (either domestic or international), and adopting new technologies. In addition, the role of the government in providing advisory support regarding training, market information, and technology choice is also recommended.

Our results also indicate that firm growth rate decreases with increasing size, suggesting that small firms grow faster than larger firms in terms of employment. Hence, national and regional policies that promote small firms are likely to create significant job opportunities, which may play an important role in reducing the serious problem of unemployment in the country. Such policies may include size-based differential taxes, support of innovation activities, skill-oriented training, and credit facilities to entrepreneurs in the sector. Policy measures should include effective implementation strategies that include continuous monitoring. However, since our results of the relationship between firm size and technical efficiency shows small firms are less efficient than larger firms in some industries, this general policy recommendation may be naïve. Thus, it may be necessary for the government to further investigate factors that slow down the growth of large firms. Such factors may include regulatory obstacles (external factors) and management system (internal factor). This could be an interesting future research area.

The outcome of growth rate autocorrelation also carries important policy implication for policymakers who want to know the continuity of jobs created and reward firms according to their performance. We have shown that small firms have the ability to create more jobs than larger firms. Thus, the persistence of this ability should be investigated. In this regard, our findings indicate that high growth events are not persistent both in small and larger firms. This suggests that policies that target sustaining employment growth need to address possible factors that include market failure, which challenges firms to sustain the jobs they create.

Finally, we would like to suggest some future research directions. In the efficiency analysis, we noted that despite the ability of the TRE model to distinguish firm-specific unobserved heterogeneity from inefficiency, the inefficiency term can still capture any possible time-invariant structural inefficiency, which leads the TRE model to underestimate overall inefficiency and in turn overestimate technical efficiency. One direction for future research is, therefore, to somehow incorporate persistent inefficiency in the TRE model in order to examine the impact of possible time-invariant structural inefficiency. Future research should also look into the effect of observable heterogeneity of firms on efficiency estimates. This study also paves the way for future research on the dynamics of firm growth trajectories in the Ethiopian manufacturing sector. It would be interesting to further investigate why employment growth registered in the previous year could not be repeated the following year. Furthermore, since firm growth is affected by other factors, future studies on firm growth should include additional firm-specific and industry-specific variables to better explain what determines firm growth process. The scope of this study is limited to manufacturing establishments that employ 10 or more persons. Thus, this study can be extended to include data on micro and small enterprises (firms with fewer than 10 employees) to check the consistency of the findings. This is particularly important to characterize firm size and firm growth rate distributions in the sector.

References

Abegaz, M. (2013). Total factor productivity and technical efficiency in the Ethiopian manufacturing sector. EDRI Working Paper 10. Addis Ababa, Ethiopia: Ethiopian Development Research Institute.

African Development Bank. (2010, September 17). Ethiopia's economic growth performance:Current situation and challenges (Economic Brief). *1(5)*. The African Development Bank Group: Chief Economist Complex.

Aggrey , N., Eliab , L., & Josep, S. (2010). Firm size and technical efficiency in East African manufacturing firms. *Current Research Journal of Economic Theory, 2*(2), 69-75.

Aigner, D., Lovell , K. C., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, *6*(1), 21-37.

Al-Muharrami, S., & Matthews, K. (2009). Market power versus efficient-structure in Arab GCC banking. *Applied Financial Economics, 19,* 1487–1496.

Amornkitvikai, Y., & Harvie, C. (2010). Identifying and measuring factors of technical inefficiency: Evidence from unbalanced panel data of Thai listed manufacturing enterprises. *Korea and the World Economy, 9*, 1-32.

Angelini , P., & Generale, A. (2008). On the evolution of firm size distributions. *American Economic Review*, *98*(1), 426-438.

Banker, R. D., & Morey, R. C. (1986). Efficiency analysis for exogenously fixed inputs and outputs. *Operations Research*, 34(4), 513-521.

Basu, S., & Fernald, J. (1995). Are apparent productive spillovers a figment of specification error? *Journal of Monetary Economics, 36*(1), 165-188.

Barnum, D., Gleanson, J., Karlaftis, M., Schumock, G., Shields, K., Tandon, S., & Walton, S. M. (2012). Estimating DEA confidence intervals with statistical panel data analysis. *Journal of Applied Statistics*, *39*(4), 815-828.

Battese, G., & Coelli, T. J. (1992). Frontier production functions, technical efficiency and panel data with application to paddy fanners in india. *Journal of Productivity Analysis, 3*, 153-169.

Battese, G., & Coelli , T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics, 20*(2), 325-332.

Bekele, T., & Belay, K. (2007). Technical efficiency of the Ethiopian grain mill products manufacturing industry. *Journal of Rural Development, 29*(6), 45–65.

Belotti, F., Daidone, S., Ilardi, G., & Atella, V. (2012). Stochastic frontier analysis using Stata. *The Stata Journal,* (2), 1-39.

Berndt, E. R., & Wood, D. O. (1975). Technology, prices and the derived demand for energy. *Review of Economics and Statistics, 57*(3), 259-268.

Bigsten, A., & Gebreeyesus, M. (2007). The small, the young, and the productive: Determinants of manufacturing firm growth in Ethiopia. *Economic Development and Cultural Change, 55*(4), 813-840.

Bottazzi, G., Cefis , E., & Dosi, G. (2002). Corporate growth and industrial structures: some evidence from the Italian manufacturing industry. *Industrial and Corporate Change, 11*(4), 705-723.

Bottazzi, G., Coad, A., Jacoby, N., & Secchi, A. (2011). Corporate growth and industrial dynamics: evidence from French manufacturing. *Applied Economics, 43*(1), 103-116.

Bottazzi , G., & Secchi, A. (2006). Explaining the distribution of firm growth rates. *The RAND Journal of Economics, 37*(2), 235–256.

Bottazzi, G., & Secchi, A. (2003). Common properties and sectoral specificities in the dynamics of U.S. manufacturing companies. *Review of Industrial Organization, 2003*, 217–232.

Bottazzi, G., & Secchi, A. (2005). Growth and diversification patterns of the worldwide pharmaceutical industry. *Review of Industrial Organization, 26*(2), 195-216.

Buchinsky, M. (1998). Recent advances in quantile regression models: A practical guide for empirical research. *Journal of Human Resources, 33*(1), 88-126.

Cabral, L. M., & Mata, J. (2003). On the evolution of firm size distribution: Facts and theory. *American Economic Review, 93*, 1075-1090.

Caves, R. (1992). Determinants of technical efficiency in Australia. In R. Caves (Ed.), *Industrial efficiency in six nations* (pp. 241-272). Cambridge, MS: MIT Press.

Caves, R., & Barton, D. (1990). *Efficiency in US manufacturing industry.* Cambridge, MS: MIT Press.

Chang , T.-S., Tone , K., & Chen-Hui , W. (2013). Past-present-future intertemporal DEA models. *Journal of the Operational Research Society,* , 1-17. doi: 10.1057/jors.2013.139

Chesher, A. (1979). Testing the law of proportionate effect. *Journal of Industrial Economics, 27*(4), 403-411.

Chirwa, E. (2001). Privatization and Technical Efficiency: Evidence from the Manufacturing Sector in Malawi. *African Development Review, 2*(2), 276-307.

Ciriaci, D., Moncada-Paternò-Castello, P., & Voigt, P. (2012). Does size or age of innovative firms affect their growth persistence? Evidence from a panel of innovative Spanish firms. *IPTS working papers on corporate R&D and innovation - NO. 03/2012*, 29. Luxembourg: European Union.

Coad, A. (2007). A closer look at serial growth rate correlation. *Review of Industrial Organization, 31*(1), 69-82.

Coad, A. (2009). *The growth of firms: A survey of theories and empirical evidence.* Cheltenham and Northampton, UK: Edward Elgar Publishing.

Coad, A., & Hölzl, W. (2009). On the autocorrelation of growth rates evidence for micro, small and large firms from the Austrian service industries, 1975–2004. *Journal of Industry, Competition and Trade, 9*, 139–166.

Coad, A., & Rao, R. (2008). Innovation and firm growth in high-tech sectors: A quantile regression approach. *Research Policy*, *37*(4), 633–648.

Cobbold, T. (2003). *A comparison of gross output and Value-Added Methods of Productivity Estimation.* Canberra: Productivity Commission Research Memorandum.

Coelli, T., Rao, P., O'Donnell, C., & Battese, G. (2005). *An introduction to effieciency and productivity analysis* (2nd ed.). New York, US: Springer.

Cornwell , C., Schmdit, P., & Sickles, R. (1990). Production frontiers with cross-sectional and time-series variation in efficiency levels. *Journal of Econometrics, 46*, 185-200.

Demirela , P., & Mazzucato, M. (2010). The evolution of firm growth dynamics in the US pharmaceutical industry. *Regional Studies, 44*(8), 1053-1066.

Dinh, H., Palmade, V., Chandra, V., & Cossar, F. (2012). *Light manufacturing in Africa: Targeted policies to enhance private investment and create jobs.* Washington DC: World Bank.

Evans, D. (1987). The relationship between firm growth, size, and age: Estimates for 100 manufacturing industries. *Journal of Industrial Economics, 35*(4), 567-581.

Fixler, D.J., & Zieschang, K.D. (1993). An index number approach to measuring bank efficiency: An application to mergers. *Journal of Banking and Finance*, 17, 99437-99450.

Fried, H. O., Lovell, K. C., & Schmidt, S. S. (2008). Efficiency and productivity. In H. O. Fried, K. C. Lovell, & S. S. Schmidt (Eds.), *The measurement of productive efficiency and productivity growth* (pp. 3-91). New York: Oxford University Press.

Gebeyehu, W. (2003). *Magnitude and trend of technical efficie ncy in the Ethiopian leather manufacturing sub-sector*. Addis Ababa: Ethiopian Economic Policy Research Institute.

Gebreeyesus , M., & Iizuka, M. (2010). *Discovery of the flower industry in Ethiopia: experimentation and coordination.* Working paper No.2010-025. Maastricht: UNU-MERIT.

Gebreeyesus, M. (2013). *Industrial policy and development in Ethiopia:Evolution and present experimentation.* WIDER Working Paper No. 2013/125. UNU-WIDER.

Green , A., & Mayes, D. (1991). Technical inefficiency in manufacturing industries. *The Economic Journal, 101*(406), 523-538.

Greene, W. (2005a). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics, 126*, 269-303.

Greene, W. (2005b). Fixed and random effects models in stochastic frontier models. *Journal of Productivity Analysis, 23*, 7-32.

GRIPS Development Forum. (2011). *Intellectual partinership for Africa: Industrial policy dialogue between Japan and Ethiopia.* Tokyo: GRIPS Development Forum.

Hart, P., & Prais, S. (1956). The analysis of business concentration: A statistical approach. *Journal of the Royal Statistical Society, 119, Series A*, 150-191.

Hossain, M., & Karumaratne, N. (2004). Trade liberalisation and technical efficiency: Evidence from Bangladesh manufacturing industries. *Journal of Development Studies, 40*(3).

Hymer, S., & Pashigian, P. (1962). Firm size and rate of growth. *Journal of Polictical Economy*, *70*, 556-569.

Ijiri, Y., & Simon, H. (1967). A model of business firm growth. *Econometrica, 35*(2), 348-355.

Jondrow, J., Lovell, K. C., Materov, I., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, *19*(2), 233-238.

Jovanovic, B. (1982). Selection and evolution of industries. *Econometrica,50*(3), 1982.

Kalirajan, K., & Shand, R. (1999). Frontier production functions and technical efficiency measures. *Journal of Economc Surveys*, *13*(2), 150-172.

Kim, N. (2003). Identifying and estimating sources of technical inefficiency in Korean maufucturing industries. *Contemporary Economic Policy, 21*(1), 132-144.

Kinda, T., Plane, P., & Véganzonès-Varoudakis, M.-A. (2009). *Firms' productive performance and the investment climate in developing economies:An application to MENA manufacturing.* (World Bank Policy Research Working Paper 4869). Washington, DC: World Bank.

Koenker, R., & Bassett, G. (1978). Regression quantiles. *Econometrica, 46*(1), 33-50.

Kuma, A. (2002). Manufacturing sector and trade liberalization in Ethiopia. Unpublished Master thesis. Addis Ababa, Ethiopia.

Kumar, M. (1985). Growth, acquisition activity and firm xize: Evidence from the United Kingdom. *Journal of Industrial Economics*, *33*(3), 327-338.

Kumbhakar , S., Lien, G., & Hardaker, B. (2012). Technical efficiency in competing panel data models:a study of Norwegian grain farming. *Journal of Productivity Analysis, 41*(2), 321-337. doi: 10.1007/s11123-012-0303-1

Kumbhakar, S. (1990). Production frontiers, panel data and time-varying technical inefficiency. *Journal of Econometrics, 46*, 201-211.

Kumbhakar, S. C., & Lovell, K. C. (2000). *Stochastic frontier analysis.* Cambridge: Cambridge University Press.

Li, W. (2013, December 13). Shoemaker puts best foot forward. Retrieved June 6, 2014, from http://africa.chinadaily.com.cn/weekly/2013-12/13/content_17172875.htm

Lundvall, B.-A., & Battese, G. (2000). Firm size, age and efficiency: Evidence from Kenyan manufacturing firms. *Journal of Development Studies, 36*(3), 146-163.

Martin-Marcos , A., & Suarez-Galvez, C. (2000). Technical efficiency of Spanish manufacturing firms: a panel data approach. *Applied Economics, 32*(10), 1249-1258.

Meeusen, W., & van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review, 18*(2), 435-444.

Melly, P. (2014, March 25). Japan brings kaisen philosophy to Ethiopia. Retrieved June 4, 2014, from http://www.bbc.com/news/business-26542963.

MoFED (Ministry of Finance and Economic Development). (2011). *Annual report on macroeconomic developments.* Addis Ababa: MoFED.

MoFED (Ministry of Finance and Economic Development). (2014). *Growth and Transformation Plan Annual Progress Report for F.Y. 2012/13.* Addis Ababa: MoFED.

Ngui-Muchai , D. M., & Muniu, J. M. (2012). Firm efficiency differences and distribution in the Kenyan manufacturing sector. *African Deveopment Review, 24*(1), 52–66. doi: 10.1111/j.1467-8268.2011.00309.x

OECD. (2001). Measuring Productivity: Measurement of Aggregate and IndustryLevel Productivity Growth, OECD Manual. Paris.

Ohno, K. (2013). *Learning to industrialize: From given growth to policy-aided value creation.* London and New York: Routledge.

Olesen, O. B., & Petersen, N. C. (2009). Target and technical efficiency in DEA: Controlling for environmental characteristics. *Journal of Productivity Analysis, 32*, 27-40.

Oliveira , B., & Fortunato, A. (2005). *Firm growth and persistence of chance: Evidence from Portuguese microdata.* Working paper from Grupo de Estudos Monetários e Financeiros (GEMF), 10.

Page, J. (2012). Can Africa industrialize? *Journal of African Economies, 21*, 86-125. doi: 10.1093/jae/ejr045

Pitt, M., & Lee, L.-F. (1981). The measurement and sources of technical inefficiency in the Indonesian weaving industry. *Journal of Development Economics, 9*(1), 43-64. doi: 10.1016/0304-3878(81)90004-3

Reichstein, T., Dahl, M. S., Ebersberger, B., & Jensen, M. B. (2010). The devil dwells in the tails: A quantile regression approach to firm growth. *Journal of Evolutionary Economics, 20*(2), 219-231. doi: 10.1007/s00191-009-0152-x

Reichstein, T., & Jensen, M. B. (2005). Firm size and firm growth rate distributions: The case of Denmark. *Industrial and Corporate Change, 14*(6), 1145-1166. doi: 10.1093/icc/dth089

Ribeiro, E. P. (2007). The dynamics of firm size distribution. *Brazilian Review of Econometrics, 2*, 199–223.

Schmidt, P., & Sickles, R. (1984). Production frontiers and panel data. *Journal of Business Economics and Statistics, 2*(4), 367-374.

Sehgal, S., & Sharma, S. (2011). Total factor productivity of manufacturing sector in India:A regional analysis for the State of Haryana. *Economic Journal of Development Issues Vol. 13 & 14 No. 1-2 (2011) Combined Issue, 13&14*(1-2), 97-118.

Simar, L., & Wilson, P. (2000). Statistical inference in nonparametric frontier. *Journal of Productivity Analysis, 13*, 49–78.

Simon, H., & Bonini, C. (1958). The size distribution of business firms. *American Economic Review, 58*(4), 607-617.

Soderbom, M., & Teal, F. (2004). Size and efficiency in African manufacturing firms: Evidence from firm-level panel data. *Journal of Development Economics, 73*(1), 369–394.

Sonobe, T., Akoten, J., & Otsuka, K. (2009). An exploration into the successful development of the leather-shoe industry in Ethiopia. *Review of Development Economics, 13*(4), 719–736.

Stanley, M. H., Amaral, L. A. N., Buldyrev, S. V., Havlin, S., Leschhorn, H., Maass, P., …, Stanley, H. E. (1996). Scaling behaviour in the growth of companies. *Nature, 379*, 804-806.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *Journal of Operational Research, 130*, 498-509.

Tone, K. (2002). A slacks-based measure of super-efficiency in data envelopment analysis. *European Journal of Operational Research, 143*, 32-41.

Tone, K. (2013). *Resampling in DEA*. GRIPS Discussion Paper 13-23. Tokyo: National Graduate Institute for Policy Studies.

Tone, K., & Tsutsui, M. (2014). How to deal with non-convex frontiers in data envelopment analysis. *Journal of Optimization Theory and Applications*. doi: 10.1007/A10957-0626-3

Tybout, J. (2000). Manufacturing firms in developing countries: How well do they do, and why? *Journal of Economic Literature, 38*(1), 11-44.

UNIDO. (2009). *Industrial Development Report.* Geneva: UNIDO.

United States Department of Commerce. (2013). *Doing business in Ethiopia: Country commercial guide for U.S. companies, 2013.* Washington, DC: USDC.

Wang, H.-J. (2002). *Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model.* Taipei, Taiwan: The Institute of Economics Academia Sinica.

Weldgiorgis, T. (2012). *Assessment of investment and export promotion policy in Ethiopia: Case study on leather and textile & apparel industries.* Unpublished paper.

World Bank. (2014). *Doing business 2014: Ccountry profile-Ethiopia.* Washington, DC: World Bank.

Yang, Z. & Paradi, J. C. (2006). Cross firm bank branch benchmarking using "handicapped" data envelopment analysis to adjust for corporate strategic effects. *Proceedings of the 39th Hawaii International Conference on System Sciences*, 1-10.

Yasuda, T. (2005). Firm growth, size, age and behavior in Japanese manufacturing. *Journal of Small Business Economics*, *24*(1), 1-15.

Appendix A

Appendix Table A.1. *Descriptive Statistics of the Output and Inputs Used in in the Analysis*

Industry		Output	Labor	Capital	Intermediate input
Food and beverages	mean	3758.528	31547.61	2031.34	1445.003
	min	3008.368	22864.25	1707.763	1197.372
	max	5385.09	45398.08	2742.864	1847.699
Textiles	mean	679.9092	20111.92	578.7222	419.89
	min	363.2159	11446.75	161.4486	213.5981
	max	863.1639	23140	945.7209	605.3663
Wearing apparel	mean	94.65079	4324.267	83.85411	49.42082
	min	40.6123	2629.75	29.7966	25.85227
	max	220.5818	7118.167	206.7029	114.0487
Tanning, leather & footwear	mean	788.7299	7319.425	397.0847	533.8238
	min	574.7596	5675.167	252.6825	348.3908
	max	1129.818	8393.833	483.3686	655.7549
Wood	mean	45.05163	1487.575	6.262759	17.59389
	min	23.95174	901.5833	4.292387	11.48773
	max	61.91834	2753.75	10.57286	21.54048
Paper and printing	mean	520.0633	6951.525	162.2329	254.4835
	min	338.6689	4511.25	116.4661	157.3581
	max	671.5735	9058.5	190.8786	334.2708
Chemicals	mean	688.9341	5535.942	352.0877	408.5127
	min	347.6034	3438.5	262.1779	261.1341
	max	1094.333	7570.417	517.7115	573.8577
Rubber and plastics	mean	595.936	5786.867	330.1535	330.0259
	min	397.2173	3066.5	274.162	206.4455
	max	956.8327	10016.42	389.7464	486.4027
Non-metals	mean	1089.343	8933.908	666.3927	486.9671
	min	532.5393	5600.667	407.3347	280.1168
	max	1786.25	13962.83	1085.902	599.0042
Fabricated metal	mean	229.3434	1967.725	69.65802	130.1234
	min	32.51451	944.8333	21.76476	20.32331
	max	580.8554	3248.083	129.9308	307.749
Furniture	mean	149.688	4114.9	88.66108	77.42142
	min	88.74252	2961.917	73.50366	50.71339
	max	211.3498	5634.167	117.9825	101.5875

Note: Output, capital and intermediate inputs are expressed in millions ('000,000) of Ethiopian Birr (ETB). Labor is measured by the total number of employees.

Appendix Table A.2. *Estimated Parameters of the Stochastic Frontier Production Function by Industrial Group (FE model)*

Parameters	Food & Beverage	Textile	Wearing apparel	Tanning, leather &footwear	Wood	Paper & printing	Chemicals	Rubber & Plastics	Non-metals	Fabricated Metals	Furniture
β_l	0.0474	0.0867	-0.148	0.213***	0.402	0.390***	0.305	0.193**	-0.0413	0.0215	0.0613
	(0.0365)	(0.119)	(0.158)	(0.0623)	(0.442)	(0.119)	(0.217)	(0.0823)	(0.0709)	(0.171)	(0.129)
β_k	0.0499**	0.0197	-0.0161	0.0690*	0.289*	-0.0563	-0.00296	0.0500	0.0842**	-0.0901	0.119**
	(0.0246)	(0.0661)	(0.112)	(0.0385)	(0.169)	(0.0899)	(0.0809)	(0.0607)	(0.0406)	(0.0571)	(0.0519)
β_m	0.854***	0.979***	1.017***	0.716***	0.833***	0.588***	0.655***	0.829***	0.742***	0.845***	0.573***
	(0.0381)	(0.0646)	(0.114)	(0.0388)	(0.290)	(0.0867)	(0.104)	(0.0616)	(0.0859)	(0.164)	(0.161)
β_{ll}	-0.0112	0.117*	-0.0238	-0.0295	-0.00826	-0.0972	0.256	-0.0484	0.171**	0.0204	0.185
	(0.0776)	(0.0669)	(0.0984)	(0.0758)	(0.0968)	(0.0876)	(0.209)	(0.0760)	(0.0672)	(0.274)	(0.117)
β_{kk}	-0.0127	-0.0108	-0.00386	0.0168	0.0564	-0.0620	0.0355	-0.0334	0.0214	0.00342	0.0114
	(0.0124)	(0.0244)	(0.0263)	(0.0237)	(0.0349)	(0.0377)	(0.0414)	(0.0290)	(0.0171)	(0.0357)	(0.0151)
β_{mm}	-0.0457	0.105*	0.0713	0.0651**	-0.0429	0.00925	0.137*	0.0480	0.0581	0.121	0.0706**
	(0.0383)	(0.0547)	(0.0758)	(0.0257)	(0.0936)	(0.0365)	(0.0798)	(0.0626)	(0.0416)	(0.0891)	(0.0359)
β_{lk}	0.00292	-0.00652	-0.0140	0.0345	-0.0354	0.120**	-0.0278	0.120**	-0.00825	-0.0192	0.0380
	(0.0182)	(0.0326)	(0.0293)	(0.0301)	(0.0810)	(0.0610)	(0.0656)	(0.0568)	(0.0218)	(0.0570)	(0.0320)
β_{lm}	0.0212	-0.0690*	-0.0605	0.00585	0.0134	-0.0367	0.0172	-0.0781	-0.126***	-0.0111	-0.165***
	(0.0530)	(0.0410)	(0.0577)	(0.0379)	(0.0564)	(0.0585)	(0.0780)	(0.0688)	(0.0449)	(0.133)	(0.0486)
β_{km}	0.0311*	0.00576	-0.00808	-0.0449**	0.0297	-0.00342	-0.0882**	-0.0334	-0.0112	-0.0537	-0.0136
	(0.0178)	(0.0199)	(0.0401)	(0.0209)	(0.0525)	(0.0278)	(0.0429)	(0.0378)	(0.0226)	(0.0536)	(0.0164)
β_t	-0.0472***	-0.0482	-0.00882	-0.00227	-0.0355	0.0319	0.0491	-0.0691*	-0.0390	0.0699	0.0563**
	(0.0135)	(0.0380)	(0.0477)	(0.0383)	(0.0933)	(0.0335)	(0.0447)	(0.0387)	(0.0267)	(0.0527)	(0.0259)
β_{tt}	0.0149***	0.0141**	0.0119	0.00783	0.00626	0.00175	0.000904	0.0199***	0.0159***	-0.00215	-0.00120
	(0.00249)	(0.00620)	(0.00864)	(0.00631)	(0.0155)	(0.00539)	(0.00745)	(0.00590)	(0.00477)	(0.00919)	(0.00415)
β_0	-0.443***	-0.426**	-0.259	-0.548***	0.870	-0.687***	-0.838***	-0.0960	-0.544***	-0.997***	-1.061***
	(0.0578)	(0.192)	(0.227)	(0.113)	(0.812)	(0.206)	(0.191)	(0.141)	(0.168)	(0.276)	(0.281)
Observations	2,380	289	228	514	160	721	463	473	1,100	356	1,079
No. of eid	482	46	40	89	35	111	74	87	285	88	246

Note: Robust standard errors in parentheses. *** significant at 1 percent significance level, ** significant at 5 percent significance level, * significant at 10 percent significance level

Appendix Table A.3. *Estimated Parameters of the Stochastic Frontier Production Function by Industrial Group (RE model)*

Parameters	Food & Beverage	Textile	Wearing apparel	Tanning, leather &footwear	Wood	Paper & printing	Chemicals	Rubber & Plastics	Non-metals	Fabricated Metals	Furniture
β_l	0.168***	0.0674	0.0420	0.208***	0.238	0.453***	0.305**	0.118***	0.0291	0.0807	0.211**
	(0.0352)	(0.0492)	(0.103)	(0.0391)	(0.168)	(0.102)	(0.143)	(0.0420)	(0.0694)	(0.138)	(0.103)
β_k	0.0904***	0.0127	0.0190	0.0843**	0.151	0.0278	0.0413	-0.0159	0.125***	-0.00746	0.119***
	(0.0189)	(0.0381)	(0.0694)	(0.0344)	(0.138)	(0.0827)	(0.0674)	(0.0532)	(0.0382)	(0.0461)	(0.0384)
β_m	0.881***	0.931***	0.895***	0.783***	0.742***	0.649***	0.721***	0.886***	0.825***	0.853***	0.622***
	(0.0331)	(0.0379)	(0.0778)	(0.0252)	(0.159)	(0.0812)	(0.0721)	(0.0399)	(0.0661)	(0.0926)	(0.130)
β_{ll}	0.0217	0.0782*	-0.0152	-0.0287	0.0161	-0.00409	0.208	0.0179	0.166**	-0.0615	0.219**
	(0.0725)	(0.0413)	(0.0678)	(0.0484)	(0.0563)	(0.102)	(0.179)	(0.0613)	(0.0677)	(0.205)	(0.103)
β_{kk}	-0.00471	-0.0202	0.00179	0.00763	0.0465*	-0.0565	0.0323	-0.0407	0.0282*	0.0185	0.0202*
	(0.0105)	(0.0158)	(0.0202)	(0.0203)	(0.0277)	(0.0408)	(0.0299)	(0.0277)	(0.0167)	(0.0263)	(0.0112)
β_{mm}	-0.0388	0.0677*	0.0336	0.0699***	-0.00920	0.0189	0.0576	0.0958	0.0724*	0.0724	0.0511*
	(0.0354)	(0.0375)	(0.0530)	(0.0204)	(0.0852)	(0.0422)	(0.0522)	(0.0606)	(0.0392)	(0.0778)	(0.0299)
β_{lk}	0.00966	-0.00576	-0.00136	0.0609*	-0.0229	0.0985	-0.0267	0.0506	-0.0137	-0.0158	0.0143
	(0.0171)	(0.0225)	(0.0250)	(0.0320)	(0.0504)	(0.0666)	(0.0527)	(0.0482)	(0.0221)	(0.0474)	(0.0225)
β_{lm}	0.0177	-0.0423	-0.0309	-0.0253	0.00733	-0.0697	-0.00511	-0.0879*	-0.119***	0.0163	-0.122***
	(0.0489)	(0.0284)	(0.0437)	(0.0342)	(0.0375)	(0.0477)	(0.0655)	(0.0498)	(0.0411)	(0.0983)	(0.0405)
β_{km}	0.0217	0.0150	-0.0122	-0.0357**	-0.0155	0.0179	-0.0490	0.00912	-0.00617	-0.0454	-0.0152
	(0.0167)	(0.0156)	(0.0267)	(0.0166)	(0.0427)	(0.0271)	(0.0346)	(0.0379)	(0.0234)	(0.0441)	(0.0110)
β_t	0.0359***	-0.0472	0.0169	-0.0161	-0.0739	0.00491	0.0508	-0.0659*	-0.0387	0.0391	0.0486**
	(0.0129)	(0.0367)	(0.0500)	(0.0345)	(0.0856)	(0.0294)	(0.0428)	(0.0386)	(0.0247)	(0.0457)	(0.0235)
β_{tt}	0.0129***	0.0141**	0.00683	0.0109*	0.0150	0.00547	0.000423	0.0158***	0.0142***	0.00480	-0.000281
	(0.00237)	(0.00601)	(0.00878)	(0.00566)	(0.0141)	(0.00476)	(0.00694)	(0.00590)	(0.00432)	(0.00804)	(0.00384)
β_0	-0.289***	-0.363***	-0.378**	-0.475***	0.328	-0.360**	-0.657***	-0.166	-0.251**	-0.631***	-0.731***
	(0.0460)	(0.107)	(0.168)	(0.106)	(0.409)	(0.140)	(0.195)	(0.118)	(0.114)	(0.135)	(0.178)
Observations	2,380	289	228	514	160	721	463	473	1,100	356	1,079
No. firms	482	46	40	89	35	111	74	87	285	88	246

Note: Robust standard errors in parentheses. *** significant at 1 percent significance level, ** significant at 5 percent significance level, * significant at 10 percent significance level

Appendix Table A.4. *Technical Efficiency Estimates by Industrial Group and Year (TRE model)*

Industry		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Food and beverages	mean	0.715	0.707	0.713	0.723	0.736	0.768	0.754	0.771	0.781	0.781
	min	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054
	max	0.983	0.971	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983
Textiles	mean	0.888	0.874	0.886	0.884	0.872	0.890	0.888	0.884	0.883	0.867
	min	0.719	0.725	0.713	0.820	0.644	0.651	0.786	0.815	0.730	0.484
	max	0.941	0.946	0.926	0.935	0.928	0.950	0.935	0.956	0.943	0.930
Wearing apparel	mean	0.847	0.825	0.849	0.862	0.855	0.862	0.849	0.846	0.852	0.867
	min	0.603	0.470	0.544	0.741	0.538	0.814	0.721	0.770	0.686	0.725
	max	0.924	0.907	0.920	0.929	0.938	0.904	0.925	0.943	0.917	0.932
Tanning, leather and footwear	mean	0.811	0.818	0.820	0.822	0.831	0.851	0.829	0.821	0.830	0.832
	min	0.186	0.218	0.521	0.553	0.560	0.624	0.357	0.507	0.679	0.343
	max	0.928	0.954	0.933	0.931	0.918	0.948	0.937	0.943	0.928	0.942
Wood	mean	0.870	0.885	0.891	0.876	0.877	0.885	0.893	0.877	0.884	0.872
	min	0.821	0.824	0.853	0.808	0.816	0.811	0.814	0.787	0.809	0.593
	max	0.924	0.928	0.925	0.925	0.932	0.921	0.930	0.907	0.934	0.936
Paper and printing	mean	0.711	0.649	0.693	0.682	0.703	0.761	0.723	0.700	0.671	0.729
	min	0.438	0.026	0.054	0.070	0.023	0.021	0.035	0.028	0.019	0.026
	max	0.939	0.910	0.896	0.866	0.888	0.934	0.926	0.894	0.856	0.895
Chemicals	mean	0.727	0.717	0.736	0.746	0.744	0.769	0.748	0.722	0.735	0.761
	min	0.069	0.044	0.062	0.123	0.211	0.314	0.249	0.408	0.031	0.025
	max	0.895	0.886	0.929	0.865	0.946	0.906	0.930	0.872	0.946	0.906
Rubber and plastics	mean	0.800	0.824	0.829	0.812	0.802	0.829	0.783	0.827	0.808	0.834
	min	0.509	0.706	0.388	0.368	0.276	0.483	0.039	0.670	0.172	0.686
	max	0.941	0.909	0.914	0.927	0.886	0.906	0.943	0.900	0.892	0.913

Non metals	mean	0.815	0.808	0.827	0.822	0.797	0.838	0.820	0.804	0.810	0.813
	min	0.473	0.530	0.508	0.479	0.190	0.583	0.226	0.508	0.197	0.083
	max	0.930	0.921	0.931	0.925	0.946	0.950	0.932	0.931	0.923	0.929
Fabricated metals	mean	0.712	0.700	0.669	0.581	0.708	0.719	0.705	0.681	0.698	0.665
	min	0.332	0.400	0.125	0.094	0.213	0.388	0.117	0.362	0.236	0.313
	max	0.887	0.838	0.884	0.856	0.926	0.865	0.925	0.887	0.919	0.844
Furniture	mean	0.814	0.788	0.814	0.822	0.816	0.836	0.835	0.817	0.816	0.838
	min	0.148	0.046	0.012	0.064	0.453	0.209	0.042	0.262	0.023	0.003
	max	0.939	0.920	0.943	0.932	0.942	0.925	0.956	0.931	0.947	0.957

Appendix Table A.5. *Parameter Estimates of the Relationship Between Firm size, Age and Technical Efficiency (OLS model)*

Variables	All firms	Food & beverages	Textiles	Wearing apparel	Tanning, leather & footwear	wood	Paper & printing	Chemicals	Rubber & plastics	Nonmetals	Fabricated metals	Furniture
OLS regression												
lnsize_{t-1}	0.0901**	-0.197***	-0.197	0.544***	0.344*	0.0845	0.0674	0.295	-0.00512	0.352**	0.995***	-0.355*
	(0.0442)	(0.0665)	(0.191)	(0.196)	(0.183)	(0.460)	(0.181)	(0.308)	(0.174)	(0.163)	(0.361)	(0.214)
$(\text{lnsize})^2_{t-1}$	-0.00490	0.039***	0.0118	0.055***	-0.0414*	-0.00248	-0.0190	-0.0372	-0.0110	-0.0422**	-0.119**	0.0524*
	(0.00498)	(0.00701)	(0.0172)	(0.0210)	(0.0214)	(0.0547)	(0.0227)	(0.0357)	(0.0200)	(0.0195)	(0.0465)	(0.0276)
lnage	-0.150***	-0.350***	-0.0963	0.100	-0.0333	-1.120	-0.385**	-0.383	0.611**	-0.262*	0.474	-0.152
	(0.0543)	(0.0968)	(0.241)	(0.330)	(0.164)	(0.773)	(0.185)	(0.238)	(0.244)	(0.151)	(0.322)	(0.168)
$(\text{lnage})^2$	0.039***	0.071***	0.00767	-0.0179	0.0201	0.167	0.097***	0.0757	-0.104**	0.0810**	-0.110*	0.0334
	(0.0109)	(0.0196)	(0.0448)	(0.0619)	(0.0322)	(0.134)	(0.0357)	(0.0463)	(0.0509)	(0.0319)	(0.0638)	(0.0342)
Ownership	-0.00105	-0.0617	0.137	0.613***	-0.0218	-0.159	-0.224*	-0.187	-0.104	-0.108	-0.233	0.193
	(0.0317)	(0.0539)	(0.0896)	(0.146)	(0.0962)	(0.178)	(0.120)	(0.115)	(0.161)	(0.126)	(0.159)	(0.171)
Constant	0.848***	1.750***	1.688***	-1.069*	0.442	3.577**	1.624***	0.864	1.033**	1.039***	-1.217	1.382***
	(0.123)	(0.223)	(0.633)	(0.590)	(0.393)	(1.513)	(0.414)	(0.810)	(0.427)	(0.366)	(0.809)	(0.498)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	5,769	1,763	228	185	420	109	591	376	360	662	259	721
R-squared	0.066	0.150	0.204	0.236	0.038	0.390	0.087	0.041	0.092	0.092	0.129	0.074

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

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

In This model, we further introduce year, industry, and region dummies into the model to control for macroeconomic effects and industrial and regional differences, respectively. However, to conserve space, coefficient estimates are not reported. Instead, the "Yes" sign is introduced to indicate that these variables are controlled for.

Appendix Table A.6. *Efficiency Estimates from Radial Model: Triangular Distribution*

Industrial group	DEA	97.50%	90%	80%	75%	50%	25%	20%	10%	2.50%
Food and beverages	1	1	1	1	1	1	1	1	0.9593	0.8871
Textiles	0.6372	0.7752	0.7255	0.6975	0.6868	0.6382	0.5932	0.583	0.5524	0.5125
Wearing apparel	0.7407	0.8821	0.8275	0.7913	0.7778	0.7203	0.6677	0.6542	0.6241	0.5771
Tanning, leather and footwear	0.78	0.9047	0.8502	0.8186	0.8071	0.758	0.7078	0.6967	0.6628	0.6175
Wood	1	1	1	1	1	1	1	1	1	1
Paper and printing	0.9613	1	1	1	0.9968	0.9365	0.874	0.8591	0.8174	0.7571
Chemicals	0.8573	0.9855	0.9343	0.9002	0.8867	0.8306	0.7743	0.7591	0.7219	0.6748
Rubber and plastics	0.7568	0.8945	0.8416	0.8089	0.7964	0.7454	0.6935	0.6815	0.6498	0.6024
non metals	0.9945	1	1	1	1	0.9869	0.9132	0.8975	0.8513	0.7896
Basic iron and steel	1	1	1	1	1	1	1	1	1	1
Fabricated metals	0.9783	1	1	1	1	0.9583	0.89	0.8742	0.8348	0.779
Machinery and equipment	0.8845	1	0.9816	0.9375	0.9212	0.8605	0.7961	0.78	0.741	0.6896
Motor vehicles	1	1	1	1	1	1	0.9995	0.9751	0.915	0.8298
Furniture	0.7837	0.9458	0.8858	0.845	0.8311	0.7743	0.7156	0.7013	0.6685	0.622

Appendix Table A.7. *Efficiency Estimates from SBM Model: Triangular Distribution*

Industrial group	DEA	97.50%	90%	80%	75%	50%	25%	20%	10%	2.50%
Food and beverages	1	1	1	1	1	1	1	1	0.8784	0.7923
Textiles	0.536	0.6343	0.5949	0.5677	0.5568	0.5148	0.47	0.4607	0.4376	0.4053
Wearing apparel	0.5226	0.616	0.575	0.549	0.541	0.5025	0.464	0.4554	0.4311	0.3999
Tanning, leather and footwear	0.5828	0.8135	0.7378	0.6882	0.6673	0.5807	0.532	0.5197	0.4912	0.4513
Wood	1	1	1	1	1	1	1	1	1	1
Paper and printing	0.9161	1	1	1	1	0.8553	0.7427	0.7219	0.6647	0.5781
Chemicals	0.6943	0.9551	0.8573	0.8013	0.7774	0.6782	0.5842	0.5698	0.5392	0.4964
Rubber and plastics	0.6216	0.8116	0.741	0.6969	0.6802	0.6073	0.5287	0.5157	0.4872	0.4479
non metals	0.9304	1	1	1	1	0.931	0.8199	0.7995	0.7464	0.6634
Basic iron and steel	1	1	1	1	1	1	1	1	1	1
Fabricated metals	0.9215	1	1	1	1	0.8563	0.7117	0.6794	0.6285	0.5782
Machinery and equipment	0.7716	1	0.9041	0.8419	0.8227	0.7497	0.6784	0.6606	0.614	0.5358
Motor vehicles	1	1	1	1	1	1	0.9069	0.7881	0.7153	0.6571
Furniture	0.6627	0.8152	0.7415	0.7037	0.6906	0.6377	0.5841	0.571	0.5396	0.4922

Appendix Table A.8. *Efficiency Estimates from Radial Model: Historical data Method*

Industrial group	DEA	97.50%	90%	80%	75%	50%	25%	20%	10%	2.50%
Food and beverages	1	1	1	1	1	1	0.9558	0.9254	0.8327	0.673
Textiles	0.6372	0.7867	0.7387	0.6876	0.6636	0.5993	0.5351	0.5172	0.4794	0.3707
Wearing apparel	0.7407	1	1	1	1	0.725	0.5005	0.4674	0.3374	0.3024
Tanning, leather and footwear	0.78	0.8525	0.7972	0.7689	0.7553	0.6818	0.6235	0.606	0.5541	0.4937
Wood	1	1	1	1	1	1	1	1	1	1
Paper and printing	0.9613	1	1	1	0.9858	0.8819	0.7749	0.7434	0.6786	0.5775
Chemicals	0.8573	1	0.9732	0.9102	0.8884	0.7986	0.6972	0.6723	0.6081	0.5197
Rubber and plastics	0.7568	1	0.932	0.8542	0.8302	0.7196	0.6084	0.5847	0.5261	0.4495
non metals	0.9945	1	1	1	1	0.8915	0.7465	0.7151	0.6455	0.5503
Basic iron and steel	1	1	1	1	1	1	1	1	1	0.9489
Fabricated metals	0.9783	1	1	1	1	0.959	0.6942	0.6114	0.4866	0.2664
Machinery and equipment	0.8845	0.9798	0.9159	0.8849	0.8732	0.8268	0.7762	0.7603	0.7055	0.5944
Motor vehicles	1	1	1	1	1	0.9907	0.7369	0.6615	0.5502	0.4831
Furniture	0.7837	0.913	0.8461	0.8085	0.7958	0.7366	0.6373	0.6029	0.537	0.4275

Appendix Table A.9. *Efficiency Estimates from SB: Historical data Method*

Industrial group	DEA	97.50%	90%	80%	75%	50%	25%	20%	10%	2.50%
Food and beverages	1	1	1	1	1	1	0.8223	0.7544	0.6114	0.5078
Textiles	0.536	0.6498	0.5713	0.5305	0.5128	0.4491	0.3891	0.3732	0.337	0.2837
Wearing apparel	0.5226	1	1	1	1	0.4652	0.3323	0.3039	0.2467	0.1874
Tanning, leather and footwear	0.5828	0.7888	0.675	0.6188	0.6025	0.5458	0.4901	0.4784	0.4444	0.4008
Wood	1	1	1	1	1	1	1	1	1	1
Paper and printing	0.9161	1	1	1	0.9672	0.7502	0.6109	0.5908	0.5334	0.4609
Chemicals	0.6943	1	0.9354	0.8182	0.7801	0.6468	0.5518	0.5324	0.4831	0.4204
Rubber and plastics	0.6216	1	0.849	0.7378	0.7007	0.5656	0.4698	0.4486	0.4051	0.3449
non metals	0.9304	1	1	1	1	0.7337	0.549	0.5176	0.4575	0.3869
Basic iron and steel	1	1	1	1	1	1	1	1	1	0.6982
Fabricated metals	0.9215	1	1	1	1	0.8616	0.5394	0.4871	0.3761	0.2114
Machinery and equipment	0.7716	0.8826	0.8033	0.7639	0.7483	0.6722	0.5453	0.5239	0.478	0.4232
Motor vehicles	1	1	1	1	1	0.9274	0.5888	0.5313	0.4344	0.3786
Furniture	0.6627	0.7622	0.7053	0.6688	0.6518	0.5477	0.4629	0.444	0.3969	0.3229

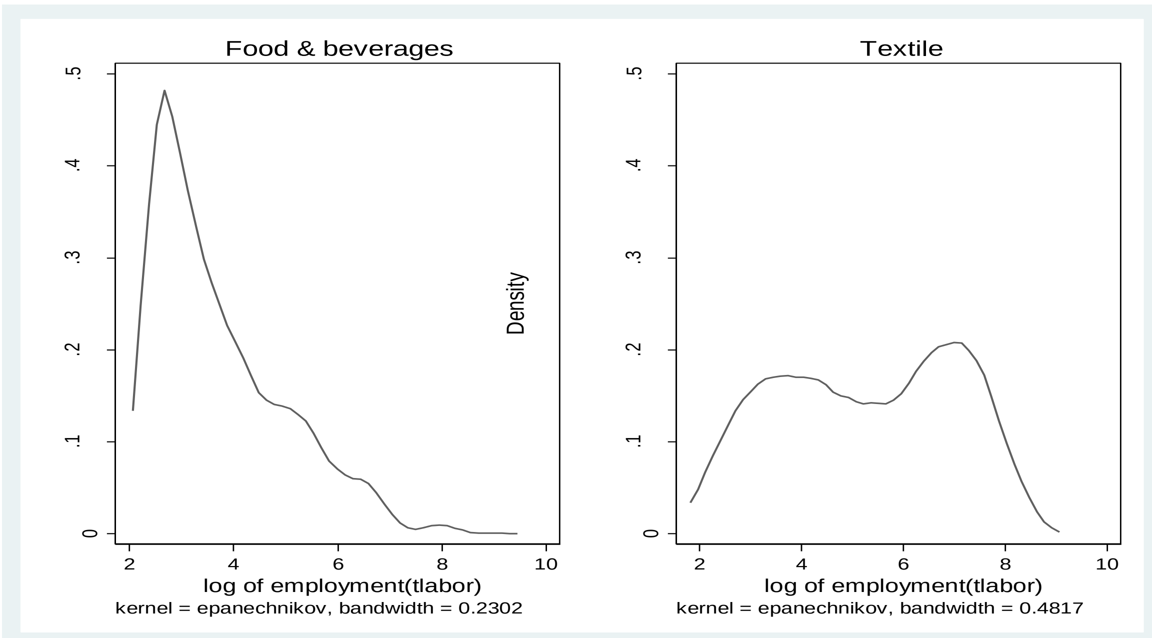
Appendix Table A.10. *Forecast Efficiency Score and Confidence Intervals - Radial Model: Forecast by Trend*

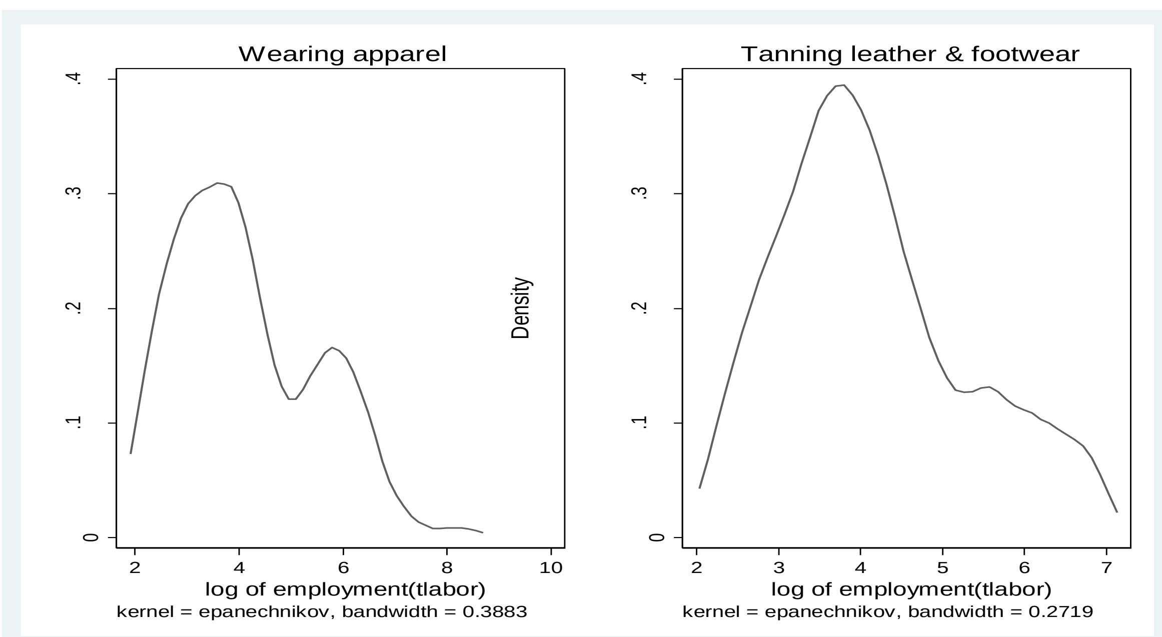
Industrial group	DEA	97.50%	90%	75%	50%	25%	10%	2.50%	Average
Food and beverages	1	1	1	1	1	0.9495	0.8217	0.6567	0.9527
Textiles	0.6862	0.7879	0.7335	0.6843	0.6287	0.5639	0.5029	0.4176	0.6209
Wearing apparel	0.7362	1	1	0.8324	0.7127	0.5175	0.3303	0.2857	0.6922
Tanning, leather and footwear	0.7896	0.8552	0.8092	0.7625	0.7022	0.6327	0.5651	0.4892	0.6943
Wood	1	1	1	1	1	1	1	1	0.9998
Paper and printing	0.9383	1	1	0.9729	0.8745	0.7656	0.6612	0.5591	0.8528
Chemicals	0.9062	1	0.993	0.9039	0.802	0.7034	0.6098	0.5153	0.7967
Rubber and plastics	0.7152	1	0.9001	0.8016	0.7117	0.5924	0.4991	0.4205	0.7033
Non metals	0.9912	1	1	1	0.9267	0.7688	0.6418	0.53	0.8712
Basic iron and steel	1	1	1	1	1	1	1	1	0.997
Fabricated metals	0.9766	1	1	1	0.9759	0.7325	0.4862	0.2868	0.8449
Machinery and equipment	0.8955	0.994	0.9342	0.8853	0.8305	0.771	0.6921	0.5943	0.8202
Motor vehicles	1	1	1	1	1	0.8457	0.6458	0.4924	0.9077
Furniture	0.8047	0.9582	0.8827	0.8244	0.7522	0.6563	0.5357	0.4434	0.7318

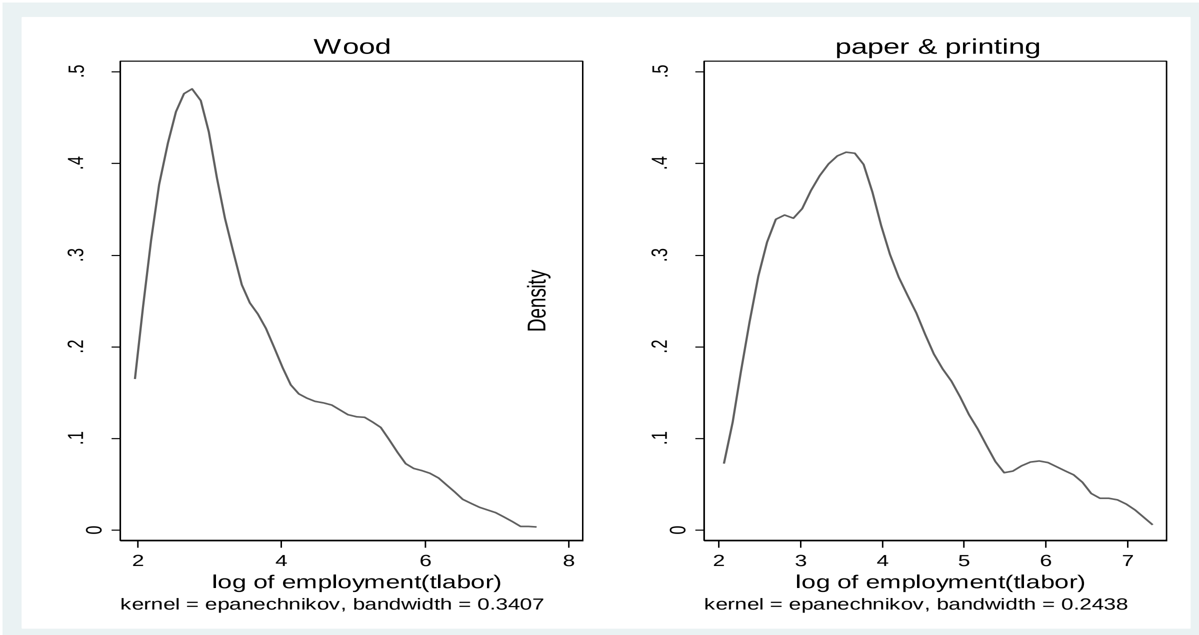
Appendix Table A.11. *Forecast Efficiency Score and Confidence Intervals - Radial Model: By Lucas weight*

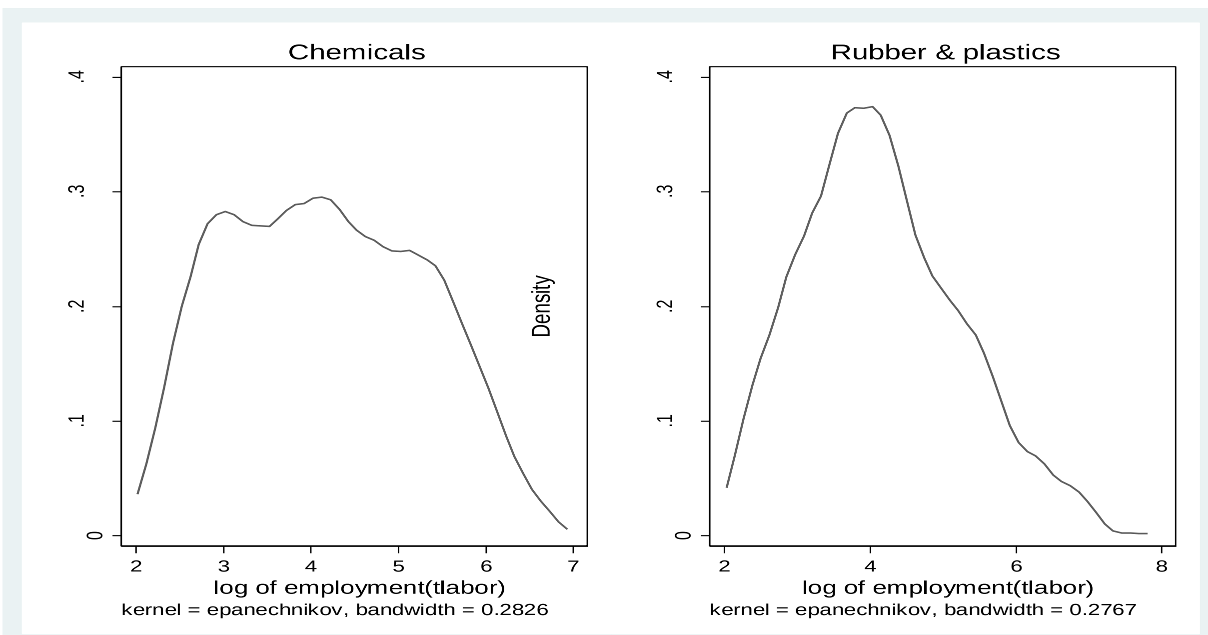
Industrial group	DEA	97.50%	90%	75%	50%	25%	10%	2.50%	Average
Food and beverages	1	1	1	1	1	1	0.9315	0.7587	0.9793
Textiles	0.6202	0.7672	0.7157	0.6641	0.6142	0.5664	0.5248	0.4168	0.6132
Wearing apparel	0.7485	1	1	0.9716	0.7338	0.5565	0.4336	0.3308	0.725
Tanning, leather and footwear	0.7695	0.8482	0.8024	0.7674	0.7217	0.6629	0.6111	0.5449	0.7131
Wood	1	1	1	1	1	1	1	1	1
Paper and printing	0.9819	1	1	0.9975	0.9263	0.8367	0.7518	0.6534	0.8994
Chemicals	0.8747	1	0.9559	0.8944	0.8305	0.7576	0.6773	0.581	0.8203
Rubber and plastics	0.777	0.9984	0.9024	0.8279	0.7429	0.6682	0.5864	0.5064	0.7452
non metals	0.941	1	1	1	0.9165	0.8297	0.7146	0.6137	0.8908
Basic iron and steel	1	1	1	1	1	1	1	1	0.9985
Fabricated metals	0.9652	1	1	1	0.9372	0.7984	0.587	0.3328	0.8669
Machinery and equipment	0.878	0.9728	0.9211	0.886	0.8497	0.815	0.7679	0.6649	0.8448
Motor vehicles	0.965	1	1	1	0.9691	0.835	0.6186	0.5163	0.893
Furniture	0.753	0.8839	0.8354	0.7944	0.7468	0.7007	0.5883	0.4912	0.7334

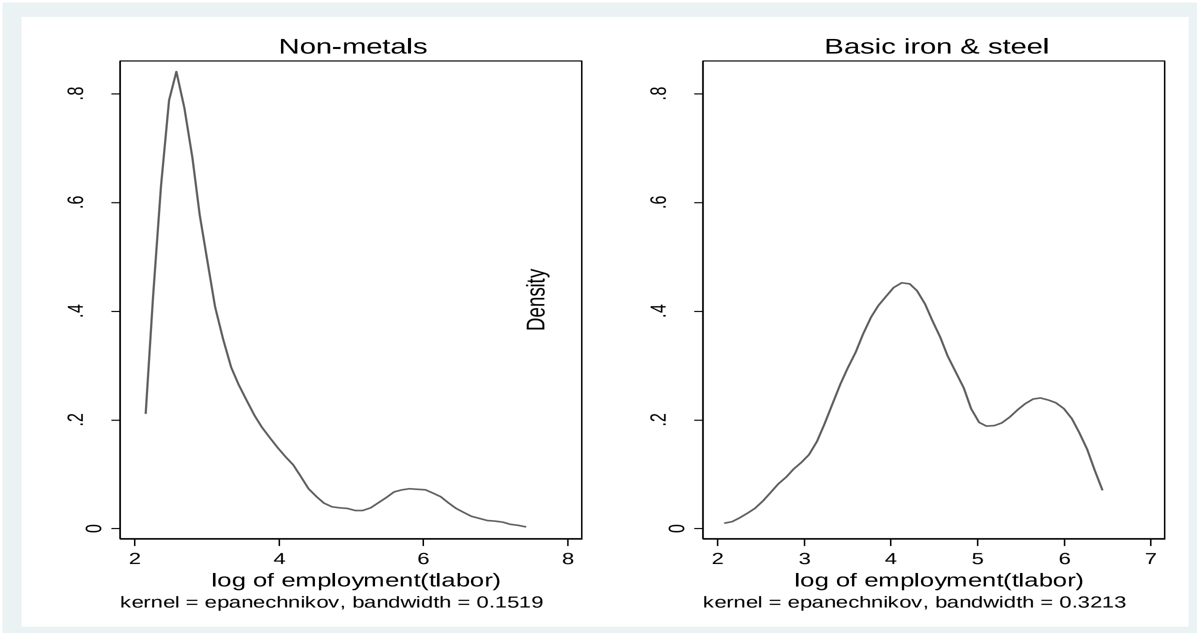
Appendix B

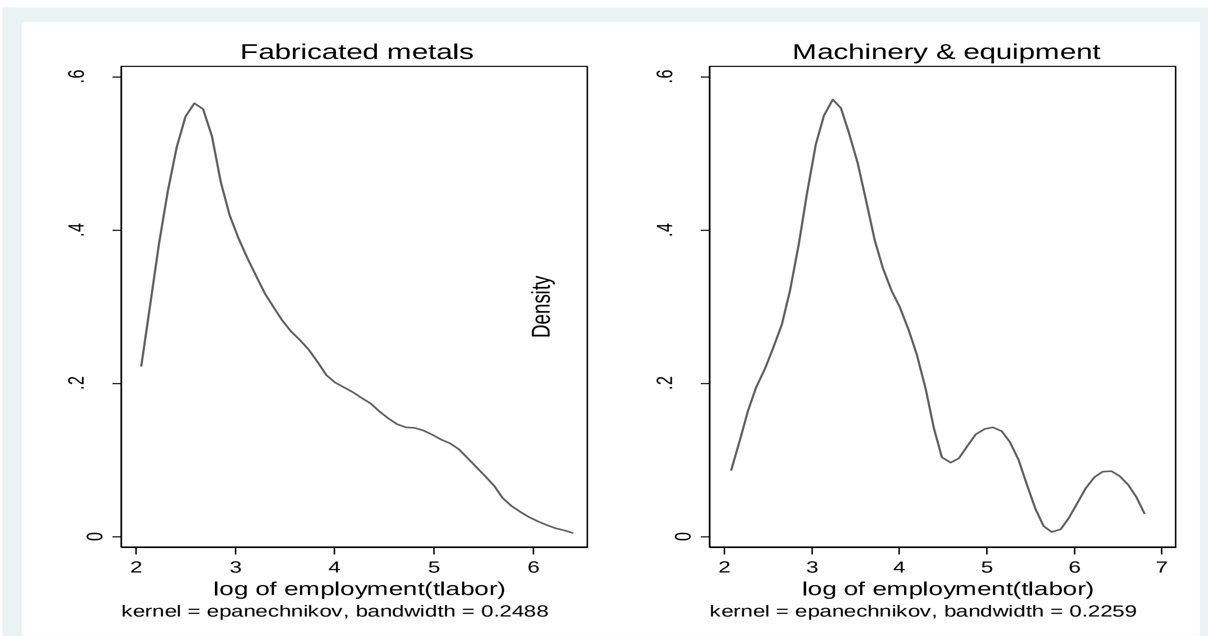

Food & beverages
Textile
Density
0
.1
.2
.3
.4
.5
2
4
6
8
10
log of employment(tlabor)
kernel = epanechnikov, bandwidth = 0.2302
log of employment(tlabor)
kernel = epanechnikov, bandwidth = 0.4817

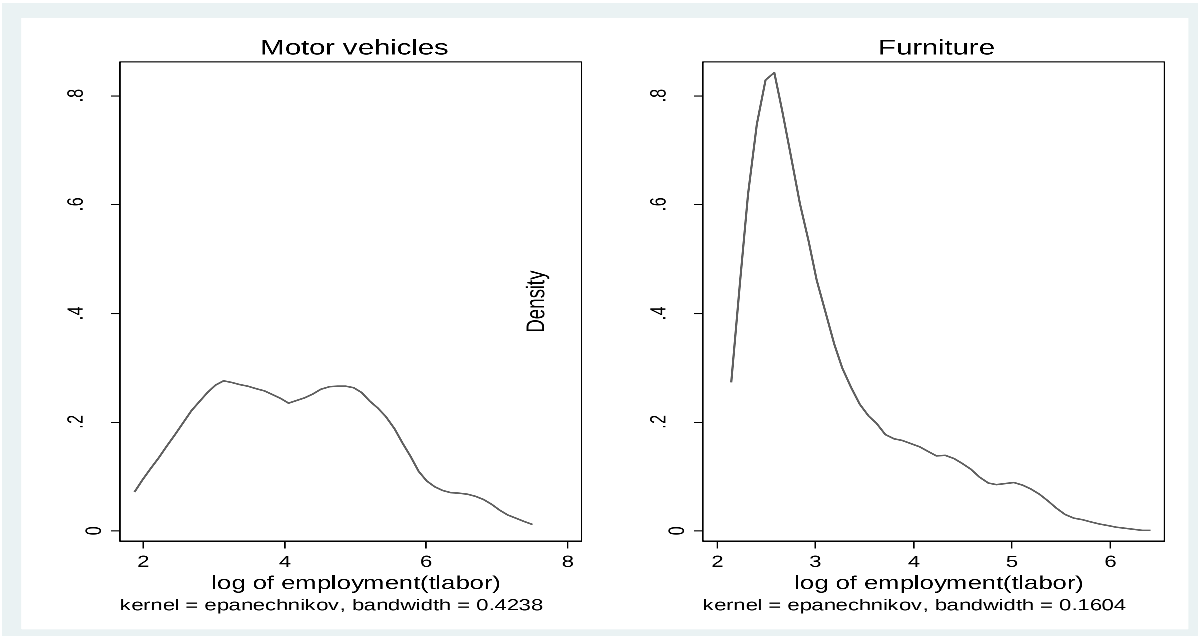

Wearing apparel
Tanning leather & footwear
Density
0
.1
.2
.3
.4
2
4
6
8
10
3
5
7
log of employment(tlabor)
kernel = epanechnikov, bandwidth = 0.3883
log of employment(tlabor)
kernel = epanechnikov, bandwidth = 0.2719


Wood
paper & printing
Density
0
.1
.2
.3
.4
.5
2
4
6
8
3
5
7
log of employment(tlabor)
kernel = epanechnikov, bandwidth = 0.3407
log of employment(tlabor)
kernel = epanechnikov, bandwidth = 0.2438

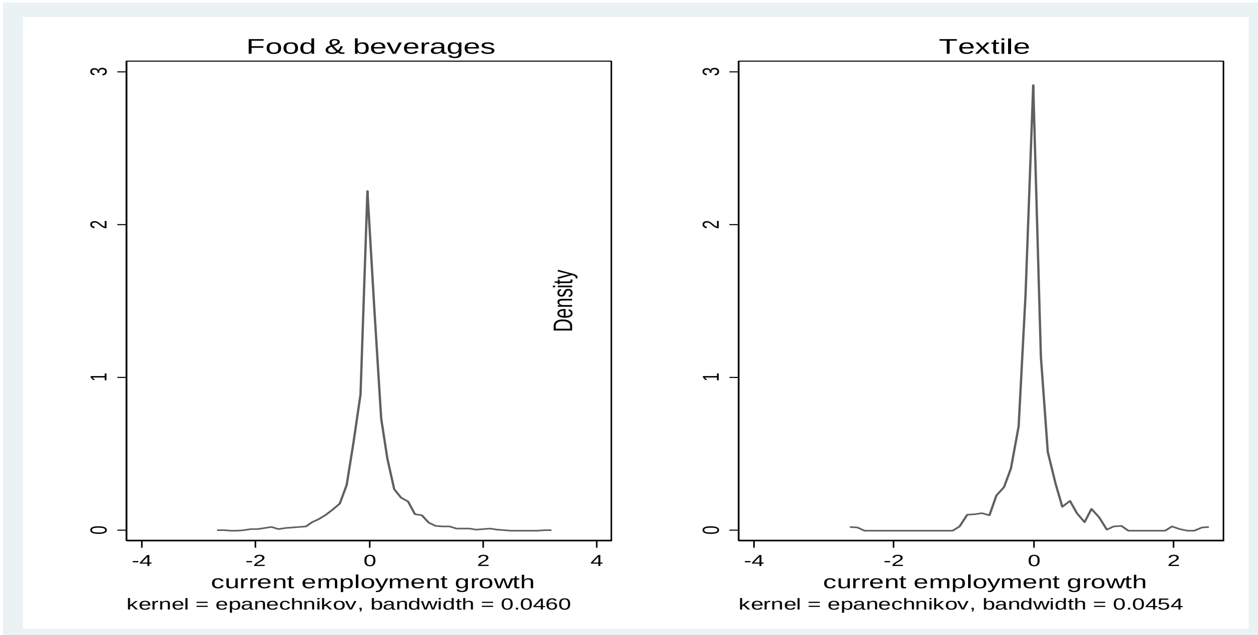

Chemicals
Rubber & plastics
Density
0
.1
.2
.3
.4
2
3
4
5
6
7
8
log of employment(tlabor)
kernel = epanechnikov, bandwidth = 0.2826
log of employment(tlabor)
kernel = epanechnikov, bandwidth = 0.2767

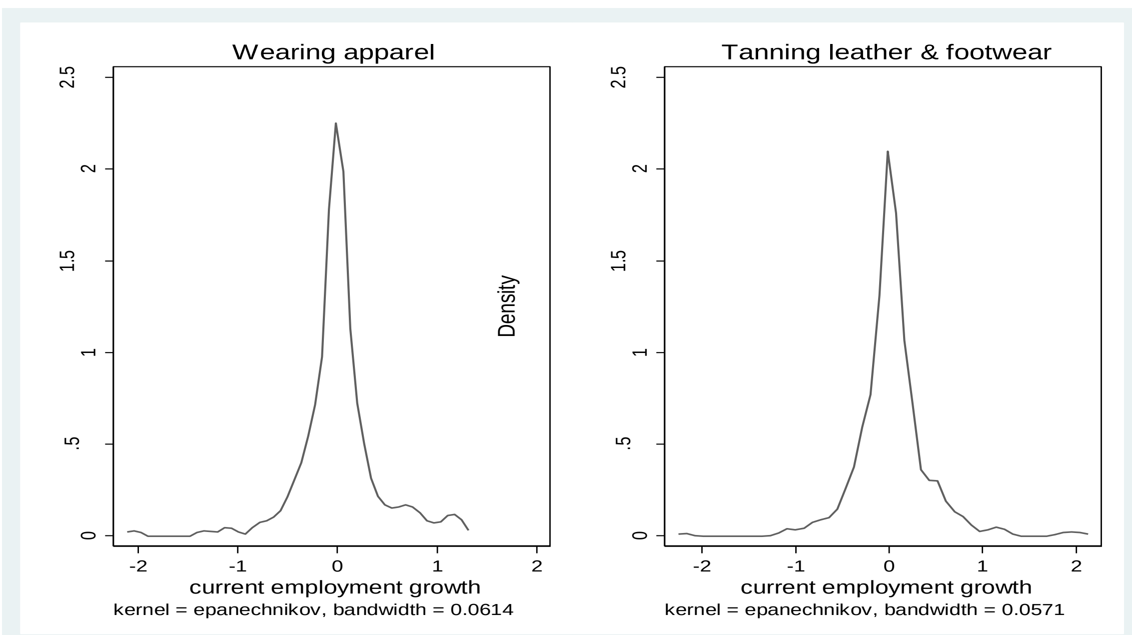

Non-metals
Density
log of employment(tlabor)
kernel = epanechnikov, bandwidth = 0.1519
Basic iron & steel
log of employment(tlabor)
kernel = epanechnikov, bandwidth = 0.3213

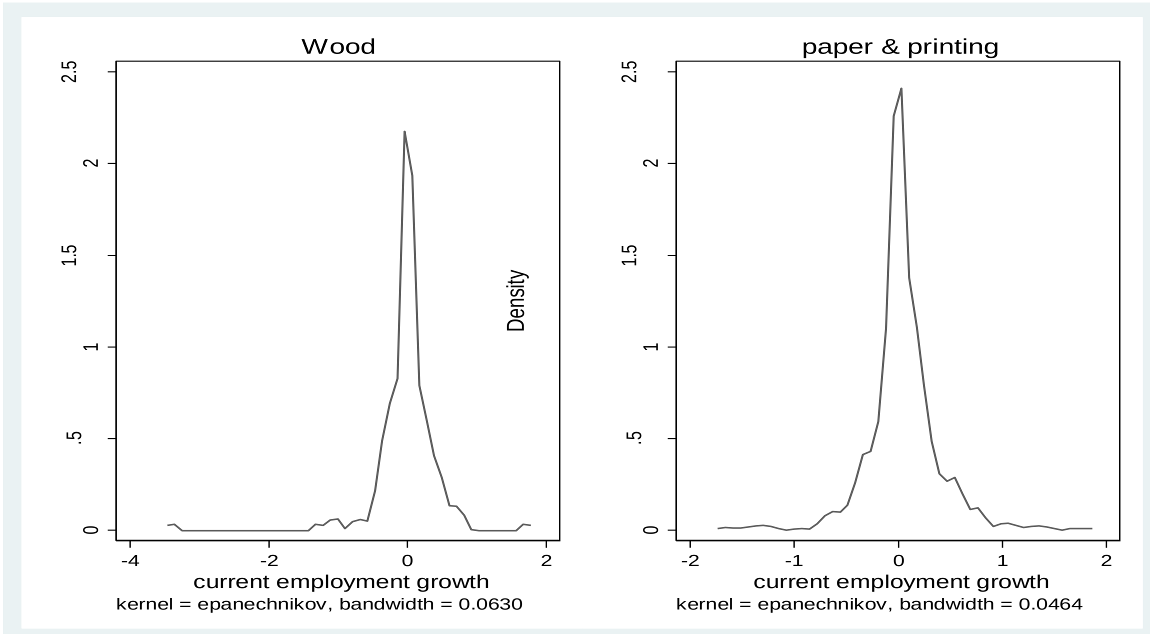

Fabricated metals
Density
log of employment(tlabor)
kernel = epanechnikov, bandwidth = 0.2488
Machinery & equipment
log of employment(tlabor)
kernel = epanechnikov, bandwidth = 0.2259



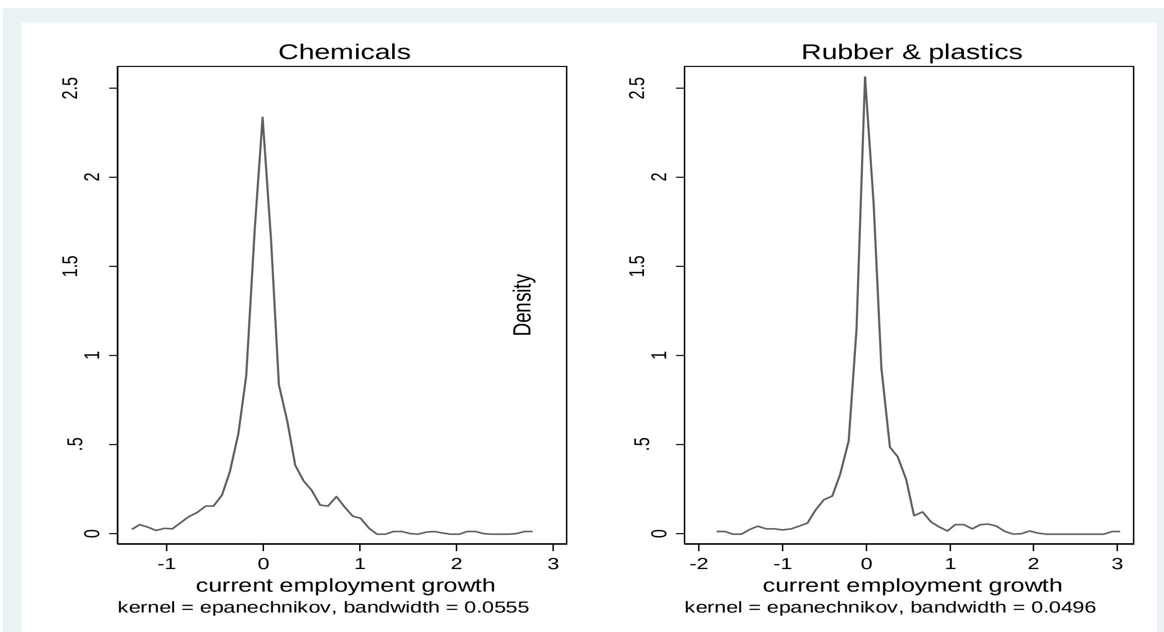
Appendix Figure B.1. Sectoral distribution of Log (size) in the Ethiopian manufacturing sector


Food & beverages
Textile
Density
current employment growth
kernel = epanechnikov, bandwidth = 0.0460
kernel = epanechnikov, bandwidth = 0.0454

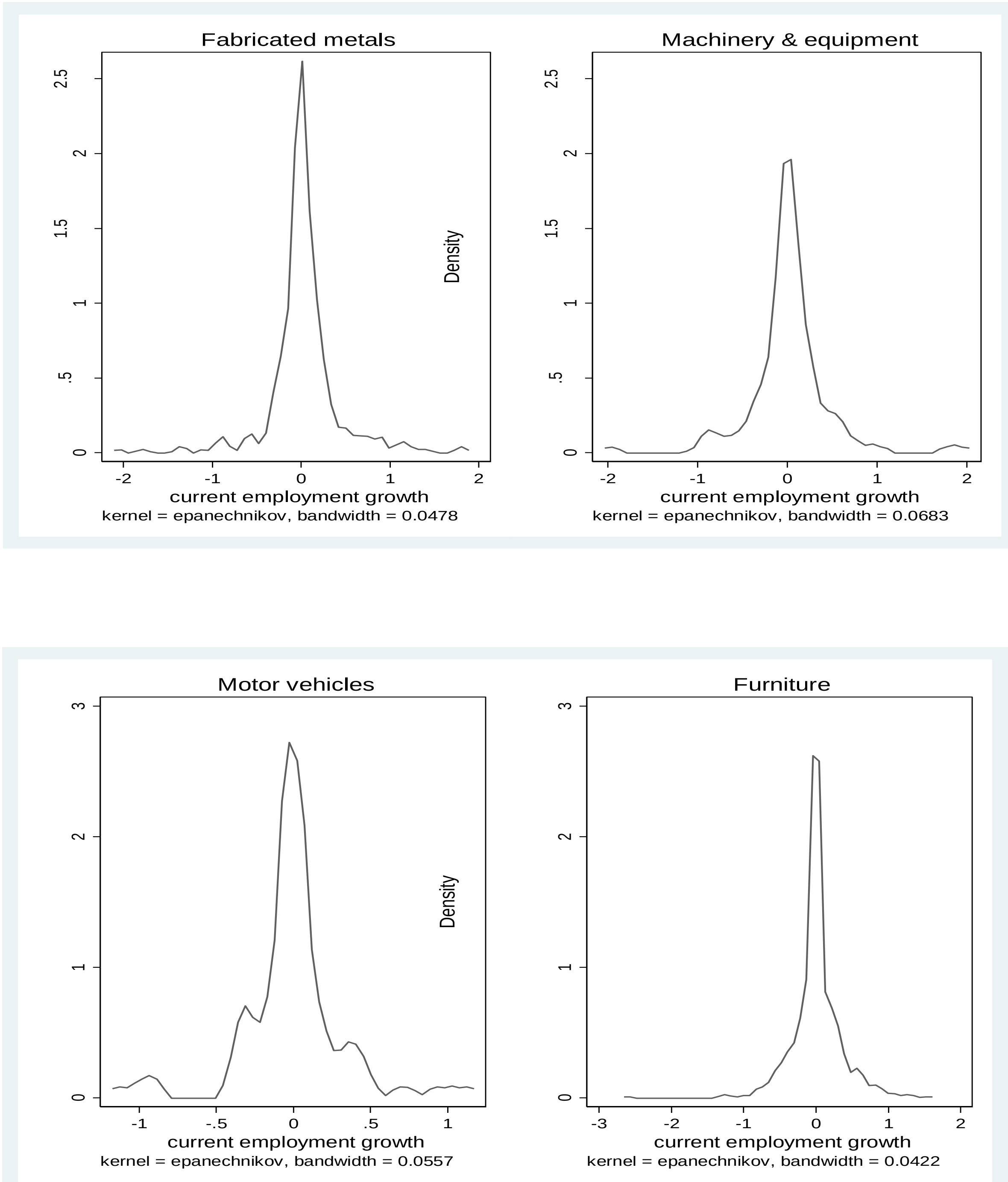

Wearing apparel
Tanning leather & footwear
Density
current employment growth
kernel = epanechnikov, bandwidth = 0.0614
kernel = epanechnikov, bandwidth = 0.0571



Wood
paper & printing
Density
current employment growth
kernel = epanechnikov, bandwidth = 0.0630
current employment growth
kernel = epanechnikov, bandwidth = 0.0464



Chemicals
Rubber & plastics
Density
current employment growth
kernel = epanechnikov, bandwidth = 0.0555
current employment growth
kernel = epanechnikov, bandwidth = 0.0496



Appendix Figure B.2. Sectoral kernel density distribution of growth rate