Measurement of Total Factor Productivity and Learning-By-Doing: An Empirical Study of Japanese Manufacturing Industries

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Statement of Authenticity

This is to certify that this research work, including its entire content and structure are my original idea. Except otherwise acknowledged, idea and /or opinion expressed are mine. Furthermore, this research, in whole or in part, has not been submitted elsewhere to qualify for any academic award. Research work carried out by a third party is acknowledged; and, that ethical procedures and guidelines have been duly followed.

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Notations/Acronyms

TFP- Total Factor Productivity

DEA- Data Envelopment Analysis

GDP- Gross Domestic Product

MITI- Ministry of International Trade and Industry

OECD- Organization for Economic Co-operation and Development

JISC- Japan Industrial Standard Classification

LP- Labour Productivity

CP- Capital Productivity

MFP- Multifactor Productivity

DMU- Decision-Making Units

METI- Japan Ministry of Economy, Trade, and Industry

CCR- Charnes, Cooper & Rhodes

CRS- Constant Return to Scale

EFFCH- Efficiency Change

TECHCH- Technical Change

TFPCH- Total Factor Productivity Change

TI- Technology Intensity

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Abstract

This study empirically investigated productivity and technological learning in Japanese Manufacturing industries. Overall efficiency of Japanese manufacturing industries declined from 65% in 2000 to 42% in 2014. Electrical Machinery, Business Oriented Machinery industry, Information Communication industry, Food industry, Furniture & Fixtures, Leather Tanning, and Lumber & Wood industry was on average 62%, 52%, 51%, 61%, 61%, 62% and 65% efficient respectively. Other industries were less than 50% efficient on average throughout the period under review. The slack analysis shows that while capital was adequately utilized, labour was needlessly in excess of what is currently required. Total Factor Productivity grew at a constant rate of -0.6% during the period under review (2000-2014) which suggests regress in TFP. At the annual level, we found that TFP shock was particularly low in the years marked with financial crisis such as 2001, and 2008-2009. We also found that TFP regress occurred in recent years (2011, 2012 & 2014). Nevertheless, positive TFP was observed in other years which were a result of technological change and efficiency improvement. We further decomposed the result into industry level in order to understand the contribution of individual industry to the overall TFP. We found that all industries showed a similar trend in comparison with the annual mean result. We also found that different industry had different learning rates/levels. While some industries had better learning after some beginning period, others showed good learning potentials at some beginning and end period implying forgetting at some mid-period. Specifically, Production Machinery, Electrical Devices & Circuit, Chemical & Pharmaceutical, Food, and Furniture & Fixtures industries showed good learning potentials for the most part of the study period. Nevertheless, the overall result showed that learning was getting worse in recent years. In other words, Japanese manufacturing industry as a whole is at forgetting stage.

CHAPTER ONE

1.0 Introduction

1.1 Japanese Manufacturing Industry and its Performance in Recent Times

History has it that Japan enjoyed very rapid growth from the 1950s to 1970s driven by industrialization. During this period, the manufacturing sector expanded strongly, making Japan the second largest economy after the US by the end of the 1960s (Ohno, 2006). However, following the burst of the Japanese economy in 1991 known widely as “bubble economy”, Japan productivity has been declining for more than two decades now (Kim, 2015), (Fukao, 2013). Japan GDP growth rate was negative from the early 1990s onward with slight recovery at few intervals of time. Particularly in 2009, Japan GDP growth was estimated at -5.5%. Although there was huge recovery in 2011, more recently, however, the GDP growth rate was estimated at approximately 0.5 (see Figure 1.1)

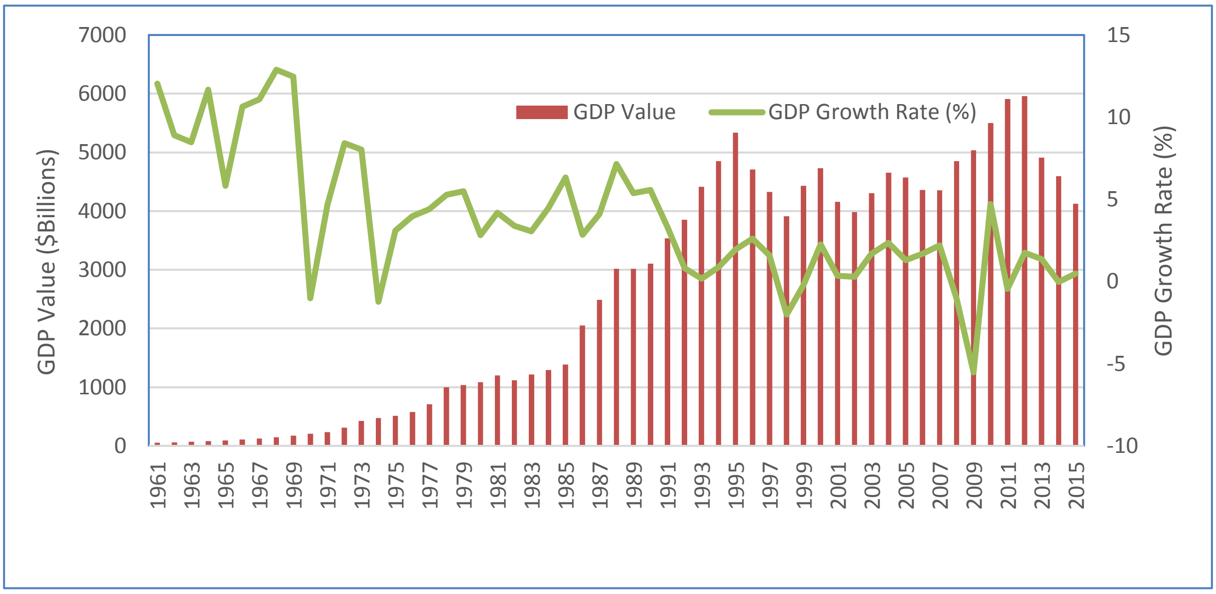


Figure 1.1: Japan GDP value and growth rate from 1961 to 2015 (Source: Author’s analysis based on World Bank Data, 2016)

Figure 1.2 depicts the changes in the competitiveness of manufacturing industries and regions (expressed as changes in the share of total value added by manufacturing industries). Unlike other emerging Asian countries, the shares of Japan and United States has declined. To regain and maintain its competitiveness, the Japanese manufacturing industries has long shifted their production base to overseas, accelerating operations and increasing overseas production percentages-a situation MITI believe may harm the local economy of Japanese by breaking employment and technological clusters.

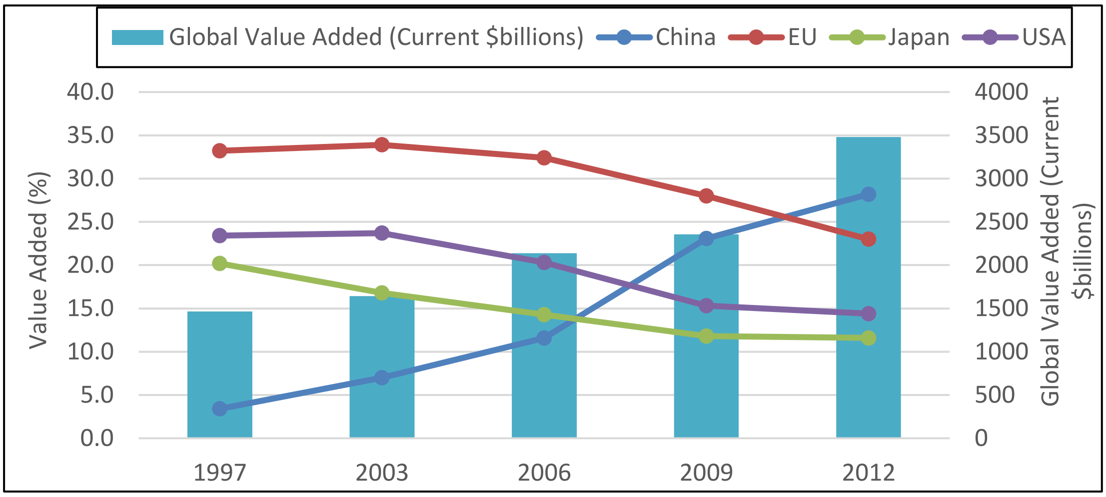


Figure 1.2. Changes in Competitiveness of Manufacturing Industries and Regions (Source: Author's analysis based on OECD Stats Data)

Despite economic stagnation for more than two decades, the Japanese industrial sector, powered by the manufacturing sector are still among the most advanced and innovative in the world. Manufacturing products such as those from electronics and automobiles are among the most technologically advanced worldwide. In 2012, the industrial sector contribution to GDP was put at 27.5% (World Economy Team, 2013) and in 2014, it declined sharply to 18.7% (World Bank, 2016). Japanese manufacturers continuous to wax stronger in automobiles, robots and other transport equipment. The Japanese share of the construction of Boeing aircraft continuous to increase steadily from 15% in B767 to about 35% in B787-the most efficient aircraft of its kind in the world according to expert opinion. Japanese robot makers have more than 70% of the global market (MITI, 2010). Major manufacturing industries in Japan include; electronic equipment, machine tools, motor vehicles, steel and non-ferrous metal, ships, chemicals, textiles and processed foods. As at 2010, the manufacturing industry was responsible for 90% of Japan export, despite fierce competition from another rising economy in Asia namely China (MITI, 2010).

Sadly though, the Japanese manufacturing industries now struggle to maintain its global competitiveness with many factors being cited as the drawbacks. One study (Kadokawa, 2009) argued that the root of the problem lies with the past successes namely; past relationship between banks and manufacturing industries which resulted in very high productivity, the seniority-based employment system, guaranteed life-long employment, enterprise based organized workforce, and the risk-sharing relationship between main manufacturer and network of subcontractors (keiretsu) which resulted to fast rate of technology transfer and further pushed up manufacturing productivity. All of these success factors also prove to be the Achilles' heel of the Japanese economy (Jurgen & Kadokawa, 2010).

Nevertheless, the Japanese government continuous expansionary monetary policy measure aimed at stimulating the economy and to boost private sector investment is thought to restore her competitiveness in the global arena sooner or later. (Kim, 2016).

1.2 Research Rationale/Justification

Among the most important indicators of economic performance are productivity and technological learning. These two components demonstrate the competitiveness of any firm in any given industry. There is perhaps no time in human history that managers are so much under pressure to utilize resources efficiently like in recent times. Due to resource depletion and severe scarcity, improving performance and exploring ways to optimize resource allocation and utilization has become a matter of necessity for survival. Given the importance of the manufacturing industries to the Japanese economy, the Asian region, and its role in the global economy, this study seeks to measure the productivity change, technical progress and technological learning in the Japanese manufacturing industries. The study will also measure technological learning and its contribution to productivity growth or otherwise in the Japanese manufacturing sector.

1.3 Research Questions

The principal focus of this research work is measuring TFP and technological learning. To achieve this, the study will answer the following questions

1. How efficient are resources (labour & capital) utilized in Japanese manufacturing industries?
2. What is the impact of technological change on the Productivity of Japanese manufacturing industries?
3. What is the path of Technological learning in Japanese manufacturing industries?
4. What are the Progress Ratio (Learning Rate) for individual Japanese manufacturing industries?

1.4 Research Objectives

1. To estimate the technical efficiency change of Japanese manufacturing Industries.
2. To estimate TFP change of Japanese manufacturing industries via Malmquist index.
3. To estimate the technological change/progress in Japanese manufacturing industries using DEA.
4. To estimate the Learning Rate of Japan Manufacturing Industries using both linear and cubic learning models.

1.5 Significance of the Study

Granted there is declining productivity (TFP) in Japan, however, measuring the contribution of TFP growth of individual industries at the 3-digit levels will help reveal those industries with potentials and those with the urgent need of intervention. Moreover, it will also be helpful to know if advances or changes in technologies in Japanese manufacturing industries are at the expense of huge cost (technological forgetting) or real cost saving (technological learning).

1.6 Scope and Limitations of the Study

The data for this study covers all manufacturing industries at the 3 digit levels classified according to Japan Standard Industrial Classification (JSIC) and span through 2000 to 2014 physical year. Labour (proxied for a number of people hired), and capital (tangible fixed assets) were used as inputs, while total sales as output. At the 3-digit classification, the total manufacturing industries were summarized into 24 distinct industries based on their specialized features. Some cost structure such as total remuneration (wages paid) which could have provided robust results were missing from the data. Additionally, the quality of labour (level of education attained by workers) could have add substance to the result if such data were to be available. Furthermore, the method of DEA which this study used for TFP estimation assumes data to be free of measurement error, and therefore become more sensitive to the presence of measurement error than the parametric techniques.

CHAPTER TWO

2.0 Literature Review

2.1 Productivity and its Economic Implications

The simplest and generic definition of productivity was perhaps that given by Rogers, (1998) in which he defined productivity to mean the ratio of output to input for a given production mix. According to one source, productivity measures the efficiency with which resources are used to generate the desired output in any given economic processes (Li & Prescott, 2009). Productivity growth (rise) could either mean more outputs are being produced with the same amount of inputs or the same level of outputs are produced with lesser inputs needed (Rogers, 1998).

Productivity can easily be understood from the viewpoint of efficiency. In this case, the allocation of productive assets in a more efficient way (Braguinsky, Ohyama, Okazak, & Syverson, 2015). An efficient firm is that which is operating at production frontier i.e. practicing the best production mix or achieving the best practice (Rogers, 1998).

At the macroeconomic level, productivity measure is used to show the strength and competitiveness of countries or region. Hence productivity growth is almost always the most important engine of economic growth for any given industry or economy. Moreover, productivity growth has the benefit of improving standard of living and providing additional goods and services (Bally et al., 1992)

2.2 Multifactor/Total Factor Productivity Measurement and It's Usage.

Different types of productivity measure exist in literature and the choice of what type(s) to use depends entirely on the reason and purpose of measuring it. Labour Productivity (LP), Capital

Productivity (CP), Multifactor or Total Factor Productivity (MFP, TFP), etc. are few of the most frequently used productivity measure. Multifactor or Total Factor Productivity (TFP) measure which is the subject matter of this research has found extensive use especially in the manufacturing sector of the economy. TFP refer to the ratio of output to a total aggregate of inputs used. Total factor productivity has also been defined to mean technology and by this definition, it refers to all methods employed by labour and capital to produce goods or services more quickly and more efficiently (Jajri, 2007). In the same paper, Jajri also argued that besides being a technological improvement, TFP also mean improvement in the quality of inputs due to factors such as human resources development and human resources management.

When only labour and capital are used as inputs, total factor productivity index measures annual change in output per unit of combined labour and capital input. According to U.S Department of Labour (1983), since TFP shows the growth in output that has been obtained from a given amount of capital and labour, it, therefore, can be interpreted as one of a number of indicators of the economic progress. The converse is also true, TFP can refer to the reduction over time in the quantity of labour and capital used to produce a unit of output. TFP growth can be decomposed into technical progress and gains in technical efficiency using Malmquist index.

TFP growth is considered to be of economic importance and has been investigated by many researchers. For example, Ikemoto (1986) estimated the TFP growth rate for several Asian economies between 1970-1980 using the Tornqvist index and found the contributions of TFP growth to the overall growth in Taipei, China and Republic of Korea to be very high. Using a manufacturing survey data of Malaysia between 1973-1989, Maison & Arshad (1992) showed TFP growth increased continuously in each year, though its contribution to the overall manufacturing sector growth was still small.

2.3 Factors Affecting Total Factor Productivity Change

Many factors have been identified in the literature to influence TFP. One of such is technological progress. When inputs including R&D are efficiently utilized such that there is a portion of output (residual) not explained by the inputs, then this residual which is also known as TFP is a result of technical progress (SriPoorni & Manonmani, 2014).

Education and skill acquisition (training) which ultimately led to higher quality of workforce or labour has also been noted to have contributed to TFP growth. According to this argument, upgrade in skill and knowledge will result in higher skill and in turn lead to more efficient workers and higher productivity (Jajri, 2007). Other factors such as economic restructuring (movement of resources from less productive to the more productive sector of the economy), capital investment, and demand intensity/ changes were found to have a great impact on TFP (Jajri, 2007).

2.4 Reasons for Measuring Productivity

Among the frequently stated reasons for measuring productivity growth, was to trace the change in technology (innovation) over time. Technology could appear either in its disembodied form such as blueprints, scientific results, new organizational techniques or its embodied form such as advances in design, quality of new vintages of capital goods and intermediate inputs (OECD, 2001). Productivity measure also helps to identify changes in technical efficiencies which in turn lead to the elimination of technical or organizational inefficiencies and movement towards best practice. Real cost saving and living standards among other things have also been cited as reasons for measuring productivity. It is thought that productivity measure can be undertaken for the purpose of identifying real cost saving in productions and for the development of living standards (OECD, 2001).

2.5 Data Envelopment Analysis

Data Envelopment Analysis (DEA) has been used extensively in efficiency and productivity measure since its introduction by Charnes, Cooper, & Rhodes, (1978) more than three decades ago. The concept of DEA is simple. DEA construct a non-parametric frontier over a data by computing a comparative ratio of weighted outputs to weighted inputs for each Decision-Making Units (DMU) relative to the best performing decision-making unit. DEA compares production units considering all resources used and identifies the most efficient units (called Frontiers) and the inefficient units in which real efficiency improvements are possible. Point D in Figure 2.1 shows the inefficient unit(s) where real improvement can be made and point A is the frontier (best practice) point relative to DEA fitted line (yellow line).

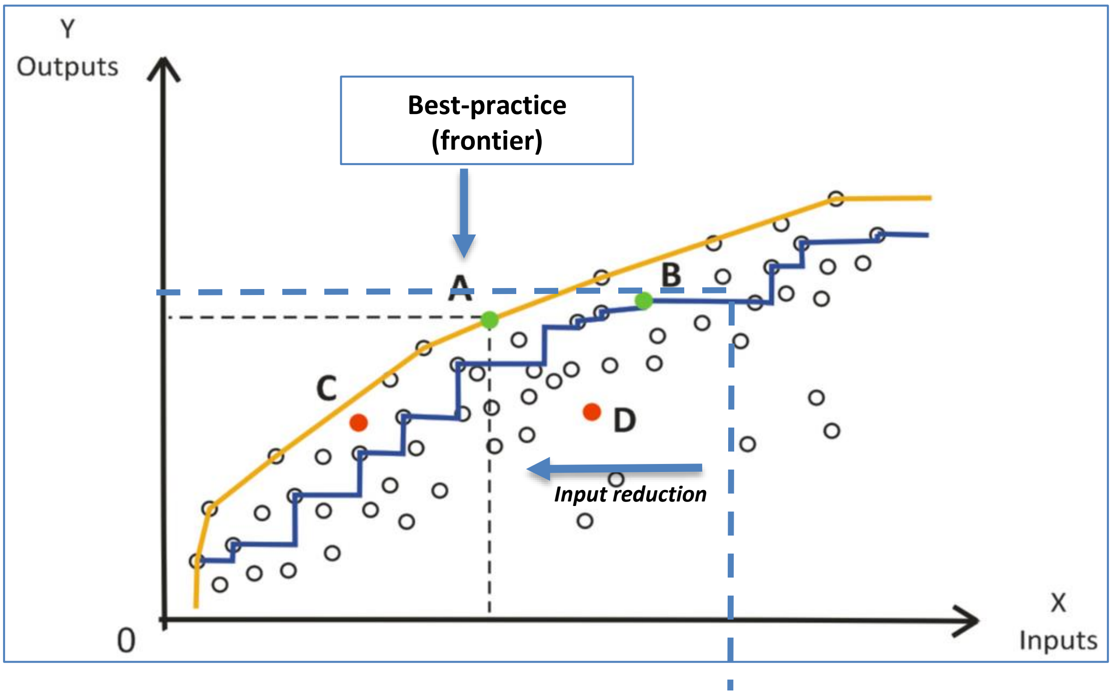


Figure 2.1: Production space with single input and single output (source: Carvalho & Marques, 2016)

DEA has a number of advantages of over the parametric measure of efficiency and productivity. In DEA, no prior knowledge of input and output relationship is needed and there are no limit or restriction on the candidate variables (inputs and outputs) to be used (Cooper, Seiford, & Tone, 2007). As a result, DEA has been used in virtually all fields of human endeavor.

Markovic et al. (2015) estimated the productivity change of Serbian banks using the method of data envelopment analysis. Carvalho & Marques (2016) computes the economies of scope using partial nonparametric methods (DEA). Rogers (1998) contrast between DEA and stochastic production frontier and underscore the simplicity of the former over the later. Jajri (2007) investigated the determinant of total factor productivity growth in Malaysia using DEA and found that innovation was the major cause of the shift in the frontier.

2.6 The Learning Curve Theory

When there are changes in fixed production inputs (cost reduction) in manufacturing process not attributable to short time fluctuation in unit prices of variable inputs, this is likely as a result of efficiency (improvement) with which the working process has changed over time. One may argue that this increased efficiency in processes was due to or can be explained by the increased familiarity with the routine of such processes. This process is called learning-by-doing. Figure 2.2 illustrates this simple but important phenomenon. Suppose that a repetitive task/process with a fixed cost C_t begin and continues from time n_t to time n_{t+1}, the unit cost began to decline as efficiency set in due to the familiarity of workers with the process/task.

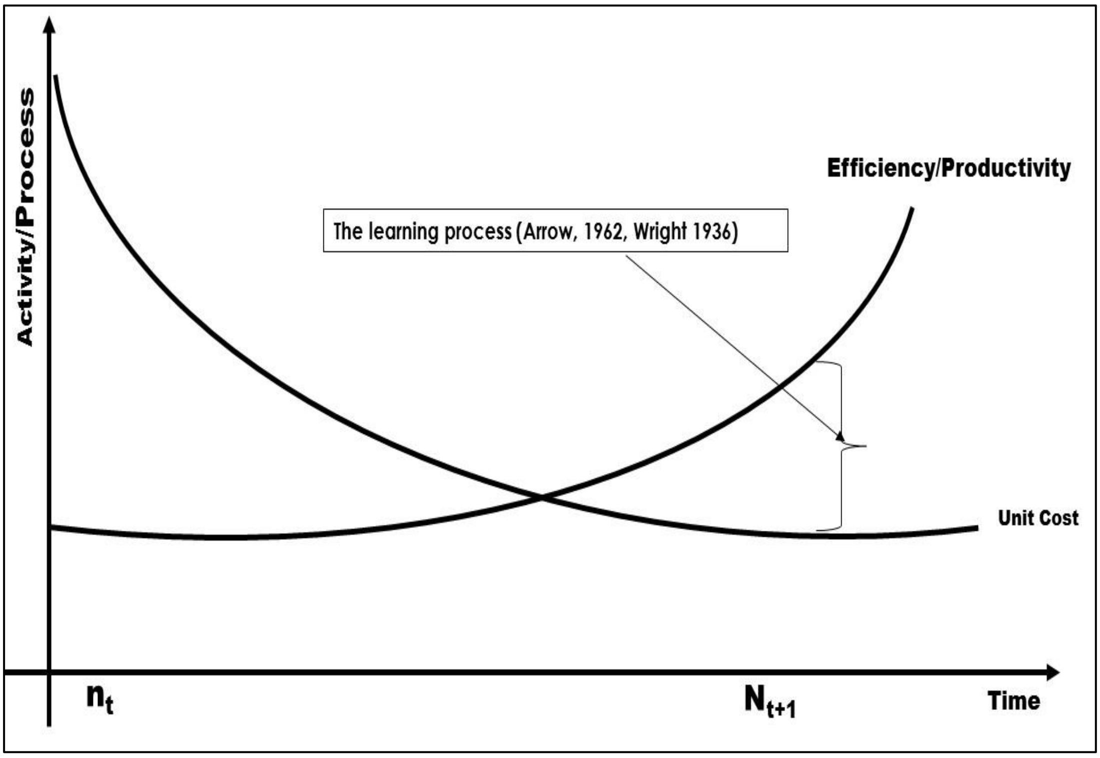


Figure 2.2: Simple Illustration of the Learning Concepts (Source: Authors Concept)

This phenomenon was first observed by T. P. Wright in 1936 when studying the factors affecting the cost of airplanes in the aircraft industry. Wright observed that the direct labour input required to produce each series of the airframe of a particular plane model diminished at a uniform rate as the production accumulated (Krawiec, Thornton, & Edesses, 1980). Learning-by-doing also reflects the efficiency gained in production processes, improvement in tooling and in the design of manufactured components and increased in proficiency of individual employees (US-EPA, 2016).

Table 2.1: List of Articles Focusing on Learning Curve Theory

Year	Researcher	Publication
1936	Wright, T. P.	Factors affecting the cost of airplanes
1953	Wyer, R.	Learning curve helps figure profits, control costs
1954	Andress, F. J.	The learning curve as a production tool
1961	Taylor, M. L.	The learning curve - A basic cost prediction tool
1962	Arrow, K.	The Economic Implications of Learning by Doing
1966	Baloff, N.	The learning curve - Some controversial issues
1967	Baloff, N. and J. W. Kennelly.	Accounting implications of product and process start-ups
1972	Consulting, Boston.	Perspectives on Experience
1974	Henderson, B.	The experience curve reviewed: V. price stability
1978	Harris, L. C., and W. L Stephens.	The learning curve: A case study
1979	Yelle, L. E.	The learning curve: Historical review and comprehensive survey
1982	Ramanathan, R.	Lecture Notes in Economics and Mathematical Systems
1986	Belkaoui, A.	The Learning Curve
1989	Bailey, C. D.	Forgetting and the learning curve
1991	Adler, P. S., & Clark, K. B.	Behind the Learning Curve: A Sketch of the Learning Process
1992	Badiru, A. B.	Computational Survey of Univariate and Multivariate Learning Curve Models
1997	Hornstein, A., & Peled, D.	External vs. Internal Learning-by-Doing in an R&D Based Growth Model
2000	Pramongkit, P., Shawyun, T., & Sirinaovakul, B.	Analysis of Technological Learning for the Thai Manufacturing Industry
2001	Ruttan, V. W.	Technology, Growth, and Development. An Induced Innovation Perspective
2005	Karaoz, M., & Albeni, M.	Dynamic Technological Learning Trends in Turkish Manufacturing Industries
2009	Asgari, B., & Yen, L. W.	Accumulated Knowledge and Technological Progress in Terms of Learning Rates: A Comparative Analysis on the Manufacturing Industry and the Service Industry in Malaysia
2012	Behrooz Asgari, Jose Luis Gonzalez-Cortez	Measurement of Technological Progress through Analysis of Learning Rates; the Case of Manufacturing Industry in Mexico

Source: Asgari & Gonzalez-Cortex (2012)

Since the work of T. P. Wright in 1936, the concept and theory of learning-by-doing have gained wide applications. For example, about a decade after the work of Wright, Wyer (1953) found that learning curve helps figure profit and control cost. Andress (1954) dedicated an entire book to learning and titled it as "the Learning Curve as a Production Tool". Taylor (1961) found that the learning can be used as a basic cost prediction tool. Arrow (1962) illustrated the practical economic implication of learning-by-doing. Table 2.1 give the historical review of the articles written on the concept of learning-by-doing. The list is by no mean exhaustive. This suggests the relevance of this very important phenomenon in cost saving and technological progress review.

2.7 Emergent of the Experience Curve

Learning is a product of cumulative experience. Learning takes place as a result of cumulative experience. The concept of experience curve is somewhat similar to the learning curve and are sometimes used interchangeably, however, the two concepts are somewhat different. From the viewpoint of Boston Consulting (1970), when a firm become more experienced in producing a particular product, its cost lower at every doubling of the cumulative output of that particular products. Just like individual workers learn, organizations as a whole also learn from purchases/procurement, capital investment, improvement in administrative processes etc.

One particularly interesting aspect of experience curve is that, just like the learning curve, different product has different experience curve. For example, Boston Consulting found that the cost of manufacturing fell by 25% for each doubling of cumulative production in semiconductor plant, a study by Rand Corporation found that doubling the cumulative output of nuclear reactor built by engineers result in a 5%-unit price reduction in both construction time and capital cost (The Economist, 2009).

The focus of the experience curve is the organization and its processes. Experience curve emphasized cost reduction in the cost of all inputs used in manufacturing and not just single input, and by extension, it applies to the cumulative learning effect from the single factor to the entire industrial settings. Notably, the experience curve has been used as a tool for long-term strategic planning since it has the ability to show how cost per unit output decline as production increases or doubled in manufacturing, marketing distribution, capital investment etc. (Karaoz & Albeni, 2005).

2.8 S-Curve Model

Since learning is dynamic and varies over time, many studies have attempted to approximate the learning curve with the S-Curve shape (Karaoz & Albeni, 2005), (Yelle, 1979), (Badiru, 1992) (Carlsson, 1996). The nonlinear approach to estimation of the learning curve is useful in that it adequately estimates the long-term annual technological progress ratio while providing a sound framework for predicting the past and future path to technological forecasting (Karaoz & Albeni, 2005).

Figure 2.3 illustrate the traditional and the S-Curve models of a learning curve. According to Karaoz & Albeni (2005), "Figure 2.3 shows that the first derivative or slope of the S-curve model show variable or dynamic learning elasticities and progress ratio while moving along the curve". This suggests that learning is progressive and is affected by time and can either be sustained or lost. When learning is lost, forgetting sets in.

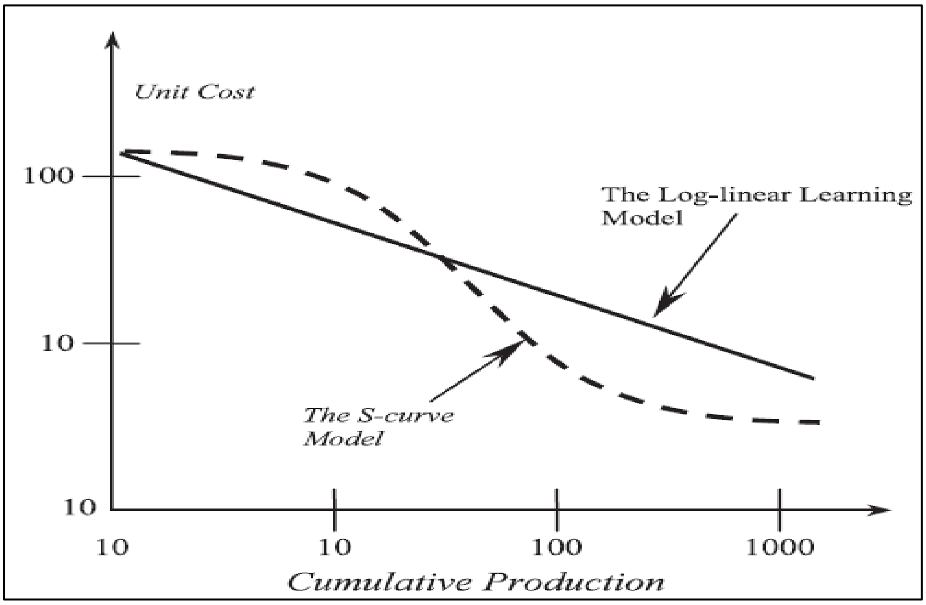


Figure 2.3: The Traditional and S-shaped Learning Curves (in log scale) (Source: Karaoz & Albeni, 2005)

2.9 Technological Learning, Progress, & Capability and its Economic Implications

Learning is crucial for the efficient development of industries and for building stock of technical progress and capability. It has also been recognized that improving productivity through building technological capability is key to economic growth and development, more so in the current global competitive economic environment. This process, scholars agreed can be achieved through continuous measuring and monitoring of technological learning (Karaoz & Albeni, 2005). The process of learning has been found to reduce unit labour requirement and can lower cost of production considerably.

Technological capability refers to an ongoing process of learning that involves experimenting with new and effective ways to accumulate and use technology. It is the accumulation of technological knowledge and the effective use of same knowledge for the purpose of economic advancement and development. Kim, 2001 argue that such ability in technological capability, when effectively utilized in areas such as production, engineering, and innovation can lead to sustained competitiveness in price and quality. Technological capability in the industry has been defined by Najmabadi and Lall (1995) to mean "skills (both technical and organizational) that are necessary for enterprises to set up, efficiently utilized, improve, and expand a plant over time, and to develop new products and processes".

How are technological capabilities built? For some, the process of technological capability involves technological learning; a process of accumulation of skills, competencies, and experiences that drive changes in the productive system (Platt & Wilson, 1999). Technological learning is the path along which technological capability are built or accumulated and the trajectory may change over time. This process of technological learning and capability building (which is time dependent) can be term as "technological change" (see Figure 2.4).

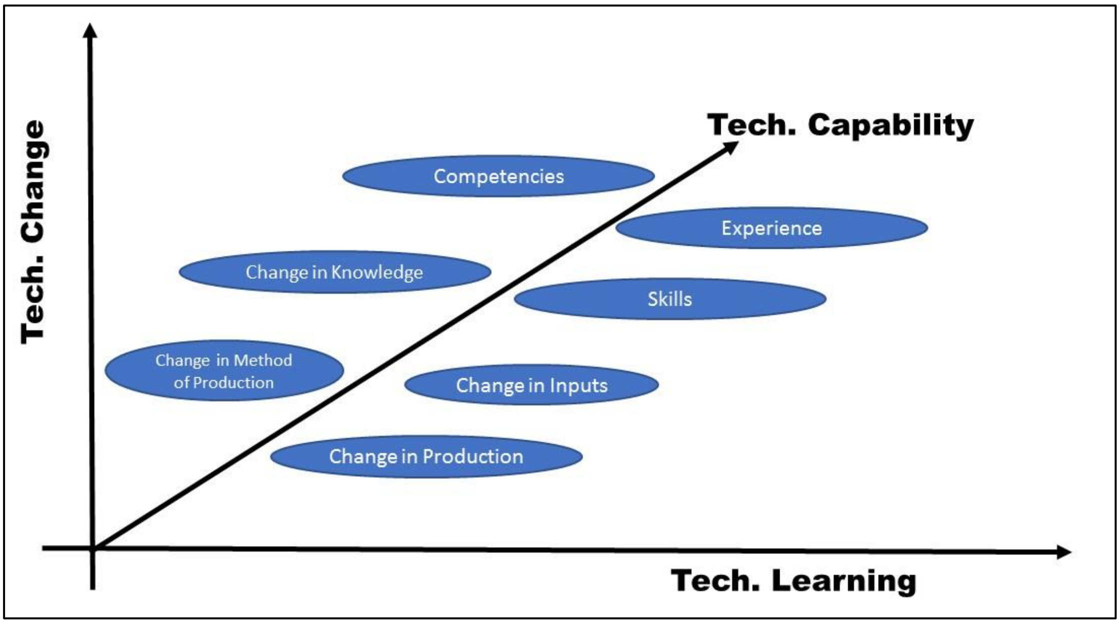


Figure 2.4: Simple Illustration of Technological Capability Building (Source: Author's Concept)

Technological change is the driving force of economic activities and the importance of this phenomenon has been documented by economics and scientists (Jackson, 1998) (Solow, 1956). Technological change refers to a change in knowledge about production, methods of production, products or inputs in making products which all spring up from invention or innovations (Jackson, 1998). It also refers to the continuous replacement and improvement of technologies or innovations, which result from interactions of new and old technologies (Asgari & Yen, 2009). As also noted by Barreto-Gomez (2001), "technological change is a proceed of cumulative social learning process or change with knowledge and experience as its pillars or base". This suggests that changes in technology over time are driven by previous knowledge of technologies which accumulates over time and which form the stock of experience that is needed for efficient implementation of innovations.

CHAPTER 3

3.0 Research Methodology

3.1 Data Collection Procedure

The input-output data used for this research was collected from Japan ministry of economy, trade, and industry (METI) official website. The variables in the data namely; the number of people hired (labour), tangible fixed assets, and sales, originally written in Japanese were translated into English.

3.2 Data Processing

To stabilize the variance of random or seasonal fluctuation in the price of inputs or factors of production, the data was deflated using consumer price index (CPI). The advantage is that it will enable us to uncover real growth in efficiency and productivity (TFP) in these industries during the period under consideration. Due to the long period considered, the time series CPI for all items published by Statistics Bureau, Ministry of Internal Affairs and Communication (Japan Statistics, 2014), with 2010 as the base year, was used to deflate the data.

The data was aggregated for each industry base on the 3-digit Japan Standard Industrial Classification (JSIC). This brings the total manufacturing industries to 24 *(see Appendix A for a summary of the manufacturing industries considered).*

3.3 Classification Based on Technological Intensity

The 24 aggregated manufacturing industries were classified into sub-sectors based on their technological intensity which reflects their R&D intensity. The OECD technology intensity definition 2011, classifies manufacturing industries into four categories based on their R&D intensity, namely; high-technology, medium-high-technology, medium low-technology and low-technology industries. However, the data for this study could only be classified into 3 categories, namely; high & medium-high-technology, Medium low-technology and low-technology. This is because it was difficult to separate the industries under the high technologies and the medium high technologies given that they overlapped (see Table 1.1). Hence the data analysis will consider both categories as one; namely high & medium-high technology industries.

Table 3.1: OECD Industrial Classification

High-technology industries	**Medium-high-technology industries**
• *Aircraft and spacecraft* • *Pharmaceuticals* • *Office, accounting, and computing machinery* • *Radio, TV and communications equipment* • *Medical, precision and optical instruments*	• *Electrical machinery and apparatus, n.e.c.* • *Motor vehicles, trailers and semi-trailers* • *Chemicals excluding pharmaceuticals* • *Railroad equipment and transport equipment, n.e.c.* • *Machinery and equipment, n.e.c*
Medium-low-technology industries	**Low-technology industries**
• *Building and repairing of ships and boats* • *Rubber and plastics products* • *Coke, refined petroleum products and nuclear fuel* • *Other non-metallic mineral products* • *Basic metals and fabricated metal products*	• *Manufacturing, n.e.c.; Recycling* • *Wood, pulp, paper, paper products, printing, and publishing* • *Food products, beverages, and tobacco* • *Textiles, textile products, leather and footwear*

Source: OECD Directorate for Science, Technology, and Industry, Economic Analysis and Statistics Division

3.4 Data Envelopment Analysis Models (DEA)

Data Envelopment Analysis (DEA) is a mathematical method involving the use of linear programming method to construct a non-parametric frontier over a data (Tim, 1996). DEA can also be defined as a non-parametric mathematical tool for assessing the relative efficiency of decision-making units (DMU) (Orku, Balikci, Dogan, & Genc, 2016). DEA was first proposed by Charnes et al 1987 called the CCR model (Charnes, Cooper and Rhodes model) and has found extensive application over the years.

The advantage of DEA over other efficiency measuring tools is that it doesn't require that the exact nature of the relationships between multiple inputs and multiple outputs be known in advance, and there is no restriction on the number of candidate variables to be used for analysis (Cooper, Seiford, & Tone, 2007). This study utilizes DEA in two-folds; first the technical efficiencies for each manufacturing industries were calculated, and second, the Malmquist DEA methods were applied to the panel data to isolate the Malmquist indices namely; total factor productivity change, technological change, and efficiency change.

The DEA CCR assume each firm as a decision-making unit (DMU) and construct a non-parametric linear programming model that can adequately intersect the data point such that observed data point lies below or above the production frontier. Using ratio form each DMU can be represented as a ratio of all outputs over all inputs, in the form $u'y_i/v'x_i$ where u and v are Qx1 and Ox1 vectors of input and output weights respectively. In order to select the optimal weight, we construct the mathematical programming problem of the form;

$$Maxu, v\ (u'yi/v'xi)$$

$$\text{st} \quad u'yj/v'xj \ \leq 1, j = 1,2, \dots, N, \qquad 1$$

$$u, v \geq 0\ (u\ and\ v\ is\ a\ non-negative\ variables)$$

Where yi, and xi are output and inputs variables respectively to be maximized.

Equation 1 involves finding the optimum values of u and v such that efficiency of i^{th} DMU is maximized subject to the constraints that all efficiency measures takes on values between zero and one. To avoid the problem of infinite estimation or solution, we can impose another constraints $v'x_i=1$ to equation 1 to get equation 2;

$$Maxu, v\ (u'yi)$$

$$\text{st} \quad v'xi = 1$$

$$u'yj - v'xj \ \leq 0, j = 1,2, \dots, N, \qquad 2$$

$$u, v \geq 0$$

The duality in linear programming enables us to derive the equivalent of envelopment form of problem 2 in the form expressed in 3;

$Min_{\theta\tau}, \theta$ 3

st $-y_i + Y\tau \geq 0$

$\theta x_i - X\tau \geq 0$

$\tau \geq 0$

where θ is a scalar and τ is Nx1 vector of constants. The value of θ defines the efficiency for the ith DMU and lies between 0 and 1. According to Farrel 1957, DMU having $\theta = 1$ implies a technically efficient decision-making unit of the production process.

3.5 Malmquist Index Measurement

In analyzing panel data, DEA-like linear program and Malmquist TFP index can be used to measure productivity change which can further be decomposed into technical/technological change and technical efficiency change (Tim, 1996).

According to Fare et al (1994), an output-based productivity change index can be specified as;

$$m_o(y_{t+1}, x_{t+1}, y_t, x_t) = \left[\frac{d_o^t(x_{t+1}, y_{t+1})}{d_o^t(x_t, y_t)} \times \frac{d_o^{t+1}(x_{t+1}, y_{t+1})}{d_o^{t+1}(x_t, y_t)}\right]^{1/2} \quad 4$$

The left side of the ratio in the parenthesis in equation 4 defines the change in technical efficiency of the production unit at x_{t+1}, y_{t+1} relative to its previous point at x_t, y_t. While the right ratio represents the shift in production technologies or technical change from time t to t+1. The product of the two ratios give the so-called Malmquist productivity change (total factor productivity (Fare et al 1994). Any value of equation 4 greater than unity implies positive TFP growth within the time period under study namely; from t to t+1. In the original work of Fare et al 1994, this index is thought to be the geometric mean of two output based Malmquist TFP indices where one index uses period t technology and the other period t+1 technology.

Under the assumption of CRS, equation 4 can be decomposed into four component distance functions involving four linear programming problems.

$max_{\emptyset,\delta}\emptyset = [d_o^t(x_t y_t)]^{-1}$

st $\quad -\emptyset y_{it} + Y_t\delta \geq 0$

$x_{it} - X_t\delta \geq 0$

$\delta \geq 0.$ 5

The remaining 3 LP models are variant of equation 5

$max_{\emptyset,\delta}\emptyset = [d_o^{t+1}(x_{t+1} y_{t+1})]^{-1}$

st $\quad -\emptyset y_{it+1} + Y_{t+1}\delta \geq 0$

$x_{it+1} - X_{t+1}\delta \geq 0$

$\delta \geq 0.$ 6

$max_{\emptyset,\delta}\emptyset = [d_o^t(x_{t+1} y_{t+1})]^{-1}$

st $\quad -\emptyset y_{it+1} + Y_t\delta \geq 0$

$x_{it+1} - X_t\delta \geq 0$

$\delta \geq 0.$ 7

$max_{\emptyset,\delta}\emptyset = [d_o^{t+1}(x_t y_t)]^{-1}$

st $\quad -\emptyset y_{it} + Y_{t+1}\delta \geq 0$

$x_{it} - X_{t+1}\delta \geq 0$

$\delta \geq 0.$ 8

3.6 Linear Model of the Learning Curve

The linear learning curve estimation will be used to estimate the progress ratio under the so-called traditional linear experience curve assumption. The most general mathematical learning model can be expressed as;

$C_t = C_1 X_t^{-\alpha},$ *9*

or equivalently logged as;

$lnC_t = lnC_1 - \alpha lnX_t$ *10*

Where

C_t is the labour input per unit of output at time t, C_1 is the labour input needed to produce the first unit of output, X_t is the cumulative number of units produce until time t, and α is the desired learning elasticity or progress index to be estimated.

Equation 10 suggests that the current level of unit cost at time t (C_t), is a function of cumulative production level X_t, and the cost of producing the first unit C_1 in the production process (Karaoz & Albeni, 2005). Since the learning effect is quantified by the value of α, it then follows that larger value of α implies better learning outcome.

The so-called progress ratio (d) is derived from the learning elasticity α. The progress indicates that every doubling of total production reduces unit production by a factor of $2^{-\alpha}$. This is expressed as;

$$d=2^{-\alpha} \qquad 11$$

For a production system exhibiting learning potential, equation 11 takes on a value between 0 and less than unity (i.e. $0 \leq d < 1$). When the value of d approaches 0, the learning becomes better and better, and whereas, the value of d close to 1 implies low learning rate. When d=1, it means there is neither learning nor forgetting, i.e. no cost saving at doubling of unit production or equivalently in economic terms, it means there is neither improvement or worsening of unit production cost (Karaoz & Albeni, 2005). The value of d>1 implies forgetting or increase in the unit cost of production at each doubling of cumulative production. The interpretation of the progress ratio (d) is somewhat straightforward (see Table 3.2)

Table 3.2: Boundary of Progress Ratio and its Meaning

d<1	d=1	d>1
Learning state	No learning, no forgetting	Forgetting stage
Unit production cost decrease as output increases	Unit production cost remains the same as output increases	Unit production cost increases as output increases
Efficiency increases	No change in efficiency	Efficiency decreases
Productivity increases	No change in productivity	Productivity decreases

Source: (Asgari & Gonzalez-Cortez, 2012)

In the learning literature, the neoclassical production function is readily used to quantify the learning curve effect, following the assumption that learning is part of productivity (Pramongkit, Shawyun, & Boonmark, 2000), (Karaoz & Albeni, 2005).

The traditional neoclassical production function states that production level Q_t, in time t, is a function of labour L_t, employed at time t, and capital K_t, invested at time t. This can be expressed as;

$$Q = A_t . L^{\beta} . K^{\gamma} \qquad 12$$

Where β and γ define the elasticity of labour and capital respectively, and their sum ($\beta + \gamma$) measure the return to scale production function.

The parameter A_t in Equation 12 is called multifactor productivity. It depicts the current level of technology or advances in knowledge base at time t.

The logarithmic form of equation 12 is expressed as;

$$lnQ_t = lnA_t + \beta lnL_t + \gamma lnK_t \qquad 13$$

Equation 12 assumes that there exists a functional relationship between A_t and cumulative production X_t which can be expressed as;

$$A_t = HX_t^{\alpha} \qquad 14$$

Where H represent the proportionality constant, and X_t^{α} is the inverse of $X_t^{-\alpha}$ earlier expressed in equation 9. The natural log form of 14 can be expressed as;

$$lnA_t = lnH + \alpha lnX_t \qquad 15$$

Also, by rearranging 9, we could get an equivalent relation as;

$X_t^{\alpha} = \frac{C_1}{C_t}$, hence, we could rewrite equation 14 in the form in (16);

$$A_t = H \frac{C_1}{C_t}, \qquad 16$$

And using the natural logarithm, 16 can be written in a linear form as;

$$lnA_t = lnH + \ln(\frac{C_1}{C_t}) \qquad 17$$

If we combine 13 and 15 and substitute for A_t, we have

$$lnQ_t = lnH + \alpha lnX_t + \beta lnL_t + \gamma lnK_t \qquad 18$$

By adding lnL_t from both sides of equation 18 and multiplying the results by -1, the following algebraic expressions ensued;

$$lnQ_t - lnL_t = lnH + \alpha lnX_t + \beta lnL_t + \gamma lnK_t - lnL_t$$

$$(lnQ_t - lnL_t = lnH + \alpha lnX_t + \beta lnL_t + \gamma lnK_t - lnL_t) \times -1$$

$lnL_t - lnQ_t = -lnH - \alpha lnX_t - \beta lnL_t - \gamma lnK_t + lnL_t$ or equivalently as;

$$ln\left(\frac{L}{Q}\right)_t = -lnH - \alpha lnX_t + (1 - \beta lnL_t) - \gamma lnK_t \qquad 19$$

As output expand the relationship between labour and capital can be expressed in the form;

$$K_t = \mu L_t^{\lambda} \qquad 20$$

Where the parameters μ *and* λ are constants. The value of λ indicates the technical biases associated with production expansion. *λ=1* indicate neutrality in technological progress whereas *λ>1,* suggests that capital labour ratio proportionally increases as output expands see (Pramongkit, Shawyun, & Boonmark, 2000), (Karaoz & Albeni, 2005).

The logarithm form of 20 is expressed as;

$$lnK_t = ln\mu + \lambda lnL_t \qquad 21$$

Combining 19 and 21, and substituting for lnK_t will result to 22;

$$ln\left(\frac{L}{Q}\right)_t = -lnH - \gamma ln\mu - \alpha lnX_t + (1 - \beta - \gamma\lambda)lnL_t \qquad 22$$

22 is the equation for empirical estimation of the learning curve which can be expressed in more simpler term as;

$$lnC_t = \theta_0 + \theta_1 lnX_t + \theta_2 lnL_t + \varepsilon_t \qquad 23$$

Where $lnC_t = ln(\frac{L}{Q})_t, \theta_0 = -lnH - \gamma ln\mu, \theta_1 = -\alpha, \theta_2 = 1 - \beta - \gamma\lambda$, and ε_t is the stochastic term.

3.7 The Cubic Learning Model Construction

The weakness of the linear curve is that it provides only a single learning rates for a specific times series and thus overlook entirely the annual changes in the learning rate that may occur year to year. To overcome this shortcoming, some scholars have developed and used the so-called cubic learning models (Karaoz & Albeni, 2005), (Asgari & Yen, 2011), (Asgari & Gonzalez-Cortez, 2012). The cubic learning model takes its root from the more generic S curve learning model since it is assumed to vary over time, and can be approximated using cubic cost function. Carlson (1973) justifies the use of the S-curve function to estimate cubic learning rates as, improvement in tooling, methods of work, materials, design and workers experience. The cubic function states that; per unit cost of output at time t is a function of a cumulative production up to a third order polynomial (cubic term) (Badiru, 1992).This form of cubic cost function can be expressed as;

$$lnC_t = lnC_1 + BlnX_t + C(lnX_t)^2 + D(lnX_t)^3 \qquad 24$$

The first derivative of 24 gives the learning elasticity for the cubic models which can be expressed as.

$$-\alpha = \frac{dlnC_t}{dlnX_t} = B + 2C(lnX_t) \quad + 3D(lnX_t)^2 \qquad 25$$

The proof of 25 has been given by (Karaoz & Albeni, 2005).

To proceed, we expressed 24 in a ratio between a unit cost of producing the first unit (C_1) and the unit production cost in time t (C_t). To do this, we subtract lnC_1 from both sides of 24 and rearrange as follows;

$$lnC_t - lnC_1 = lnC_1 + BlnX_t + C(lnX_t)^2 + D(lnX_t)^3 - lnC_1 \qquad 26$$

$lnC_t - lnC_1 = BlnX_t + C(lnX_t)^2 + D(lnX_t)^3$ or equivalently as;

$$ln\left(\frac{C_1}{C_t}\right) = -(BlnX_t + C(lnX_t)^2 + D(lnX_t)^3) \qquad 27$$

Recall from 17 that $lnA_t = lnH + \ln(\frac{C_1}{C_t})$, hence by substituting for $\ln(\frac{C_1}{C_t})$, we have a new relation as;

$$lnA_t = lnH - BlnX_t - C(lnX_t)^2 - D(lnX_t)^3 \qquad 28$$

Furthermore, by substituting for lnA_t in 13 above, we have the following expression;

$$lnQ_t = lnH - BlnX_t - C(lnX_t)^2 - D(lnX_t)^3 + \beta lnL_t + \gamma lnK_t \qquad 29$$

Recall the relation between labour and capital as earlier expressed in 20 and 21 above. By expressing 29 entirely in terms of labour, we will have a new relation in the form;

$$lnQ_t = lnH - BlnX_t - C(lnX_t)^2 - D(lnX_t)^3 + \beta lnL_t + \gamma\ (ln\mu + \lambda lnL_t) \qquad 30$$

And by adding lnL_t to both sides of 30 and rearranging like terms, we have a final empirical model for cubic learning model as;

$$ln\left(\frac{L}{Q}\right)_t = -lnH - \gamma ln\mu + BlnX_t + C(lnX_t)^2 + D(lnX_t)^3\ (1 - \beta - \lambda)lnL_t \qquad 31$$

or equivalently in an abridge form as;

$$lnC_t = \theta_1 + BlnX_t + C(lnX_t)^2 + D(lnX_t)^3 + \theta_2 lnL_t \qquad 32$$

Where $\theta_1 = -lnH - \gamma ln\mu$, $\theta_2 = (1 - \beta - \lambda)$ and $lnC_t = ln\left(\frac{L}{Q}\right)_t$

CHAPTER 4

4.0 Model Estimation/Data Analysis

4.1 Preliminary Investigation/Exploratory Data Analysis

Two very important assumptions surround the estimation of efficiency and productivity, namely; constant return to scale (or simply return to scale) and variable return to scale (increasing or decreasing return to scale). We shall begin our data analyses by testing for these two assumptions and choose the most appropriate assumption for our DEA estimation of efficiency and productivity.

First, we begin by exploring our data. The most generic form of data exploration is the graphical illustration. In our case, we used line graph since panel time series data is involved. The advantage is that one can readily see the trend or causal relationship exhibited by the variables under study.

Figures 4.1.0a to 4.1d show multiple line graphs of average annual sales, average annual capital invested, average annual number of people engaged and annual value additions in Japanese manufacturing industries from 2000 to 2014, for total manufacturing, high & medium-high-tech, medium-low-tech and low-tech industries respectively. The trend in total manufacturing (Figure 4.1a) showed a gradual increase in sales, capital invested and valued addition from 2000 to 2008 and decrease slightly between 2009 and 2011, and there rise steadily.

The same pattern/trend was observed in all other sub-sectors (High & medium-high-tech, medium-low-tech and low-tech). Labour, however, drops sharply in 2003 but increases steadily thereafter for most industries except in high & medium-high-tech industries. For these industries, Labour drops sharply in 2002, rose in 2003 and 2004 but drops again in 2005. Although it rises to its peak in 2007, it, however, have been declining since 2007 till date (2014). Overall, we conclude that capital invested somewhat affects sales directly in that as capital slightly grew sales also grew. However, from the foregoing, labour does not show direct impacts on sales (output) and therefore it is difficult to tell what assumption is best at this point.

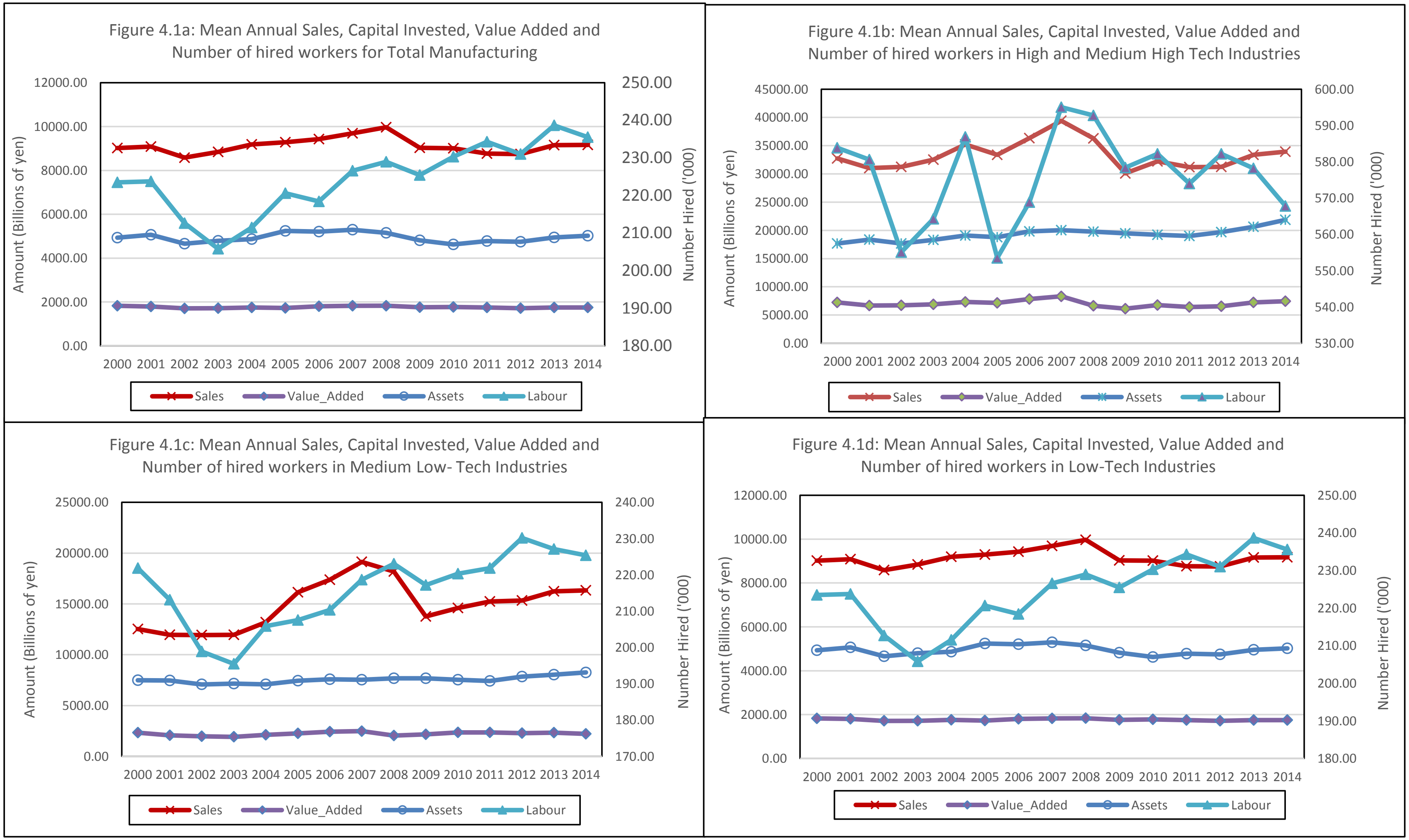


Figure 4.1abcd: Mean Annual Sales, Capital Invested, Value added, and Labour in Japanese Manufacturing Industry

Nevertheless, we proceed on the alternative test. In their famous paper on “A Theory of Production”, Cobb and Douglass, (1928) proposes that return to scale should be assumed if the sum of elasticity of labour and capital (α and β) equals unity, else other assumptions should be investigated. To test for this, we run a Cobb-Douglass production function on our data and check for the elasticity of labour and capital (see Appendix B) and the sum equals 0.9338. if we round up this to the nearest whole number, we get unity or otherwise, it remains less than unity. Again, it is difficult to conclude what assumption to use. To solve this dilemma, we estimated the technical efficiencies using both assumptions and accessed the performance (see Appendix C), the result shows that efficiencies estimated from both assumptions agree most of the time. This suggests that both assumptions fit our data well. Hence, we proceed with the so-called return to scale assumption for the remainder of this research.

4.2 Technical Efficiency and Productivity Growth Estimation

4.2.1 Estimating Technical Efficiency via Data Envelopment Analysis

Using the constant return to scale assumption, we estimated the technical efficiencies of all manufacturing industries via DEA approach. The overall results in Table 4.1 show that nearly all the manufacturing industries are technically inefficient considering their use of labour and capital. The yearly average showed a continuous decrease in technical efficiency irrespective of the industry with a mean technical efficiency of 48% from 2000 to 2014. Different industries seem to operate at different efficiency level as indicated by the industry average (column). This implies that there is no optimal use of these resources (labour and capital). Optimal allocation or use of resources imply that a firm operates with 100 percent efficiency (details of this result will be discussed in the next section).

Table 4.1: Summary of Technical Efficiencies for Japanese Manufacturing Industries (2000-2014)

Manufacturing Industry	Business oriented machinery	Ceramic, stone & clay products	Chemical and allied products	Electrical machinery, equipment & supplies	Electronic parts, devices and electronic circuits	General-purpose machinery	Information & comm. Electronic equipment	Iron and steel	Production machinery	Transport equipment	Beverages, Tobacco & Feed	Food	Furniture and fixtures	Leather tanning, leather products & fur skins	Lumber and wood products	Miscellaneous manufacturing industries	Printing and allied industries	Pulp, paper and paper products	Textile mill products	Fabricated metal and products	Non-ferrous metals & products	Petroleum and coal products	Plastic products	Rubber products	Industry Average
2000	77	43	47	100	75	67	93	35	64	62	63	75	75	95	79	71	62	41	45	53	38	100	71	39	**48**
2001	76	40	45	96	64	63	66	32	57	63	60	79	72	52	77	77	64	39	43	53	32	100	67	45	**61**
2002	67	38	43	91	65	57	60	31	51	63	54	75	68	50	83	64	58	39	39	52	29	100	57	40	**57**
2003	63	35	37	100	59	54	54	29	54	56	53	64	66	49	72	62	50	34	37	45	26	100	51	32	**53**
2004	64	29	36	85	58	55	56	33	58	53	53	61	66	88	68	51	49	32	37	49	27	100	55	32	**54**
2005	53	25	31	44	43	36	48	29	47	43	40	49	52	69	59	41	39	25	25	43	27	100	46	25	**43**
2006	54	28	32	52	45	40	49	29	51	46	39	51	57	54	70	48	41	28	30	45	37	100	47	28	**46**
2007	46	26	31	47	39	37	48	31	48	45	34	48	51	61	52	50	37	26	27	44	39	100	42	27	**43**
2008	42	26	31	43	40	39	46	36	45	43	38	55	54	48	54	54	39	28	28	44	35	100	41	29	**43**
2009	50	31	41	57	50	44	54	33	43	56	54	73	66	63	66	63	54	37	53	56	39	100	46	31	**52**
2010	49	29	36	50	42	40	46	33	45	49	46	64	58	62	59	49	45	31	45	49	36	100	40	30	**47**
2011	39	23	29	37	32	36	38	29	39	41	31	54	56	53	57	39	38	26	27	39	28	100	37	26	**40**
2012	36	25	31	41	33	36	38	27	39	44	34	57	61	54	59	44	40	28	29	43	27	100	41	27	**41**
2013	34	24	29	42	32	32	34	28	35	38	31	51	55	52	58	37	36	28	26	40	25	100	38	23	**39**
2014	37	26	32	47	36	37	34	31	43	38	36	56	58	73	61	39	35	31	27	44	30	100	40	25	**42**
AVG	**52**	**30**	**35**	**62**	**48**	**45**	**51**	**31**	**48**	**49**	**44**	**61**	**61**	**62**	**65**	**53**	**46**	**32**	**35**	**47**	**32**	**100**	**48**	**31**	**48**

4.3 Estimation of Efficiency Change, Technical Progress and Total Factor Productivity Change.

This section focusses on the analysis of efficiency change, technological change and total factor productivity change (TFPC). As discussed elsewhere in this research work, total factor productivity growth can be explained by efficiency change and technological change given that all other factors remain constant.

Table 4.2 show the result of the estimated annual Malmquist productivity index. This result shows the annual efficiency change, technical progress and total factor productivity growth across all industries. In this result, the industry effect is held constant. Shaded cells show the positive efficiency change, technical progress, and total factor productivity growth. Positive total factor productivity was observed in 7 out of the 15 years under review namely 2002, 2003, 2004, 2006, 2007,2010 and 2013 respectively. Positive TFP growth was either a result of innovation (technological change) or efficiency improvement (catching up) (see Chapter 5 for detail discussion).

Table 4.2: Malmquist Index Summary of the Annual Means

year	EFFCH	TECHCH	PECH	SECH	TFPCH
2001	0.934	0.980	0.997	0.937	0.915
2002	0.938	1.096	0.949	0.988	1.027
2003	0.923	1.103	0.945	0.976	1.018
2004	1.010	1.059	0.993	1.018	1.070
2005	0.803	1.214	0.823	0.976	0.975
2006	1.070	0.968	1.081	0.990	1.035
2007	0.940	1.114	0.941	0.999	1.047
2008	1.009	0.944	1.015	0.994	0.952
2009	1.219	0.699	1.162	1.049	0.852
2010	0.899	1.216	0.963	0.934	1.094
2011	0.825	1.200	0.866	0.953	0.990
2012	1.044	0.925	1.007	1.036	0.966
2013	0.930	1.095	0.946	0.983	1.018
2014	1.097	0.903	1.055	1.040	0.990
Mean	0.969	1.027	0.978	0.990	0.994

EFFCH-efficiency change, TEHCH-technical change, PECH-pure efficiency change, SECH-scale efficiency change, TFPCH-total factor productivity change

4.4 Industry Level Analysis

This section investigates the total factor productivity growth/change for individual industries from 2001 to 2014. Furthermore, the section also attempts to explain sources of TFP growth or decline during the period under consideration. For the purpose of comparison, we classified the industries into high-medium-high-tech, medium-low-tech, and low-tech industries respectively.

4.4.1 High-Medium-High-Tech

Table 4.3 summarized the result of TFP growth across all industries for high-medium-high-tech industries. Shaded portions of the cells show TFP growth as explained by efficiency change and technical progress, and the years such growth took place.

The result showed that most industries had moderately positive TFP growth in all the years under review except in 2001, 2008, 2009 and 2012 respectively. very few industries showed positive TFP in 2013, however, 2014 seems to be a recovery year for most industries after showing negative TFP in the previous year.

Table 4.3: Total Factor Productivity in High and Medium High Tech Industry*

Manufacturing Industry		2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
	EFFCH	95.0	89.1	94.8	102.5	66.1	109.0	94.2	104.0	112.1	92.9	89.0	99.0	89.3	117.2
	TECHCH	96.1	109.8	111.4	105.0	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	109.4	90.2
General-purpose machinery	TFPCH	91.3	97.8	105.6	107.7	80.3	105.3	105.0	98.4	78.2	113.1	106.9	91.5	97.7	105.7
	EFFCH	89.2	90.3	104.5	107.9	81.1	109.2	93.2	93.8	95.4	105.6	86.1	99.6	90.0	123.1
	TECHCH	96.1	109.8	111.6	104.8	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	109.4	90.2
Production machinery	TFPCH	85.7	99.2	116.6	113.0	98.5	105.5	103.9	88.7	66.6	128.5	103.3	92.0	98.5	111.0
	EFFCH	98.1	88.7	93.9	101.6	82.5	101.6	85.0	91.1	119.7	98.5	78.3	93.5	94.7	108.2
Business oriented	TECHCH	96.1	109.8	111.2	105.3	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	109.4	90.2
machinery	TFPCH	94.2	97.4	104.4	107.0	100.3	98.2	94.7	86.2	83.5	119.9	94.0	86.3	103.6	97.6
	EFFCH	84.8	101.9	91.1	98.4	74.1	105.0	87.2	101.2	125.6	83.9	77.2	102.6	94.6	115.0
Electronic parts, devices	TECHCH	96.1	109.8	112.3	104.3	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	109.4	90.2
and electronic circuits	TFPCH	81.5	111.8	102.3	102.7	90.1	101.4	97.1	95.7	87.6	102.1	92.7	94.7	103.6	103.7
	EFFCH	96.3	94.5	109.9	85.3	51.7	118.0	90.2	92.0	131.3	87.3	74.3	112.5	101.9	110.6
Electrical machinery,	TECHCH	96.1	109.8	112.1	104.4	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	109.4	90.2
equipment & supplies	TFPCH	92.5	103.7	123.3	89.0	62.9	114.0	100.5	87.1	91.6	106.3	89.2	103.9	111.5	99.7
	EFFCH	70.7	91.5	90.1	103.2	86.3	102.7	96.8	95.4	118.6	84.6	84.0	99.7	88.5	99.3
Information & comm.	TECHCH	98.4	109.8	108.9	107.2	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	109.4	90.2
Electronic equipment	TFPCH	69.5	100.4	98.2	110.6	105.0	99.2	107.8	90.2	82.8	103.0	100.9	92.1	96.8	89.6
	EFFCH	97.0	94.2	85.8	99.3	84.7	105.0	96.2	101.3	130.8	88.6	79.2	106.7	95.5	107.7
Chemical &	TECHCH	99.8	109.8	108.5	107.8	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	109.4	90.2
Pharmaceutical Industries	TFPCH	96.8	103.4	93.0	107.0	103.0	101.4	107.2	95.9	91.3	107.8	95.1	98.5	104.5	97.2
	EFFCH	102.6	99.5	89.4	94.0	81.4	107.3	98.2	95.8	127.8	87.6	83.8	107.0	87.8	100.1
	TECHCH	98.2	109.8	109.7	106.7	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	109.4	90.2
Transport equipment	TFPCH	100.7	109.3	98.1	100.4	98.9	103.6	109.5	90.6	89.2	106.6	100.6	98.8	96.1	90.3
	EFFCH	91.3	95.7	93.3	81.8	88.0	108.4	92.7	102.4	116.8	94.5	79.7	108.0	94.4	110.5
Ceramic, stone & clay	TECHCH	98.1	109.8	109.6	107.0	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	109.4	90.2
products	TFPCH	89.5	105.0	102.2	87.5	107.0	104.7	103.3	96.8	81.5	115.1	95.7	99.7	103.4	99.7
	EFFCH	91.3	97.6	93.4	113.2	88.8	101.7	104.6	117.1	92.4	100.1	87.6	91.0	103.8	111.7
	TECHCH	101.6	109.8	107.5	108.7	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	109.4	90.2
Iron and steel	TFPCH	92.7	107.1	100.4	123.0	107.9	98.2	116.6	110.7	64.5	121.8	105.2	84.0	113.6	100.8

EFFCH-efficiency change, TEHCH-technical change, and TFPCH-total factor productivity change.

**shaded cells show total TFP growth as explained by corresponding efficiency change and technical progress.*

4.4.2 Medium-Low-Tech Industry.

Table 4.4 show the result of TFP growth estimation for medium-low-tech industries using Malmquist index. The result shows that industries such as petroleum & coal products showed positive TFP growth for most of the years under review. It however losses it TFP growth in recent times (2008, 2009, 2013 and 2014). Other industries under this category also had a similar trend (see chapter five for detail analysis and discussion).

Table 4.4: Total Factor Productivity in Medium-low-tech Industry*

Manufacturing Industry		2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Petroleum and coal products	EFFCH	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	TECHCH	110.8	105.0	102.6	110.4	118.9	101.3	110.0	90.5	71.6	119.6	118.0	97.4	100.0	92.5
	TFPCH	110.8	105.0	102.6	110.4	118.9	101.3	110.0	90.5	71.6	119.6	118.0	97.4	111.3	92.5
Plastic products	EFFCH	93.7	85.0	90.3	107.4	82.8	104.0	89.0	97.2	112.3	87.8	91.6	109.4	92.5	106.1
	TECHCH	96.1	109.8	111.6	104.4	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	100.0	90.2
	TFPCH	90.1	93.3	100.8	112.1	100.6	100.4	99.2	92.0	78.4	106.9	110.0	101.0	101.2	95.7
Rubber products	EFFCH	117.8	88.8	80.6	97.6	80.3	108.4	96.9	106.5	109.1	97.8	84.0	104.5	87.0	108.8
	TECHCH	98.1	109.8	109.5	106.9	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	100.0	90.2
	TFPCH	115.5	97.5	88.3	104.4	97.6	104.7	108.0	100.8	76.2	119.1	100.9	96.5	95.2	98.2
Non-ferrous metals & products	EFFCH	84.3	91.4	88.8	105.4	97.9	140.5	104.0	89.0	111.6	92.1	78.5	97.5	92.2	118.6
	TECHCH	100.9	109.8	107.6	108.6	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	97.9	90.2
	TFPCH	85.1	100.3	95.5	114.4	119.0	135.7	115.9	84.2	77.9	112.1	94.2	90.1	100.9	107.0
Fabricated metal and products	EFFCH	101.4	98.2	85.8	109.0	87.0	106.7	97.7	99.4	126.5	87.0	80.2	109.4	93.5	109.2
	TECHCH	96.1	109.8	112.3	104.1	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	101.3	90.2
	TFPCH	97.4	107.8	96.4	113.4	105.7	103.0	108.8	94.1	88.3	105.9	96.3	101.0	102.4	98.5

EFFCH-efficiency change, TEHCH-technical change, and TFPCH-total factor productivity change.

**shaded cells show total TFP growth as explained by corresponding efficiency change and technical progress.*

4.4.3 Low-tech Industry

Many industries under this category showed positive TFP growth for at least few years of the study. Fluctuations in TFP growth were explained by fluctuations in efficiency change and technical progress. Overall, the industry average shows that there were positive TFP growth in 2002, 2003, 2004, 2006, 2007, 2010 and 2013 in the order 3.4%, 2.4%, 10.4%, 2.2%, 3.7%, 5% and 0.7% respectively in the low-tech industrial group. Negative TFP growth was observed in the other years under review (see Table 4.5).

Table 4.5: Total Factor Productivity in Low-tech Industry*

Manufacturing Industry		2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
	EFFCH	104.2	95.3	85.1	96.0	79.8	104.9	93.0	114.4	132.9	87.7	85.4	105.1	90.2	108.3
	TECHCH	96.1	109.8	112.6	103.9	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	94.1	90.2
Food	TFPCH	100.1	104.6	95.8	99.7	97.0	101.3	103.7	108.3	92.7	106.7	102.5	97.1	98.7	97.7
	EFFCH	96.1	90.2	97.8	98.8	76.6	96.1	87.2	113.3	141.9	84.1	68.0	110.0	91.8	116.1
	TECHCH	100.9	109.8	107.7	108.5	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	94.9	90.2
Beverages, Tobacco & Feed	TFPCH	97.0	99.0	105.4	107.2	93.1	92.8	97.2	107.2	99.1	102.3	81.7	101.6	100.4	104.7
	EFFCH	95.7	90.2	95.6	99.5	69.3	116.4	91.0	105.5	187.4	84.3	59.9	108.0	88.5	106.7
	TECHCH	96.1	109.8	112.0	104.1	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	100.0	90.2
Textile mill products	TFPCH	91.9	99.0	107.2	103.6	84.2	112.4	101.4	99.8	130.8	102.6	71.9	99.8	96.9	96.2
	EFFCH	97.6	108.3	86.1	95.0	86.2	119.3	74.7	103.0	121.6	89.7	96.8	104.3	98.4	104.6
	TECHCH	96.1	109.8	112.6	103.9	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	99.9	90.2
Lumber and wood products	TFPCH	93.8	118.9	97.0	98.7	104.7	115.2	83.2	97.4	84.9	109.2	116.2	96.3	107.7	94.4
	EFFCH	96.7	94.2	96.3	100.3	79.8	109.4	88.5	106.6	122.3	87.2	97.3	108.2	90.0	106.7
	TECHCH	96.1	109.8	112.6	103.9	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	100.2	90.2
Furniture and fixtures	TFPCH	92.9	103.3	108.4	104.2	97.0	105.7	98.7	100.9	85.4	106.1	116.9	100.0	98.5	96.3
	EFFCH	94.3	100.0	86.7	95.1	79.5	108.7	93.1	108.4	133.0	84.2	82.1	109.9	99.7	108.7
	TECHCH	99.9	109.8	108.7	107.6	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	100.2	90.2
Pulp, paper and paper products	TFPCH	94.2	109.8	94.2	102.4	96.6	105.0	103.8	102.6	92.8	102.5	98.6	101.5	109.1	98.1
	EFFCH	102.6	90.0	87.2	98.1	78.8	104.4	90.9	105.6	138.6	83.0	83.7	106.6	90.7	97.2
	TECHCH	96.1	109.8	112.1	104.5	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	100.0	90.2
Printing and allied industries	TFPCH	98.6	98.8	97.8	102.5	95.8	100.8	101.3	99.9	96.8	101.1	100.5	98.4	99.3	87.7
	EFFCH	54.6	96.3	96.7	180.5	78.8	78.2	113.5	78.4	131.4	98.5	84.7	102.6	95.4	141.8
Leather tanning, leather products	TECHCH	96.1	109.8	112.6	103.9	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	95.4	90.2
& fur skins	TFPCH	52.5	105.7	108.9	187.4	95.8	75.6	126.5	74.2	91.7	119.9	101.7	94.8	104.4	127.9
	EFFCH	109.4	83.1	96.4	83.1	80.4	115.0	105.2	108.2	116.9	77.4	79.7	113.0	83.8	104.5
Miscellaneous manufacturing	TECHCH	96.3	109.8	111.3	105.8	121.6	96.6	111.5	94.6	69.8	121.7	120.1	92.3	99.9	90.2
industries	TFPCH	105.4	91.2	107.3	87.8	97.7	111.1	117.3	102.4	81.6	94.2	95.7	104.4	91.7	94.3
Industry Average (TFP)		91.8	103.4	102.4	110.4	95.8	102.2	103.7	99.2	95.1	105.0	98.4	99.3	100.7	99.7

EFFCH-efficiency change, TEHCH-technical change, and TFPCH-total factor productivity change.

**shaded cells show total TFP growth as explained by corresponding efficiency change and technical progress.*

4.5 Technological Learning Model Estimation (Linear & Cubic Models)

4.5.1 Model Estimation and Evaluation.

This section focused on the estimation of annual technological learning elasticities (learning coefficient) and the progress ratio (PR) or learning levels in Japanese manufacturing industries. All learning elasticities were estimated for the 24-industrial sector for the period of 2000-2014. This was to enable us to study the trend and pattern of technological learning in Japanese manufacturing industries. To achieve this, we utilized the various models constructed for learning elasticity and progress ratio (for linear and cubic respectively) as earlier shown in the methodology section. The results are presented hereunder.

4.5.2 The Linear Learning Elasticity and Progress Ratio

Table 4.6 shows the model estimation for linear learning elasticity for each industry. The regression statistics (R^2 and F) suggest a poor fitting which may imply that linear learning model does not fit the data well. The last column of Table 4.5 shows the estimated progress ratio for each industry. Shaded cells show industries with learning potentials during the period under study. The weakness of the linear model of the learning curve is that it assumed learning to be constant and hence ignore the time variance (dynamic) of the learning system.

4.6: Learning elasticities & progress ratio estimated using linear model*

TI	Manufacturing Industry	φ0	φ1	φ2	R^2	F	d
High & medium-high-tech	Business oriented machinery	-6.697	0.266	-0.027	0.067	0.658	1.202
	General purpose machinery	-1.418	-0.129	-0.034	0.345	0.079	0.914
	Production machinery	-8.07	0.481	-0.086	0.112	0.491	1.396
	Electrical machinery & equipment	-16.116	0.492	0.291	0.724	0.021	1.406
	Electronic parts, devices & circuits	-0.643	-0.164	-0.056	0.244	0.244	0.893
	Information com. & elect equipment	-2.704	-0.168	0.035	0.312	0.106	0.890
	Chemical and pharmaceutical	-6.31	0.259	-0.069	0.522	0.012	1.197
	Ceramic, stone and clay products	-1.874	-0.055	-0.064	0.42	0.038	0.962
	Iron and steel	16.266	-1.545	-0.05	0.568	0.006	0.343
	Transport equipment	-1.874	-0.139	-0.012	0.089	0.57	0.908
Medium-low-tech	Fabricated metal products	-1.229	-0.157	-0.01	0.041	0.78	0.897
	Non-ferrous metals and products	3.523	-0.434	-0.129	0.44	0.031	0.740
	Petroleum and coal products	-4.454	0.081	-0.147	0.554	0.008	1.058
	Plastic products	-7.696	0.375	-0.027	0.127	0.443	1.297
	Rubber products	-2.788	-0.049	-0.016	0.041	0.778	0.967
Low-tech	Food	-9.63	0.517	-0.053	0.638	0.002	1.431
	Beverages, tobacco and feed	-19.4	0.976	0.157	0.381	0.057	1.967
	Printing and related industries	-6.25	0.193	0.022	0.234	0.202	1.143
	Textile mill products	0.835	-0.316	-0.014	0.425	0.036	0.803
	Leather tanning, products & fur skins	-5.228	0.036	0.132	0.198	0.267	1.025
	Furniture and fixtures	0.258	-0.212	-0.096	0.58	0.005	0.863
	Lumber and wood products	-2.938	0.024	-0.06	0.284	0.135	1.017
	Pulp, paper and paper products	-2.968	-0.05	-0.018	0.048	0.747	0.966
	Miscellaneous industries	-0.788	-0.509	0.162	0.555	0.008	0.703

**Shaded cells indicate learning scenario with per unit cost efficiency gain (real cost savings) in the manufacturing process by the corresponding industry. TI-technology Intensity*
Unshaded cells indicate forgetting scenario with a loss in efficiency and increase in per unit production cost.

4.5.3 The Cubic Learning Model Estimation

Table 4.7 show the learning elasticities of all manufacturing industries estimated using the cubic models. Unlike the linear model, the cubic models seem to fit the data well judging by the regression statistics (R^2 and F). Most industries had high coefficient of determinations R^2, implying that higher percentage of the variations in the data set was explained by the model. F statistic, on the other hand, shows that the model significantly fit the data at 5% level for most industries.

Table 4.7: Regression Result of Learning elasticities estimated using Cubic model

Manufacturing Industry	φ1	φ2	B	C	D	R^2	F
Food	-43.845	0.844	4.197	-0.198	0.003	0.689	0.013**
Beverages, Tobacco & Feed	-649.874	0.559	107.035	-5.976	0.111	0.741	0.006***
Textile mill products	264.737	-0.445	-46.554	2.747	-0.054	0.584	0.049**
Lumber and wood products	-117.086	-0.207	22.430	-1.442	0.031	0.330	0.357
Furniture and fixtures	110.715	-0.106	-22.501	1.495	-0.033	0.639	0.026**
Pulp, paper and paper products	-383.761	0.295	64.247	-3.651	0.069	0.273	0.481
Printing and allied industries	-201.979	0.161	35.585	-2.145	0.043	0.685	0.014**
Chemical and allied products	-318.166	0.444	47.905	-2.477	0.043	0.622	0.032**
Petroleum and coal products	-156.016	0.241	24.773	-1.378	0.025	0.564	0.060*
Plastic products	-245.230	0.316	42.196	-2.490	0.049	0.339	0.341
Rubber products	101.654	-0.164	-18.212	1.069	-0.021	0.068	0.942
Leather tanning, leather products & fur skins	-49.360	0.573	13.012	-1.284	0.041	0.618	0.033**
Ceramic, stone & clay products	-441.507	-0.011	75.871	-4.371	0.084	0.678	0.015**
Iron and steel	-375.003	-1.823	66.241	-3.702	0.069	0.762	0.004***
Non-ferrous metals & products	-879.143	-0.474	149.262	-8.407	0.157	0.693	0.012**
Fabricated metal and products	-329.021	-0.952	58.220	-3.334	0.063	0.467	0.143
General-purpose machinery	-1166.432	-0.132	192.930	-10.644	0.196	0.523	0.089*
Production machinery	-421.321	1.145	68.770	-3.886	0.073	0.187	0.687
Business oriented machinery	-356.687	0.198	61.234	-3.559	0.069	0.334	0.349
Electronic parts, devices and electronic circuits	-185.363	0.177	29.184	-1.575	0.028	0.281	0.463
Electrical machinery, equipment & supplies	474.105	0.790	-80.520	4.396	-0.080	0.758	0.004***
Information & comm. Electronic equipment	-852.519	-0.147	134.796	-7.112	0.125	0.740	0.006***
Transport equipment	521.653	-1.853	-73.539	3.596	-0.058	0.625	0.031**
Miscellaneous manufacturing industries	-355.865	-0.083	65.394	-4.034	0.083	0.740	0.006***

***, **, * significant at 1%, 5% and 10% respectively.

4.5.3.1 Dynamic Technological Learning in Japanese Manufacturing Industries.

The annual technological learning level (progress ratio) for all manufacturing industries were calculated and presented in Table 4.8. Shaded cells emphasize technological learning during the period under review. The result in Table 4.8 show technological learning for most industries at the early stage of this study (2001-2007), however, technological learning became so bad in the later stage (2008-2014). This is true regardless of the industrial tech group. The next chapter will give the detail discussion of this findings.

Table 4.8: Annual Technological Learning Level (progress ratio) for Japanese Manufacturing Industries*.

TI	Manufacturing Industry	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	Average
	Business oriented machinery	1.136	0.950	0.911	0.910	0.927	0.952	0.982	1.020	1.059	1.092	1.131	1.168	1.198	1.237	1.277	1.063
	General purpose machinery	1.407	0.942	0.871	0.883	0.941	0.972	1.007	1.044	1.081	1.109	1.141	1.174	1.206	1.239	1.268	1.086
	Production machinery	1.378	1.026	0.903	0.839	0.804	0.788	0.784	0.789	0.798	0.806	0.818	0.834	0.851	0.870	0.892	0.879
	Electrical machinery & equipment	1.307	1.362	1.342	1.301	1.244	1.200	1.152	1.108	1.071	1.042	1.011	0.976	0.944	0.911	0.879	1.123
High & medium-high-tech	Electronic parts, devices & circuits	1.150	1.032	0.977	0.945	0.927	0.916	0.910	0.907	0.907	0.908	0.910	0.913	0.918	0.923	0.928	0.945
	Information com. & elect equipment	1.753	0.968	0.873	0.874	0.910	0.957	1.021	1.097	1.179	1.252	1.323	1.365	1.405	1.446	1.478	1.193
	Chemical and pharmaceutical	1.141	0.985	0.935	0.917	0.912	0.914	0.921	0.931	0.943	0.955	0.969	0.983	0.998	1.014	1.029	0.970
	Ceramic, stone and clay products	1.171	0.953	0.900	0.890	0.903	0.928	0.954	0.985	1.017	1.047	1.077	1.109	1.141	1.175	1.211	1.031
	Iron and steel	1.037	0.898	0.872	0.878	0.901	0.938	0.984	1.043	1.108	1.153	1.206	1.259	1.305	1.356	1.412	1.090
	Transport equipment	0.687	0.940	1.077	1.158	1.208	1.238	1.253	1.256	1.253	1.247	1.238	1.228	1.216	1.201	1.185	1.159
	Fabricated metal products	0.994	0.908	0.903	0.918	0.945	0.978	1.016	1.057	1.097	1.131	1.166	1.205	1.247	1.289	1.333	1.079
	Non-ferrous metals and products	1.449	0.900	0.784	0.755	0.759	0.790	0.860	0.962	1.061	1.146	1.259	1.366	1.476	1.595	1.725	1.126
Medium-ow-tech	Petroleum and coal products	0.941	0.881	0.868	0.869	0.877	0.892	0.909	0.928	0.947	0.960	0.972	0.986	1.000	1.015	1.029	0.938
	Plastic products	1.130	0.981	0.943	0.935	0.940	0.952	0.970	0.992	1.016	1.038	1.061	1.084	1.107	1.131	1.156	1.029
	Rubber products	0.903	0.976	1.001	1.009	1.012	1.011	1.007	1.001	0.995	0.989	0.983	0.977	0.970	0.963	0.956	0.984
	Food	1.021	0.982	0.963	0.951	0.942	0.935	0.930	0.925	0.921	0.918	0.915	0.913	0.911	0.909	0.907	0.936
	Beverages, tobacco and feed	1.175	0.951	0.931	0.960	1.009	1.060	1.116	1.175	1.242	1.306	1.375	1.431	1.489	1.553	1.614	1.226
	Printing and related industries	1.084	0.982	0.965	0.969	0.984	1.003	1.024	1.047	1.071	1.093	1.115	1.137	1.158	1.180	1.202	1.068
	Textile mill products	0.789	0.951	1.014	1.038	1.047	1.043	1.031	1.010	0.990	0.976	0.961	0.944	0.927	0.911	0.896	0.969
Low-tech	Leather tanning, products & fur skins	0.750	0.895	1.037	1.186	1.304	1.413	1.511	1.609	1.688	1.748	1.817	1.869	1.914	1.965	2.032	1.516
	Furniture and fixtures	0.885	0.966	0.978	0.974	0.962	0.946	0.932	0.916	0.899	0.886	0.874	0.860	0.846	0.830	0.815	0.905
	Lumber and wood products	1.010	0.937	0.925	0.927	0.935	0.949	0.966	0.982	0.999	1.014	1.028	1.044	1.060	1.078	1.095	0.997
	Pulp, paper and paper products	1.234	1.010	0.953	0.936	0.938	0.949	0.967	0.990	1.015	1.040	1.064	1.089	1.114	1.140	1.168	1.040
	Miscellaneous industries	1.175	0.968	0.940	0.947	0.985	1.044	1.118	1.191	1.272	1.337	1.401	1.459	1.518	1.571	1.620	1.236

*shaded cells indicate learning scenario with per unit cost efficiency gain (real cost savings) in the manufacturing process by the corresponding industry.
Unshaded cells indicate forgetting scenario with loss in efficiency and increase in per unit production cost.
TI-technology intensity

Chapter Five

5.0 Results and Discussion

This section discussed the results of the data analyses in comparison with literature (similar studies) and industrial or economic policies of the Japanese government in recent times. An attempt was also made to reveal the underlying reasons for positive productivity growth and learning potentials and /or lack of them as seen in the various sections of the data analyses.

5.1 How Efficient are Resources (Capital & Labour) Utilized in Japanese Manufacturing Industries?

To answer this question, we will examine in details the technical efficiencies of the Japan manufacturing industries. It is important to differentiate between technical efficiency and engineering efficiency. By technical efficiency, we mean the effective or optimal use of the factors of production namely; labour and capital as in our case.

5.1.1 Technical Efficiency in Japanese Manufacturing Industries.

Figure 5.1 compare the result of technical efficiencies at the industrial technology intensity level. The result showed decreasing efficiencies for all industrial-tech group from 2001-2014, with little recovery in the year 2009.

However, this recovery was not sustained and there was further decline in technical efficiency from 2010 to 2013. This decline in efficiency along the years cut across all the industrial tech group and may suggest that these industries faced similar internal (managerial or corporate strategy with unfavorable outcome) or external unfavorable business conditions such as loss of market share or competitiveness. In comparison with the industry average and the trend line, it can be concluded that technical efficiencies are decreasing at an alarming rate. The trend showed that there is no evidence to suggest any turn of event.

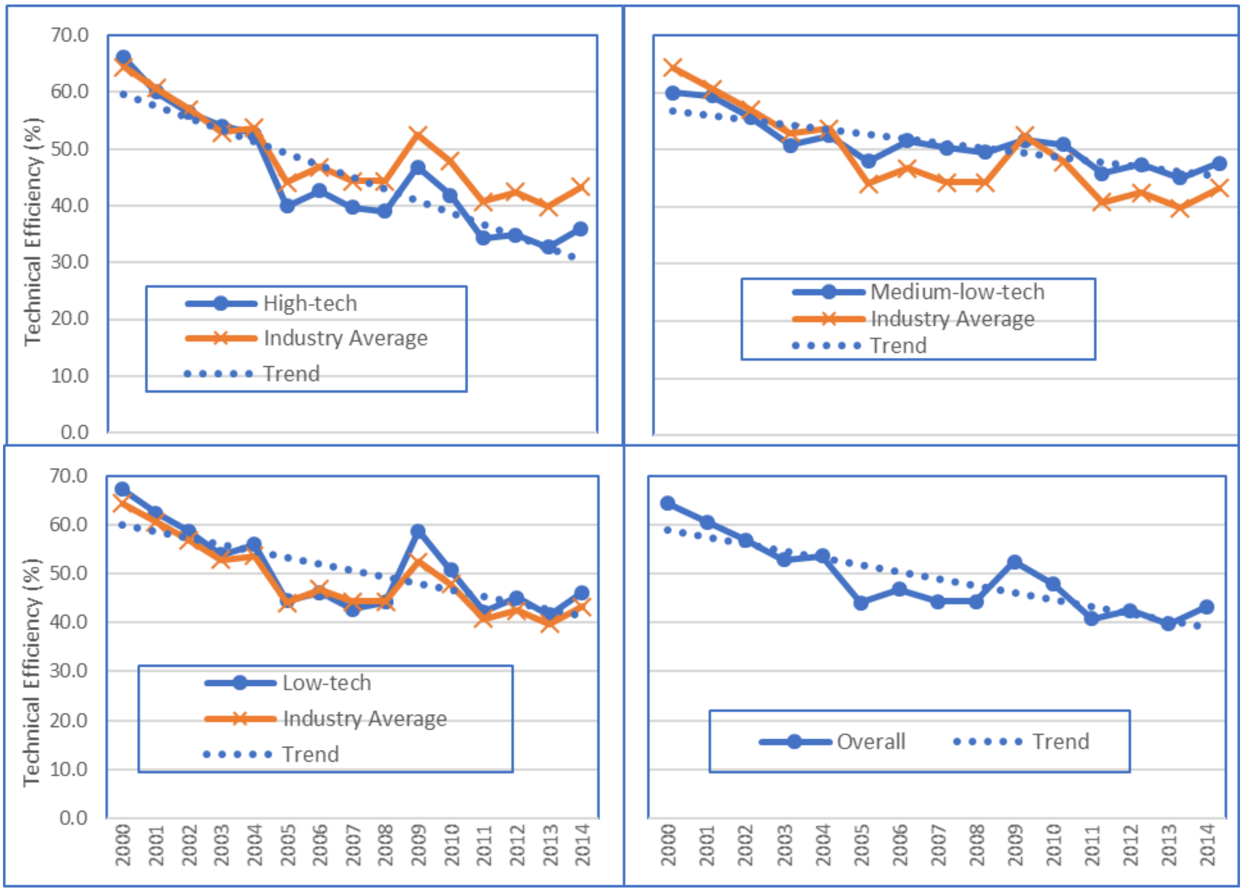


Figure 5.1: Technical efficiency of Japanese Manufacturing Industries (200-2014)

5.1.2 Technical Efficiency (High Tech and Medium High Tech Industries)

Figure 5.2 illustrates the technical efficiencies of all the industries under high and medium-high technology intensity. Electrical machinery and supplies operated optimally (with about 100% efficiency) between 2000 and 2003, and thereafter it's efficiency declines sharply to about 43% in 2005 and remains relatively that way for another nine years (2006-2014). Ceramic, stone & and clay products show a technical efficiency of 92.6% in the year 2000 and gradually lost over 60% of its efficiency with time, to as low as 33.7%. Generally, for all industries in this category, technical efficiencies seem to decrease continuously during the period from 2000 to 2008 and a slight recovery in 2009. Chemical & Pharmaceutical Industries and Others (Iron & Steel, Ceramic & Clay products, and Transport) had the lowest technical efficiency in comparison with the high-tech industries. In all, these industries are technical inefficient considering their use of labour and capital.

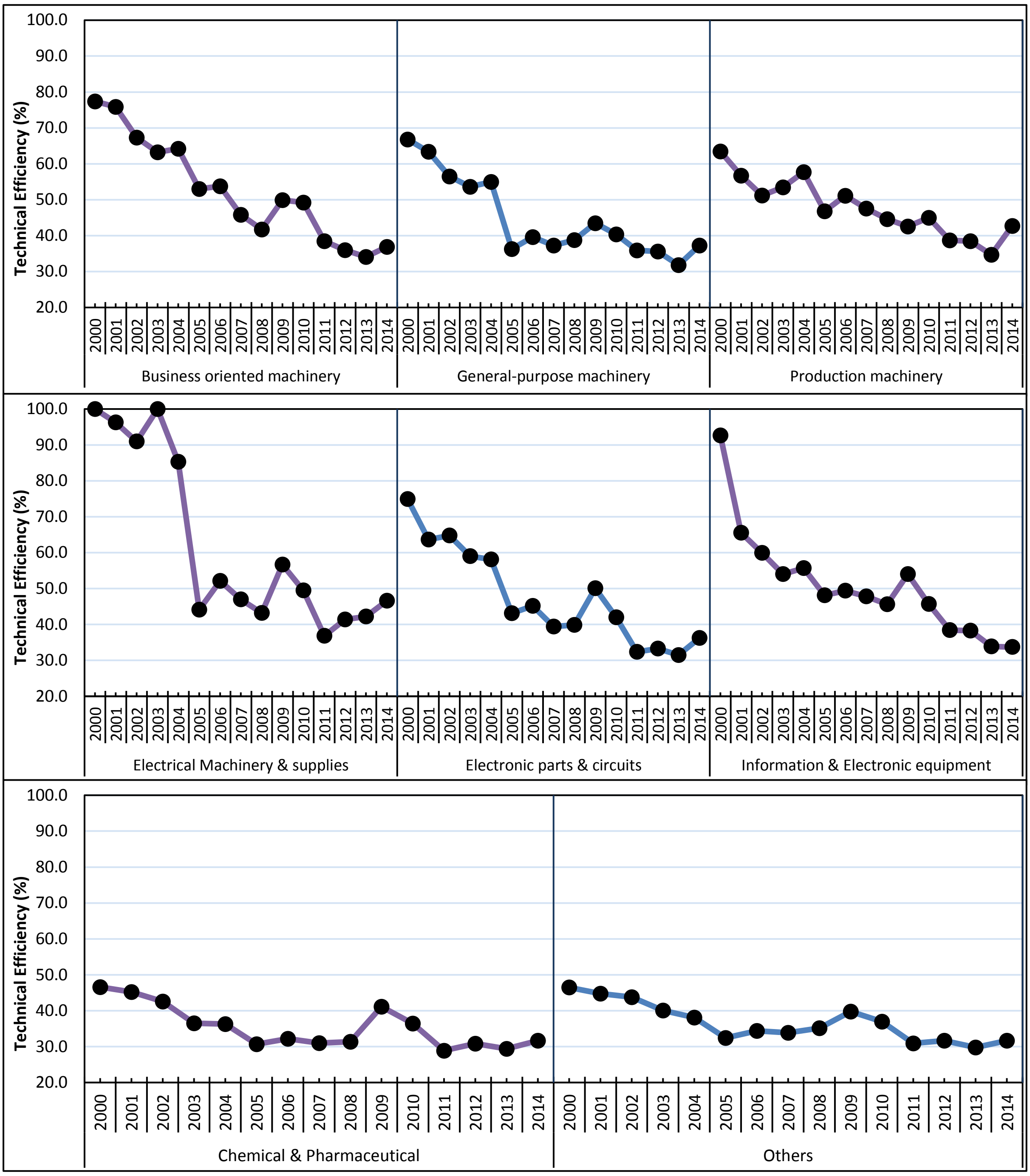


Figure 5.2: Technical efficiencies of high and medium high-tech in Japanese manufacturing industries (200-2014)

5.1.3 Medium-Low-tech Industries

Figure 5.3 shows the technical efficiencies of medium-low-tech industries. Petroleum and Coal industry was technically efficient throughout the period of study (2000-2014). Plastic industry was 71.2% efficient in 2000, however, its efficiency decreases to as low as 41% in the year 2008 and a slight recovery to 46% in 2009. Thereafter, the efficiency decreases continuously for the remainder of the period under study. For all industries in this category except petroleum and coal products, technical efficiency seems to recover slightly in 2009. Generally, technical efficiencies tend to decrease over the years (2000-2014) for all industries.

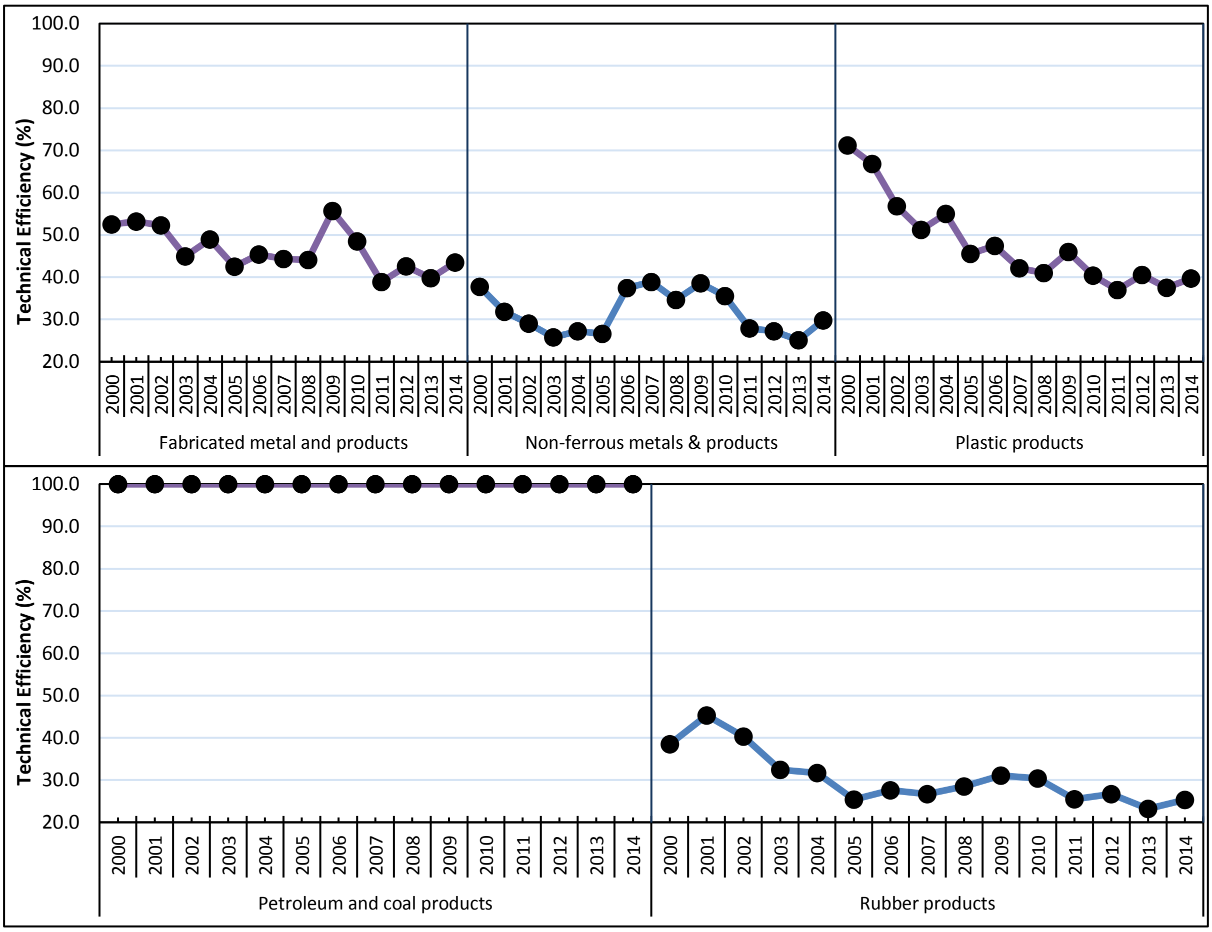


Figure 5.3: Technical efficiencies of medium-low-tech in Japanese manufacturing industries (200-2014)

5.1.4 Low-tech Industries

Leather tanning & fur skins industry was the most technically efficient in the year 2000 (95.4%), 2004 (87.5%) and 2014 (73.2%) compare to all other industries in the low-tech industrial category, yet the technical efficiency of it decrease in other years of the study. Although all industries in these categories are technically inefficient, however, industries such as; food, lumber & wood products, furniture and fixtures, printing and allied industries seem to be more efficient in comparison to textile & mill products, and pulp, paper & paper products.

All industries seem to recover slightly in the year 2009.

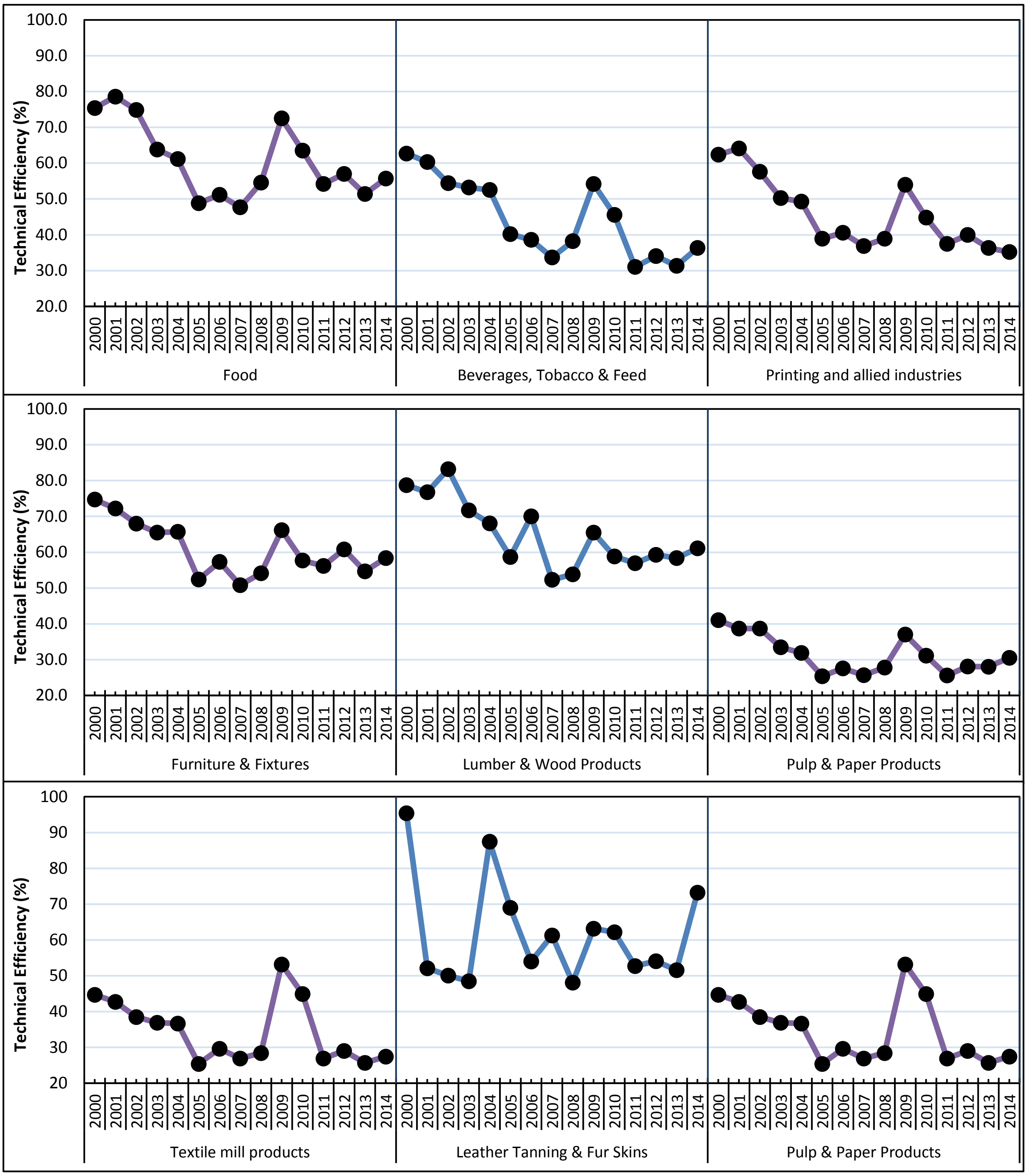


Figure 5.4: Technical efficiencies of low-tech in Japanese manufacturing industries (200-2014)

5.1.5 Input Slack Analysis

When technical inefficiency is reported, the slack analysis helps to identify which input was inefficiently applied and which was efficiently applied in the production mix. This is called input slack analysis. In the words of Ferrier and Lovell (1990) “slack may essentially mean allocative inefficiency”. Following this argument, it means that slack (excess labour or capital as in our case) are the managerial decisions that inefficiently allocate inputs in the production mix. The slack analysis (see Appendix D) showed that while capital was completely used up most of the time, labour, however, was needlessly in surplus. The slack analysis showed labour to be in excess of what is currently required given the return on output (sales). While it is easy to speculate on the basis of the slack result that the low technical efficiency may be due to excess or inefficient use of labour in the production mix, however, since sales was the output for this analysis, we do not want to ignore the impact of externalities, such as market price, market share loss (shrinking market), unfavourable weather, and competition which may be adversely affecting returns on sales.

5.1.6 Conclusion on Technical Efficiency

From the foregoing, it can be concluded on the basis of available labour and capital, that Japanese manufacturing industries are technically inefficient. Since technical efficiency is an integral part of overall economic efficiency (Tim, 1996), the low and declining technical efficiency in Japanese manufacturing industries have a number of implications especially for the Japanese economy, given that manufacturing is the backbone of the Japanese economy. Studies on technical efficiency of Japanese manufacturing industries are rare. Mitra and Sato (2007) investigated agglomeration economies in Japan as explained by technical efficiency, growth, and unemployment. Their study used industrial level data from the manufacturing sector and found technical efficiency to be particularly low at prefectural levels.

5.2 What is the Impact of Efficiency and Technological Change on the Productivity of Japanese Manufacturing Industries?

This question bothered on the technical progress and efficiency change and their impact on total factor productivity. Using the Malmquist index, we estimated the TFP and thereafter decompose same into efficiency change and technological progress (see Table 4.2, 4.3, & 4.4 respectively for the results). We represent the result in a line graph for ease of inference.

5.2.1 Impact of Efficiency Change, Technological Change on Total Factor Productivity Change in Japanese Manufacturing Industries.

5.2.2 Annual TFP Growth (Means)

Total factor productivity grew by 2.7% in 2002, 1.8% in 2003 and 7% in 2004. TFP growths in 2002 and 2003 were due to technical progress (innovation) only and not in response to efficiency change. TFP growth in 2004, however, was due to 10% efficiency change and approximately 6% shift in technical progress. Although there was a huge technological shift (21.4%) in 2005, this, however, does not result to positive TFP change/growth (Table 5.1).

In 2006, there was 3.5% TFP growth which was a result of 7% efficiency change (catching up) and perhaps also due to other factors but not technological progress (innovation) since there was technical regress of -3.2% in the same year. However, 4.7% TFP growth in the following year (2007) was among other things, due to technical progress of about 11.4%. There were 9% and 21.9% efficiency changes in the year 2008 and 2009 respectively, however, these changes in efficiency could not result to positive TFP growth. The negative TFP growth observed in 2008 and 2009 was in part, due to technical regress observed in the same years (see Table 5.1/Figure 5.5).

Table 5.1: Malmquist Index Summary of the Annual Means (recalculated for actual Growth) *

year	EFFCH	TECHCH	PECH	SECH	TFPCH
2001	-6.6	-2.0	-0.3	-6.3	-8.5
2002	-6.2	9.6	-5.1	-1.2	2.7
2003	-7.7	10.3	-5.5	-2.4	1.8
2004	1.0	5.9	-0.7	1.8	7.0
2005	-19.7	21.4	-17.7	-2.4	-2.5
2006	7.0	-3.2	8.1	-1.0	3.5
2007	-6.0	11.4	-5.9	-0.1	4.7
2008	0.9	-5.6	1.5	-0.6	-4.8
2009	21.9	-30.1	16.2	4.9	-14.8
2010	-10.1	21.6	-3.7	-6.6	9.4
2011	-17.5	20.0	-13.4	-4.7	-1.0
2012	4.4	-7.5	0.7	3.6	-3.4
2013	-7.0	9.5	-5.4	-1.7	1.8
2014	9.7	-9.7	5.5	4.0	-1.0
Mean	-3.1	2.7	-2.2	-1.0	-0.6

EFFCH-efficiency change, TEHCH-technical change, PECH-pure efficiency change, SECH-scale efficiency change, TFPCH-total factor productivity change
**shaded cells emphasize positive change*

Total factor productivity grew by 9.4% in 2010 and 1.8% in 2013. These growths were due to shift in technology (innovation) rather than improvement in efficiency per se. Although there was an improvement in efficiency of about 4.4%, and 9.7% in 2012 and 2014 respectively, however, these improvements did not result in positive TPF growth. Overall, the yearly average shows that there was an annual regress in TPF (-0.6%) despite technical progress/growth of about 2.7% (Table 5.1).

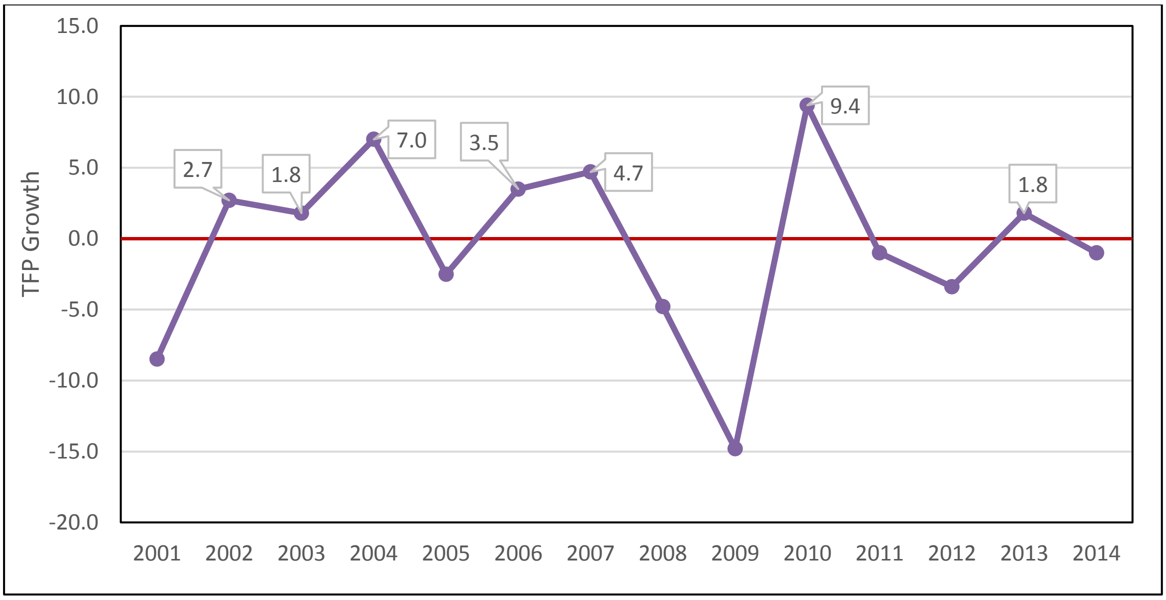


Figure 5.5: Total factor productivity growth in Japanese manufacturing industries (2001-2014)

Figure 5.5 gives the pictorial overview of the Malmquist index annual mean change as earlier seen in Table 5.1. TFP growth was all time higher in 2010 (about 9.4%) due to technical progress or 21.6% shift in technology (the highest in the period under consideration). 2004 recorded the second highest TFP growth of about 7.0% which was, among other things due to 5.9% change in technology (innovation) and 1.0% efficiency change (catching up). There was a technical progress (innovative efforts) in 2012 (19.8%) and 2013 (9.5%), however, this progress or shift in technology could not raise the TFP these years.

5.2.3 Industry Level Analysis

This section investigates the total factor productivity growth or change for individual industries from 2001 to 2014. Furthermore, the section also attempts to explain sources of TFP growth or decline during the period under consideration.

5.2.4 Total Factor Productivity in High & Medium-high-tech Industry

a. Machinery Industry

For the purpose of this study, the machinery industry was grouped into 5 categories according to Japan Standard Industrial Code (JSIC) depending on product specialization. These includes; general purpose machinery, production machinery, business-oriented machinery, electronic parts, devices & circuit, and electrical machinery & equipment. There was no TFP growth in 2001 for these industries (machinery, Table 5.1), however, in 2002 electronic parts, devices and circuit TFP grew by 11.8% which was due to efficiency improvement of approximately 2% and technical progress of approximately 10%. In the same year, electrical machinery & equipment TFP grew by 3.7% which was due to 9.8% technical progress and perhaps other factors outside the scope of this study and not efficiency improvement per se.

Table 5.1: Total Factor Productivity in High and Medium High Tech Industry (recalculated for actual Growth) *

Manufacturing Industry		2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	AVG
General-purpose machinery	EFFCH	-5.0	-10.9	-5.2	2.5	-33.9	9.0	-5.8	4.0	12.1	-7.1	-11.0	-1.0	-10.7	17.2	-3.3
	TECHCH	-3.9	9.8	11.4	5.0	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	9.4	-9.8	3.6
	TFPCH	-8.7	-2.2	5.6	7.7	-19.7	5.3	5.0	-1.6	-21.8	13.1	6.9	-8.5	-2.3	5.7	-1.1
Production machinery	EFFCH	-10.8	-9.7	4.5	7.9	-18.9	9.2	-6.8	-6.2	-4.6	5.6	-13.9	-0.4	-10.0	23.1	-2.2
	TECHCH	-3.9	9.8	11.6	4.8	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	9.4	-9.8	3.6
	TFPCH	-14.3	-0.8	16.6	13.0	-1.5	5.5	3.9	-11.3	-33.4	28.5	3.3	-8.0	-1.5	11.0	0.8
Business oriented machinery	EFFCH	-1.9	-11.3	-6.1	1.6	-17.5	1.6	-15.0	-8.9	19.7	-1.5	-21.7	-6.5	-5.3	8.2	-4.6
	TECHCH	-3.9	9.8	11.2	5.3	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	9.4	-9.8	3.6
	TFPCH	-5.8	-2.6	4.4	7.0	0.3	-1.8	-5.3	-13.8	-16.5	19.9	-6.0	-13.7	3.6	-2.4	-2.3
Electronic devices and circuits	EFFCH	-15.2	1.9	-8.9	-1.6	-25.9	5.0	-12.8	1.2	25.6	-16.1	-22.8	2.6	-5.4	15.0	-4.1
	TECHCH	-3.9	9.8	12.3	4.3	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	9.4	-9.8	3.6
	TFPCH	-18.5	11.8	2.3	2.7	-9.9	1.4	-2.9	-4.3	-12.4	2.1	-7.3	-5.3	3.6	3.7	-2.4
Electrical machinery & equipment	EFFCH	-3.7	-5.5	9.9	-14.7	-48.3	18.0	-9.8	-8.0	31.3	-12.7	-25.7	12.5	1.9	10.6	-3.2
	TECHCH	-3.9	9.8	12.1	4.4	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	9.4	-9.8	3.6
	TFPCH	-7.5	3.7	23.3	-11.0	-37.1	14.0	0.5	-12.9	-8.4	6.3	-10.8	3.9	11.5	-0.3	-1.8
Information & Electronic equipment	EFFCH	-29.3	-8.5	-9.9	3.2	-13.7	2.7	-3.2	-4.6	18.6	-15.4	-16.0	-0.3	-11.5	-0.7	-6.3
	TECHCH	-1.6	9.8	8.9	7.2	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	9.4	-9.8	3.7
	TFPCH	-30.5	0.4	-1.8	10.6	5.0	-0.8	7.8	-9.8	-17.2	3.0	0.9	-7.9	-3.2	-10.4	-3.9
Chemical & Pharmaceutical Industries	EFFCH	-3.0	-5.8	-14.2	-0.7	-15.3	5.0	-3.8	1.3	30.8	-11.4	-20.8	6.7	-4.5	7.7	-2.0
	TECHCH	-0.2	9.8	8.5	7.8	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	9.4	-9.8	3.8
	TFPCH	-3.2	3.4	-7.0	7.0	3.0	1.4	7.2	-4.1	-8.7	7.8	-4.9	-1.5	4.5	-2.8	0.2
Transport equipment	EFFCH	2.6	-0.5	-10.6	-6.0	-18.6	7.3	-1.8	-4.2	27.8	-12.4	-16.2	7.0	-12.2	0.1	-2.7
	TECHCH	-1.8	9.8	9.7	6.7	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	9.4	-9.8	3.7
	TFPCH	0.7	9.3	-1.9	0.4	-1.1	3.6	9.5	-9.4	-10.8	6.6	0.6	-1.2	-3.9	-9.7	-0.5
Ceramic, stone & clay products	EFFCH	-8.7	-4.3	-6.7	-18.2	-12.0	8.4	-7.3	2.4	16.8	-5.5	-20.3	8.0	-5.6	10.5	-3.0
	TECHCH	-1.9	9.8	9.6	7.0	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	9.4	-9.8	3.7
	TFPCH	-10.5	5.0	2.2	-12.5	7.0	4.7	3.3	-3.2	-18.5	15.1	-4.3	-0.3	3.4	-0.3	-0.6
Iron and steel	EFFCH	-8.7	-2.4	-6.6	13.2	-11.2	1.7	4.6	17.1	-7.6	0.1	-12.4	-9.0	3.8	11.7	-0.4
	TECHCH	1.6	9.8	7.5	8.7	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	9.4	-9.8	4.0
	TFPCH	-7.3	7.1	0.4	23.0	7.9	-1.8	16.6	10.7	-35.5	21.8	5.2	-16.0	13.6	0.8	3.3

EFFCH-efficiency change, TEHCH-technical change, and TFPCH-total factor productivity change.

**shaded cells show total TFP growth as explained by corresponding efficiency change and technical progress.*

TPF growths in general purpose machinery were 5.5%, 7.7%, 5.3%, 5.0%, 13.1%, 6.9%, and 5.7% in 2003, 2004, 2006, 2007, 2010, 2011, and 2014 respectively. Table 4.3 shows that these TFP growths were mainly due to efficiency changes and technical progress that took place accordingly in these years.

TFP growth was negative for general purpose machinery in 2005, 2008, 2009, 2012 and 2013 respectively. Similarly, TFP growths in production machinery was estimated as; 16.6%, 13.0%, 5.5%, 3.9%, 28.5%, 3.3% and 11.0% in 2003, 2004, 2006, 2007, 2010, 2011, and 2014 respectively but was negative for other years considered for this study. Evidence also point to efficiency changes and technical progress, among other things, as sources of TFP growth observed in this industry.

Business-oriented machinery show positive TFP growths only in 2003 (4.4%), 2004 (7.0%), 2005 (0.3%), 2010 (19.9%) and 2013 (3.6%) which were mainly explained by technical progress (innovation) rather than efficiency improvements.

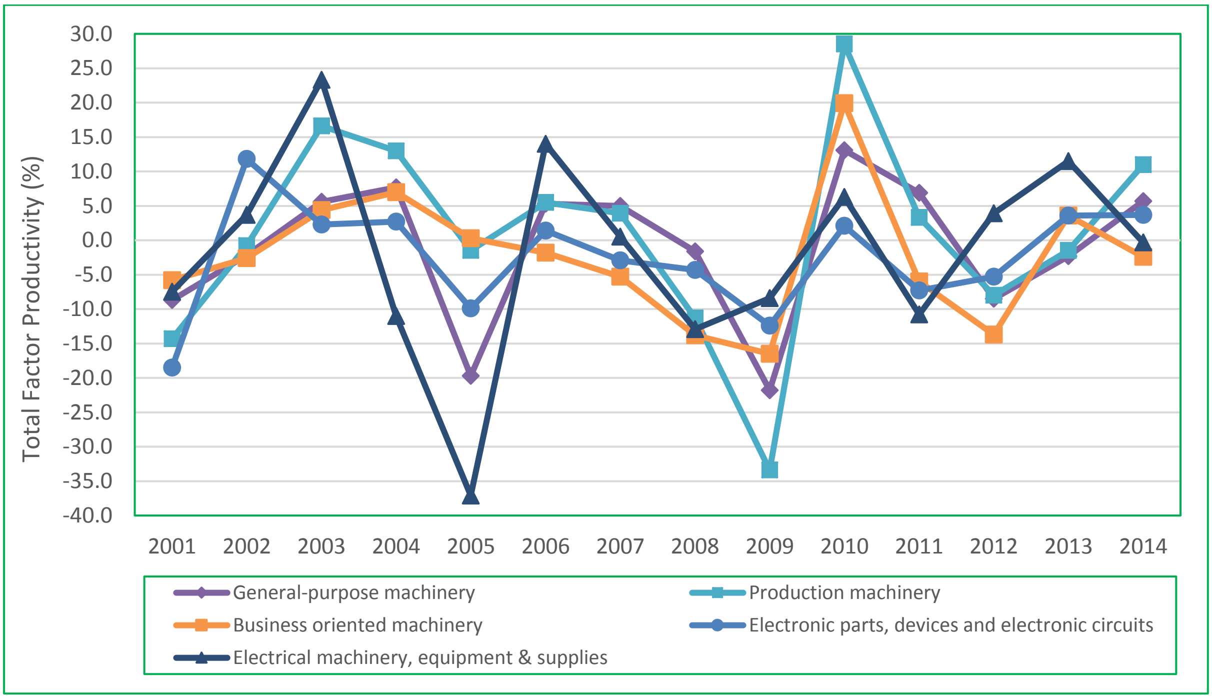


Figure 5.6a: Total factor productivity growth in Machinery industries (2001-2014)

Electrical parts, devices and circuits showed positive TFP growth in 2003, 2004, 2006, 2010, 2013, and 2014 respectively in the order 2.3%, 2.7%, 1.4%, 2.1%, 3.6% and 3.7%. These TFP growths were the product of efficiency change and technical progress in this industry in these years. Although there was technical progress in this same industry in 2005, 2007, and 2011, however, it can be inferred that these innovative efforts could not result to positive TFP growth for these years. Similarly, electrical machinery, equipment & supplies showed positive TFP growth in the order 23.3%, 14.0%, 0.5%, 6.3%, 3.9% and 11.5% in 2003, 2006, 2007, 2010, 2013 and 2013 respectively. The TFP growth in this industry for these years was a result of improvements in efficiencies and progress in technological accumulations.

The summary of machinery industries showed that positive TFP growths were observed 2002, 2003, 2007, 2010 and 2014 for most industries (see Figure 4.6). Notably, the highest TFP growths were observed in 2003 (about 23%) in Electrical Machinery and in 2010 (about 28.5%) in Production Machinery. Overall, the result showed that General Purpose Machinery grew at a constant rate of -1.1%, Production Machinery grew at constant rate of 0.8%, Business Oriented Machinery grew at a constant rate of -2.3%, Electronic Devices and Circuits grew at -2.4%, and Electrical Machinery and Equipment grew at -1.8% respectively on average between 2000-2014.

b. Chemical/Pharmaceutical and Other High-tech Industries

Total factor productivity growths were positive in Chemical & Pharmaceutical industry mostly for the early half of the period under review (2002, 2004, 2005, 2006 and 2007). In the later part, only 2010 and 2013 had positive TFP growth. Positive or negative TFP growth in this very important industry was mainly attributed to progress in technology rather than improvement in efficiency. For Information comm. & Electronic Equipment industry, positive TFP growth was observed for about six years, namely; in the year 2002, 2004, 2005, 2007, 2011 and 2012 respectively. The highest TFP growth of 10.2% was observed in 2004 for this industry. TFP growth for this industry was mainly due to technical progress and not necessarily due to efficiency change/improvement.

Figure 5.6b show the trend in TFP growth for Chemical & Pharmaceutical, Ceramics & Clay, Iron & Steel and Transport industry. Iron & steel shows positive TFP growth for most of the period under review. It grew by 23% in 2004, approximately 17% in 2007, about 22% in 2010 and about 14% in 2013. It's productivity, however, fell by more than 30% in 2009. Overall, these industries showed positive TFP growth in 2002, 2004, 2007, and 2010 as illustrated in Figure 5.6b. All industries classified under the high & medium-high-tech industry showed negative TFP growth, technical regress and efficiency loss in 2009.

The overall result shows that Chemical & Pharmaceutical industries grew at a constant rate of 0.2% between 2000 and 2014, while Iron & Steel grew at 3.3% during the same period. Other industries grew at a negative rate.

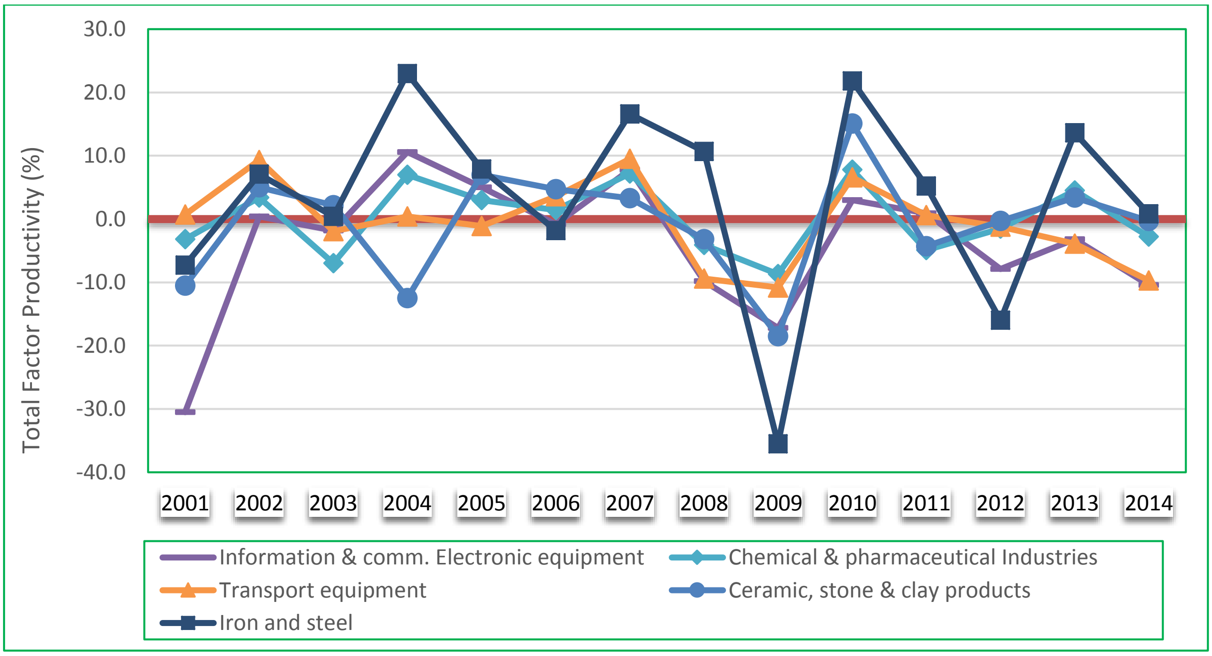


Figure 5.6b: Total factor productivity growth in Chemical/Pharmaceutical and other High-tech industries (2001-2014)

5.2.5 Total Factor Productivity in Medium Low-tech Industry

Total factor productivity growth was positive and consistent in Petroleum and Coal products from 2001 to 2007 and from 2010-2011 and finally in 2013. Significant TFP growth of about 10% and above were observed in the year 2001, 2004, 2005, 2005, 2010, 2011 and 2013. Table

5.2 showed that positive TFP growth in Petroleum & Coal product industry was due primarily to technological progress and not necessarily efficiency changes for these years. There was negative TFP growth in 2008 & 2009, 2012 and 2014 in this industry.

Plastic products show a positive TFP growth of about 12.1% in 2004 which was due to 7.4% efficiency improvement and 4.4% technical progress, and 10% in 2011 which was mainly as a result of 9.4% change in efficiency and perhaps other factors not considered for this study. Slight positive TFP growth in the Plastic industry was also observed in other years, which were mainly a result of technological progress. However, TFP growths were negative in 2001, 2002, 2007, 2009, and 2014 despite significant improvement in efficiencies and technological progress in these years (9.8% & 11.5% in technical progress in 2002 & 2007, and 12.1% & 6.1% efficiency improvements in 2009 & 2014 respectively).

Rubber products industries had positive TFP growth of 15.5% in 2001, 4.4% in 2004, 4.7% in 2006, 8% in 2007 19.1% in 2010 and 0.9% in 2012. While some TFP growth were mainly a result of technical progress such as those in 2004, 2007, 2010 and 2011, others TFP growths were due to efficiency changes/improvements. There were about 9.8%, 9.5% and 21.6% technical progress in Rubber products 2002, 2003 and 2005, this, however, did not result in positive TFP growths. Furthermore, 9.1%, 4.5% and 8.8% efficiency improvements in 2009, 2012 and 2014 could not result in positive TFP growth in Rubber products industries.

Non-ferrous metal industries showed positive TFP growth in 2002 (0.3%), and significant positive growth between 2004 and 2007 in the magnitude 14.4%, 19%, 35.7% and 15.9%. it loses the momentum between 2008 and 2009 and recovers slightly in 2010, losses it again between 2011 and 2012 and recovered again in 2013 and 2014 (see shaded cells in Table 5.2). Positive TFP

growth in the Non-ferrous metal industry was either due to technical progress, efficiency changes/improvements or both factors. 2006 saw the highest TFP growth in this industry. A similar trend in TFP growth was also noticed in Fabricated Metal industry.

Table 5.2: Total Factor Productivity in Medium-low-tech Industry (recalculated for actual Growth) *

Manufacturing Industry		2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
	EFFCH	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	TECHCH	10.8	5.0	2.6	10.4	18.9	1.3	10.0	-9.5	-28.4	19.6	18.0	-2.6	0.0	-7.5
Petroleum and coal products	TFPCH	10.8	5.0	2.6	10.4	18.9	1.3	10.0	-9.5	-28.4	19.6	18.0	-2.6	11.3	-7.5
	EFFCH	-6.3	-15.0	-9.7	7.4	-17.2	4.0	-11.0	-2.8	12.3	-12.2	-8.4	9.4	-7.5	6.1
	TECHCH	-3.9	9.8	11.6	4.4	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	0.0	-9.8
Plastic products	TFPCH	-9.9	-6.7	0.8	12.1	0.6	0.4	-0.8	-8.0	-21.6	6.9	10.0	1.0	1.2	-4.3
	EFFCH	17.8	-11.2	-19.4	-2.4	-19.7	8.4	-3.1	6.5	9.1	-2.2	-16.0	4.5	-13.0	8.8
	TECHCH	-1.9	9.8	9.5	6.9	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	0.0	-9.8
Rubber products	TFPCH	15.5	-2.5	-11.7	4.4	-2.4	4.7	8.0	0.8	-23.8	19.1	0.9	-3.5	-4.8	-1.8
	EFFCH	-15.7	-8.6	-11.2	5.4	-2.1	40.5	4.0	-11.0	11.6	-7.9	-21.5	-2.5	-7.8	18.6
	TECHCH	0.9	9.8	7.6	8.6	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	-2.1	-9.8
Non-ferrous metals & products	TFPCH	-14.9	0.3	-4.5	14.4	19.0	35.7	15.9	-15.8	-22.1	12.1	-5.8	-9.9	0.9	7.0
	EFFCH	1.4	-1.8	-14.2	9.0	-13.0	6.7	-2.3	-0.6	26.5	-13.0	-19.8	9.4	-6.5	9.2
	TECHCH	-3.9	9.8	12.3	4.1	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	1.3	-9.8
Fabricated metal and products	TFPCH	-2.6	7.8	-3.6	13.4	5.7	3.0	8.8	-5.9	-11.7	5.9	-3.7	1.0	2.4	-1.5

EFFCH-efficiency change, TEHCH-technical change, and TFPCH-total factor productivity change.

**shaded cells show total TFP growth as explained by corresponding efficiency change and technical progress.*

Figure 5.7 shows that most industries in the medium-low-tech industry showed positive TFP growth in 2004, 2005, 2006, 2007 and 2010. However, the overall result shows that Petroleum & Coal industry grew at a constant rate of 4.3%, the Plastic industry grew at -1.3%, Rubber industry grew at 0.2%, Non-ferrous Metal grew at 2.3% and Fabricate metal industry grew at a constant rate of 1.4% between 2000 and 2014. All industries suffer from negative TFP shock in 2009.

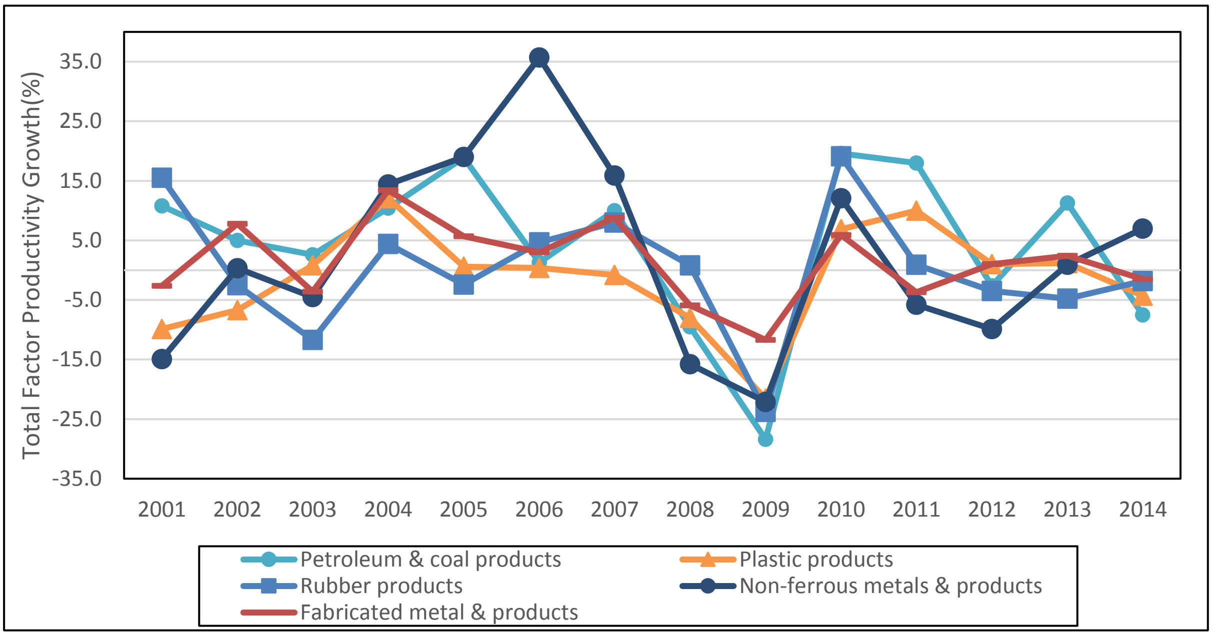


Figure 5.7: Total factor productivity growth in medium-low-tech industries (2001-2014)

5.2.6 Total Factor Productivity Growth in Low-tech Industry

The Food industry shows positive TFP growth in 2001 and 2002 which were due to efficiency change and technical progress respectively. Other years showing positive TFP growth in the food industry includes; 2006, 2007, 2008, 2010 and 2011. While positive TFP growths in 2006 and 2008 were mainly due to efficiency improvement, TFP growth in other years was mainly a result of technological accumulation. TFP growth was negative in the year 2003, 2004 and 2005, despite huge technical progress in these years. Similarly, despite efficiency improvement in the year 2009, 2012, 2013 and 2014, TFP growth was negative in Food industry.

TFP grew by 5.4% and 7.2% in 2003 and 2004 respectively in the Beverages, Tobacco & Feed industry. These growths were a result of technological progress made in those years. However, Positive TFP growth in 2008 in this industry was a function of efficiency improvement and perhaps other factors not considered for this study. 2.3% growth in TFP in 2010 was a result of 21.7% technical progress made in the same year in this industry.

Furthermore, positive TFP growth observed in 2012, 2013 and 2014 for Beverages, Tobacco & Feed industry were mainly a function of efficiency improvements and not technical progress. Negative TFP growth occurred in 2002, 2005, 2007, and 2011 despite advances in technology.

TFP grew by 7.2%, 3.6%, 12.4%, 12.4%, 1.1%, 30.8% and 2.6% in 2003, 2004, 2006, 2007, 2009 and 2010 respectively in Textile Mill Industry. While some TFP growth in this industry were a function of technological progress such as those in 2003, 2004, 2007 and 2010, others were a result of efficiency improvement, such as those in 2006 and 2009.

There was positive total factor productivity growth in Lumber & wood products in 2002, 2005, 2006, 2010 and 2011 in the order 18.9%, 4.7%, 15.2%, 9.2%, and 16.2% respectively. In Furniture & Fixtures, positive TFP growth was observed between 2002 to 2004, and then in 2006, 2008, 2010 and 2011. Similarly, there was positive TFP growth in Pulp & Paper industry for most of the period considered for the study. Most TFP growth in the Wood industry was a result of technical progress, efficiency improvement or both.

Other industries in the low-tech group such as Printing and Leather Tanning showed positive TFP growth in at least 5 or more times in the period under study. Table 5.3 shows that technical progress, efficiency improvement or both accounts for these growths.

Table 5.3: Total Factor Productivity in Low-tech Industry (recalculated for actual Growth) *

Manufacturing Industry		2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
	EFFCH	4.2	-4.7	-14.9	-4.0	-20.2	4.9	-7.0	14.4	32.9	-12.3	-14.6	5.1	-9.8	8.3
	TECHCH	-3.9	9.8	12.6	3.9	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	-5.9	-9.8
Food	TFPCH	0.1	4.6	-4.2	-0.3	-3.0	1.3	3.7	8.3	-7.3	6.7	2.5	-2.9	-1.3	-2.3
	EFFCH	-3.9	-9.8	-2.2	-1.2	-23.4	-3.9	-12.8	13.3	41.9	-15.9	-32.0	10.0	-8.2	16.1
	TECHCH	0.9	9.8	7.7	8.5	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	-5.1	-9.8
Beverages, Tobacco & Feed	TFPCH	-3.0	-1.0	5.4	7.2	-6.9	-7.2	-2.8	7.2	-0.9	2.3	-18.3	1.6	0.4	4.7
	EFFCH	-4.3	-9.8	-4.4	-0.5	-30.7	16.4	-9.0	5.5	87.4	-15.7	-40.1	8.0	-11.5	6.7
	TECHCH	-3.9	9.8	12.0	4.1	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	0.0	-9.8
Textile mill products	TFPCH	-8.1	-1.0	7.2	3.6	-15.8	12.4	1.4	-0.2	30.8	2.6	-28.1	-0.2	-3.1	-3.8
	EFFCH	-2.4	8.3	-13.9	-5.0	-13.8	19.3	-25.3	3.0	21.6	-10.3	-3.2	4.3	-1.6	4.6
	TECHCH	-3.9	9.8	12.6	3.9	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	-0.1	-9.8
Lumber and wood products	TFPCH	-6.2	18.9	-3.0	-1.3	4.7	15.2	-16.8	-2.6	-15.1	9.2	16.2	-3.7	7.7	-5.6
	EFFCH	-3.3	-5.8	-3.7	0.3	-20.2	9.4	-11.5	6.6	22.3	-12.8	-2.7	8.2	-10.0	6.7
	TECHCH	-3.9	9.8	12.6	3.9	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	0.2	-9.8
Furniture and fixtures	TFPCH	-7.1	3.3	8.4	4.2	-3.0	5.7	-1.3	0.9	-14.6	6.1	16.9	0.0	-1.5	-3.7
	EFFCH	-5.7	0.0	-13.3	-4.9	-20.5	8.7	-6.9	8.4	33.0	-15.8	-17.9	9.9	-0.3	8.7
	TECHCH	-0.1	9.8	8.7	7.6	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	0.2	-9.8
Pulp, paper and paper products	TFPCH	-5.8	9.8	-5.8	2.4	-3.4	5.0	3.8	2.6	-7.2	2.5	-1.4	1.5	9.1	-1.9
	EFFCH	2.6	-10.0	-12.8	-1.9	-21.2	4.4	-9.1	5.6	38.6	-17.0	-16.3	6.6	-9.3	-2.8
	TECHCH	-3.9	9.8	12.1	4.5	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	0.0	-9.8
Printing and allied industries	TFPCH	-1.4	-1.2	-2.2	2.5	-4.2	0.8	1.3	-0.1	-3.2	1.1	0.5	-1.6	-0.7	-12.3
	EFFCH	-45.4	-3.7	-3.3	80.5	-21.2	-21.8	13.5	-21.6	31.4	-1.5	-15.3	2.6	-4.6	41.8
	TECHCH	-3.9	9.8	12.6	3.9	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	-4.6	-9.8
Leather tanning, leather products & fur skins	TFPCH	-47.5	5.7	8.9	87.4	-4.2	-24.4	26.5	-25.8	-8.3	19.9	1.7	-5.2	4.4	27.9
	EFFCH	9.4	-16.9	-3.6	-16.9	-19.6	15.0	5.2	8.2	16.9	-22.6	-20.3	13.0	-16.2	4.5
	TECHCH	-3.7	9.8	11.3	5.8	21.6	-3.4	11.5	-5.4	-30.2	21.7	20.1	-7.7	-0.1	-9.8
Miscellaneous manufacturing industries	TFPCH	5.4	-8.8	7.3	-12.2	-2.3	11.1	17.3	2.4	-18.4	-5.8	-4.3	4.4	-8.3	-5.7
Industry Average (TFP)		-8.2	3.4	2.4	10.4	-4.2	2.2	3.7	-0.8	-4.9	5.0	-1.6	-0.7	0.7	-0.3

EFFCH-efficiency change, TEHCH-technical change, and TFPCH-total factor productivity change.

**shaded cells show total TFP growth as explained by corresponding efficiency change and technical progress.*

Miscellaneous industry referred to all industries not elsewhere classified. Positive TFP growth was observed in 2001, 2003, 2006, 2007, 2009 and 2012 in this industry, and for the most part, efficiency improvement account for greater part of this TFP growth.

Figure 5.8 shows the trend in TFP growth for the low-tech industries. Different industry tends to have positive TFP growth in different time period. However, 2009 seems to be the year with negative TFP growth common to all industry except textile mill products. Overall, the industry average shows that there were positive TFP growth between 2002 to 2004, 2006 to 2007, 2010 and 2013 in the order 3.4%, 2.4%, 10.4%, 2.2%, 3.7%, 5% and 0.7% respectively. Accordingly, on average, the Food industry grew at a constant rate of 0.4%, Lumber & Wood Industry grew at 1.3%, Furniture & Fixtures grew at 1.0%, Pulp & Paper industry grew at 0.8%, and Leather Tanning industry grew at a constant rate of 4.8% between 2000 and 2014. Other industries grew at a negative rate during the period under review.

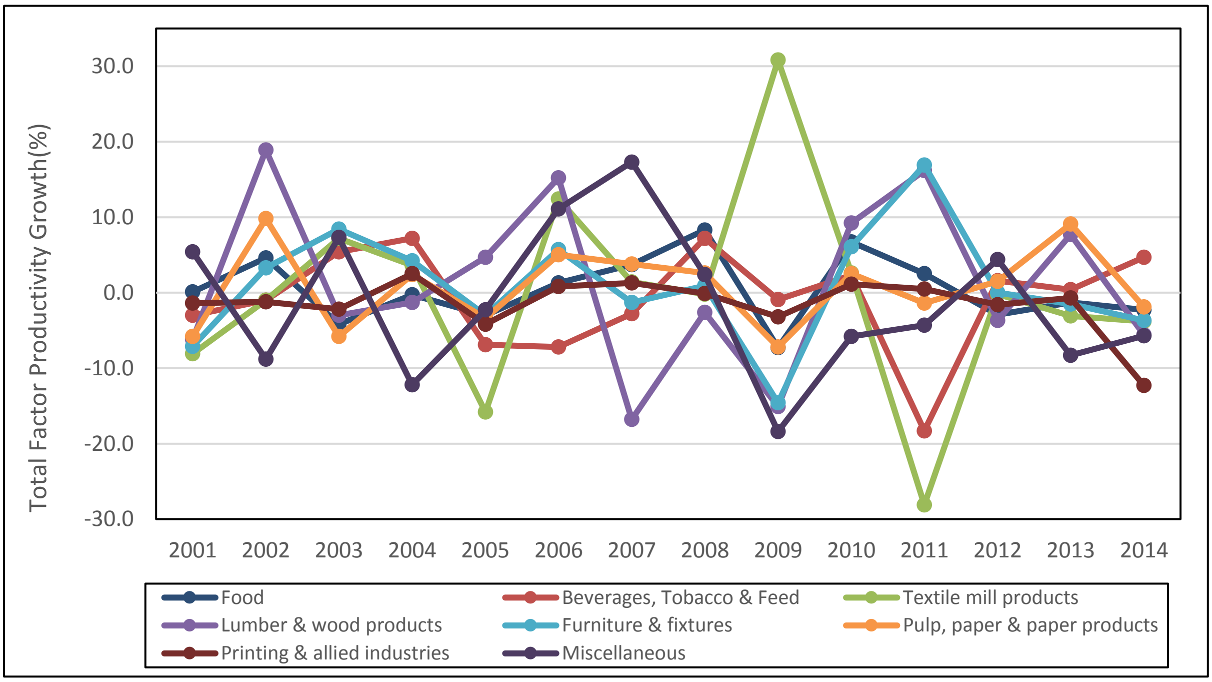


Figure 5.8: Total factor productivity growth in low-tech industries (2001-2014)

5.2.7 Conclusion on Total Factor Productivity Growth.

The results discussed above showed that total factor productivity of the Japanese manufacturing industries grew at a negative rate of (-0.6%) on the average throughout the period under review (2000-2014). However, when we focused our attention on specific growth and regress in TFP, we found peak (positive growth) and low (negative growth) in TFP growth. We believe that this crest and trough movement in TFP were not a random occurrence. We try to explain these movements via the following foci lenses

a. ***The Externality Factor***. There is basically five-time period with particularly low striking (negative) TFP shock in Figure 5.5, namely; 2001, 2005, 2008 and 2009. The world economy including the industrial sector (manufacturing) was hit by financial crises in 2001 which subsequently forced the market to shrink globally. This accounted for the shock observed in 2001.

The negative TFP shock in 2005 may among other things, be linked to stiff competition presented by the emerging markets such as the rise of China and India few years after the economic meltdown of 2001. The post economic recovery from the world's worst recession in 2001 gave rise to Emerging Markets (EMs) and accordingly, commentators have argued that this present huge challenge to incumbents (MITI, 2010) (OECD, 2011) (World Bank, 2012).

On the other hand, the high negative TFP shocks in 2008 & 2009 could be traced to the 2008 global financial crisis which affected the global economy in no small measure. A report by The Economist (2009), showed that Japan industrial production fell by 12% in the post 2008 financial crises. A similar study by Moore and Mirzaei (2016) on the impact of the global financial crisis on industry growth showed that fixed capital formation, output, and value added all grew negatively in 2009 for 23 industries in 82 countries as a result of the aftermath of 2008 financial crises. Particularly the negative TFP shock in the machinery industries (Figure 5.6) bear a striking resemblance with Moore and Mirzaei study where the crest and trough movement were observed in the same years. This suggests that the impact of economic shocks especially those at global level seems to have a similar impact on the industrial sector.

b. ***The Internal Factors***: Many studies have been done to explain Japan decline productivity (Kim, 2015), (Fukao, 2013) (Kim & Lee, 2015) (Miyagawa, Sakuragawa, & Takizawa, 2005). These researchers provided many factors that are likely to be responsible for Japan declining (low) TFP. For example, Kim and Lee (2015) found that negative TPF growth from 1986-2002 was a result of the Plaza accord of 1985 and the burst of the bubble economy in the 1990s. They argued that the 1990s depression was so much that firms with great technological capabilities went out of business and this cause prolonged delay in technical progress throughout the 1990s and perhaps the early 2000s.

Miyagawa, et al. (2005) found labour hoarding to have contributed to low productivity growth in Japan. Despite its advantages of guaranteeing employee talent and accumulated tacit knowledge in human resources, labour hoarding becomes a huge risk to the company during economic shocks. Similarly, seniority and lifetime employment were also another structural problem cited as reasons for productivity decline in both manufacturing and non-manufacturing sector in Japan. Although these were previously praised as the vital elements that contributed immensely to the Japanese miracle age (economic success) in the 70s, nevertheless some researchers (Jurgen & Kadokawa 2010, Hattori & Maeda 2000, and Adhikari 2005) have argued that the same employment relations (seniority & lifetime employment) have contributed to low TFP growth and by extension Japan economic stagnation.

Another often cited structural problem affecting Japan total factor productivity is the aging demography. More recently, Liu & Westelius (2016) studied the impact of demographics on productivity and inflation in japan and found aging population and declining population as contributory factors to the low total factor productivity in japan, thereby confirming the opinion held by several earlier studies.

The existence of the so-called “zombie” firms and Basel capital requirement have also caused low productivity in Japanese industrial sector and undue economic stagnation. Ahearne and Shinada (2005) use industry and firm-level data and found productivity to be particularly low in industries with known heavy concentration of “zombie” firms which they argued was exacerbated by the wrong reallocation of market share. The authors opined that the continuous provision of financial support to inefficiency and debt-ridden firms (zombie firms) by banks have prevented more productive firms from gaining access to the market, thereby strangling the already turbulent economy suffering from decade-long productivity. Similarly, Yoshino and Taghizadeh-Hesary (2015) argued that Basel capital requirements which made Japanese banks reluctant to lend money to start-ups and SMEs have discouraged innovation and technological progress. The consequence of which is low TFP growth.

Fukao (2013) argued that the expansion of large firms’ supply chain globally and relocation of factories abroad hindered the spread of spillovers of R&D from large firms to medium-sized enterprise. The result is low technological change (technical progress), the main component of TFP growth. According to Saito (2015); in response to the pressure to be more productive, Japanese manufacturer expands FDI and shift production sites abroad, and what remain within the border are head offices and R&D offices with less contribution to direct value-added productions. A similar opinion was expressed by (MITI, 2010) when it found that Japanese manufacturing industries continued to expand oversee production to the detriment of the local economy.

c. ***Economic/manufacturing Frontier***: One may speculate that Low TFP in Japanese manufacturing industries may be due to economic/manufacturing frontier following the argument put forward by Farell, et al (1994). In their study on “productivity growth, technical progress and efficiency change in industrialized countries”, the authors found that countries operating at efficiency frontiers or near efficiency frontiers usually encounter slow technical progress and efficiency change (components whose product account for TFP). Following this argument, we conjectured that this might explain why Japanese manufacturing industries whose performance were already at frontier show regress in TFP.

5.3 What is the Path of Technological Learning and Progress Ratio (Learning Rates) in Japanese Manufacturing Industries?

The answer to this question lies in the thorough examination of two frequently used learning curve model; log-linear and cubic (S-curve) model. To estimate the learning rates for each of the 24 manufacturing industries. This study estimated both models (see chapter four for the results) and compare the results. To answer the research questions in this section, we proceed as follows;

5.3.1 Linear Learning Model Result

As discussed elsewhere in this study, industries whose calculated progress ratio are less than unity ($d<1$) show learning potentials (refer to Table 2.1 for an explanation on progress ratio). Figure 5.10 is a radar chart showing the progress ratio of all manufacturing industries grouped under three quadrants (1st, 2nd, and 3rd quadrant, for high & medium high-tech, medium-low-tech and low-tech respectively).

Under the first quadrant (high & medium high-tech industrial category), six industries show learning potentials as indicated by the data callouts (progress ratio). General Purpose Machinery industry showed learning potential of 91.4%, implying that its unit production cost decreased to approximately 91% of the previous value for each doubling of production. Alternatively, we could also interpret this as; General Purpose Machinery industry had its unit production cost decreased at a constant rate of approximaely 9% for each doubling of production between 2000 and 2014.

Electronic Devices & Circuit and Information Com. & Electronic Equipment industries showed learning potentials of 89% each, suggesting that these two industries decreased their unit production cost at a constant rate of 11% for each doubling of cumulative production during the period under review. Ceramic & Clay Products industry had learning potential of 96% which means its unit production cost decreased by approximately 4% for each doubling of production between 2000 and 2014.

Iron & Steel industry decreased its unit production cost to 34.3% over its previous value, the highest cost saving industry according to the linear estimation. Transport Industry had approximately 91% learning potentials. From the foregoing, Iron & Steel had a better learning potential, followed by Information Com. & Electronic and Electronic Parts & Circuits respectively.

Unit production cost declined by 89.7% on average in Fabricated Metal industry from 2000 to 2014 when the cumulative production doubles. The non-ferrous Metal industry also cut down its unit production cost by 74% over its previous value during the same period at doubling of experience or production. And lastly, at doubling of cumulative production, unit production cost declined by 96.7% in Rubber industry in the same period. Non-ferrous Metal shows the highest learning potential in the medium-low-tech industry. For low-tech industry group, only Textile Mill, Furniture & Fixtures, Pulp & Paper, and Miscellaneous Industries show learning potentials with 80.3%, 86.3%, 96.6%, and 70.3% unit cost efficiency gain (unit labour cost reduction) respectively at each doubling of cumulative production.

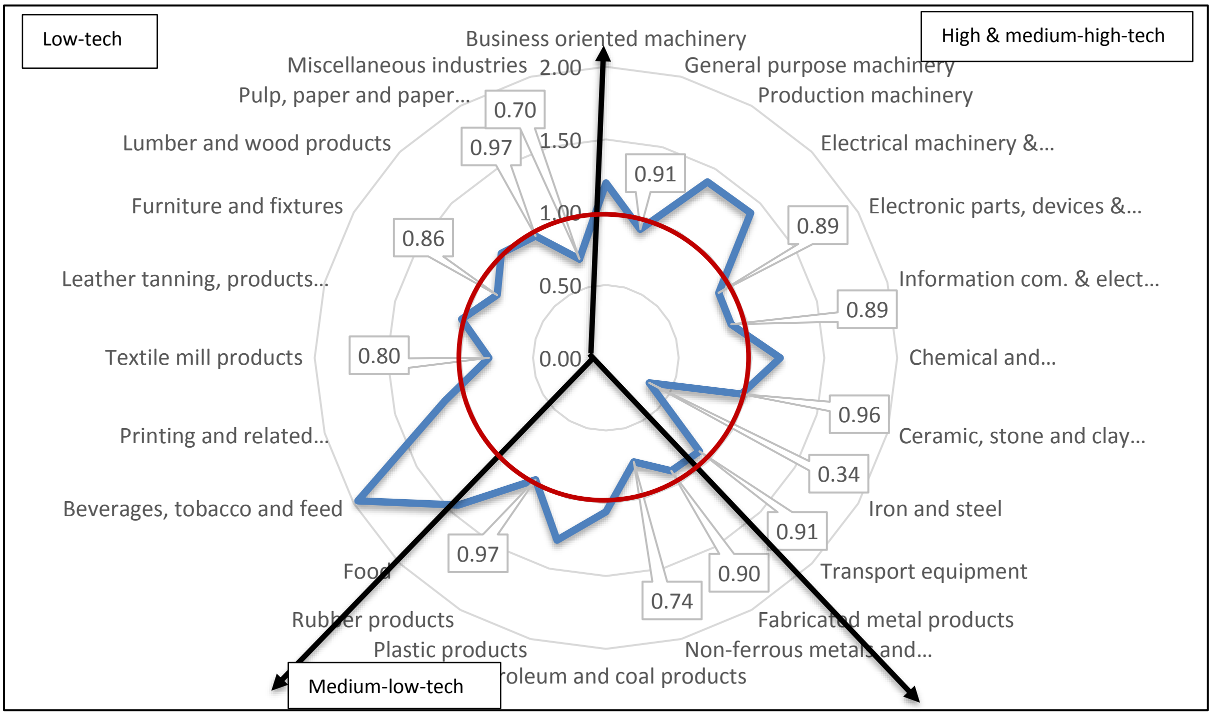


Figure 5.9: Radar chart showing Linear Learning Levels in Japanese Manufacturing Industries (200-2014), Data callouts emphasize industries with learning potentials.

Red circle emphasizes neutral line (1.00, i.e. neither learning nor forgetting

Industries with progress ratio/learning level above unity (d>1) show forgetting instead of learning and by extension loss in cost efficiency. This implies an increase in unit production cost at each doubling of cumulative production. For example, Figure 5.10 shows that Business Oriented Machinery had a learning level of 1.20 (see Table 4.6). This implies that this industry showed forgetting or per unit cost efficiency lost, i.e. unit production cost increased by 20% for each doubling of production. Other High-tech industries with poor learning level are; Production Machinery, Electrical Machinery, and Chemical & Pharmaceutical industries. Industries with a loss in cost efficiency in medium & low-tech are; Petroleum & Coal, Plastic, Food, Beverages, Tobacco & Feed, Printing, Leather Tanning and Lumber & Wood industries. These industries demonstrated poor learning potentials and thus increased their unit production cost at each doubling of cumulative productions according to the linear model of the learning curve. Some studies (Karaoz & Albeni, Asgari & Yen, 2011, and Asgari & Gonzalez-Cortez, 2012) have shown that linear learning curve does not always provide good technological learning when time series data is involved as it lacks the capacity to check the dynamism of learning over time. The next section will investigate the technological learning system in Japanese manufacturing industries via a more appropriate model (the cubic model).

5.3.2 Dynamic Cubic Learning Model Results

a) High & medium-high-tech Industry

Business-Oriented Machinery industry showed dynamic learning potentials between 2001 and 2006 and thereafter lost its efficiency in cost saving/reduction at each doubling of cumulative production for the rest of the years (2007 to 2014, Figure 5.10). Similarly, General Purpose Machinery industry cut down its unit production cost by at least 90% at each doubling of cumulative production, between 2001 and 2005. However, there was an increase in unit production cost for every doubling of cumulative production for the rest of the years for this industry. This is called early learning and later forgetting. This trend in early learning potentials (cost saving) and forgetting in a later stage (cost increase) at each doubling of cumulative production was also exhibited by Information & Electronic Equipment, Ceramics & Stone, and Iron & Steel industries.

Electrical Machinery & Equipment showed learning potential (unit cost reduction) only in recent times (2011 to 2014). This implies that the industry has reduced its unit labour cost at each doubling of cumulative production beginning from 2011 to 2014. The progress ratio for this industry shows that the learning was continuous and was getting better and better in the last four years of the study.

Two industries under the high-tech industrial group showed dynamic and continuous learning potentials in almost all the years under review, namely; Electrical Parts & Circuits and

Chemical & Pharmaceuticals (Figure 5.10). The former showed continuous efficiency gain or cost reduction in unit production at each doubling of cumulative production from 2002 to 2014 implying huge technological learning resulting from innovative activities. The later also had a good learning potential from 2001 to 2012 but lost its unit cost efficiency gain at every doubling of cumulative production in the last two years of the study namely; 2013 and 2014.

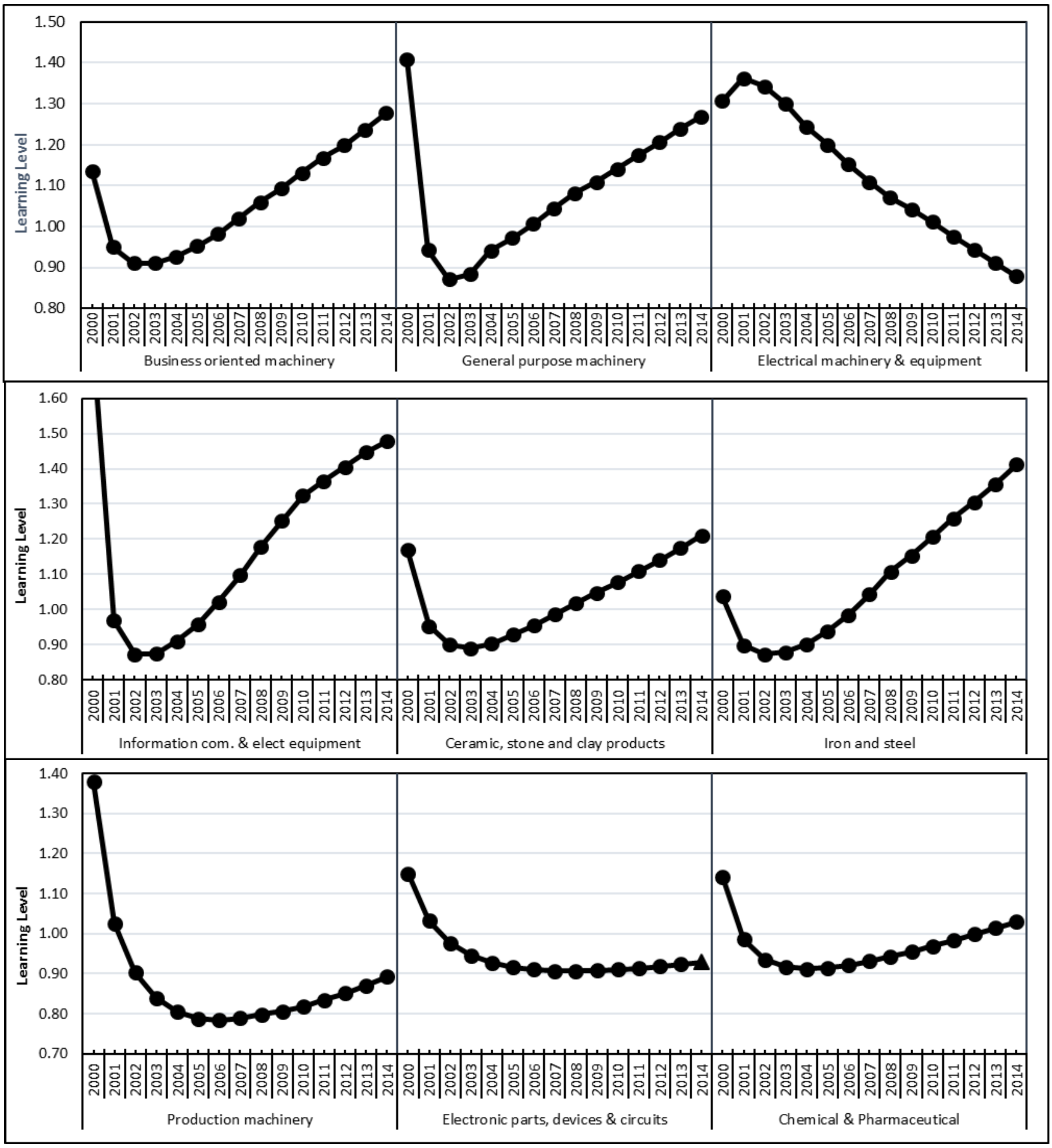


Figure 5.10: Dynamic Learning Curve for High-tech Industries
Dotted points (lines) below 1.00 on the graph indicates good learning potential

b) Medium-low-tech Industry

Fabricated Metal, Non-ferrous Metal, and Plastic industries all showed technological learning potentials and unit cost reduction for each doubling of cumulative production only at the beginning of the period under study (from 2000-2007, Figure 5.11). These industries, however, lost their unit cost efficiency gain and increased unit production cost considerably from 2008 to 2014 and perhaps beyond. Petroleum & Coal industry showed a continuous learning potential for the larger part of the time under review (2000 to 2011). During this period, this industry's unit production cost declined to about 90% on the average. However, the unit cost efficiency gain was lost in the last two years of the study (2013 & 2014). This implies forgetting phase for this industry from 2013 and beyond.

Rubber industry showed declined in unit cost production between 2000 and 2001 and thereafter lost its unit cost efficiency gain, thereby increasing unit production cost for more than half a decade (2002 to 2007). And from 2008 and beyond, there was continuous good learning potential and real cost saving for this industry.

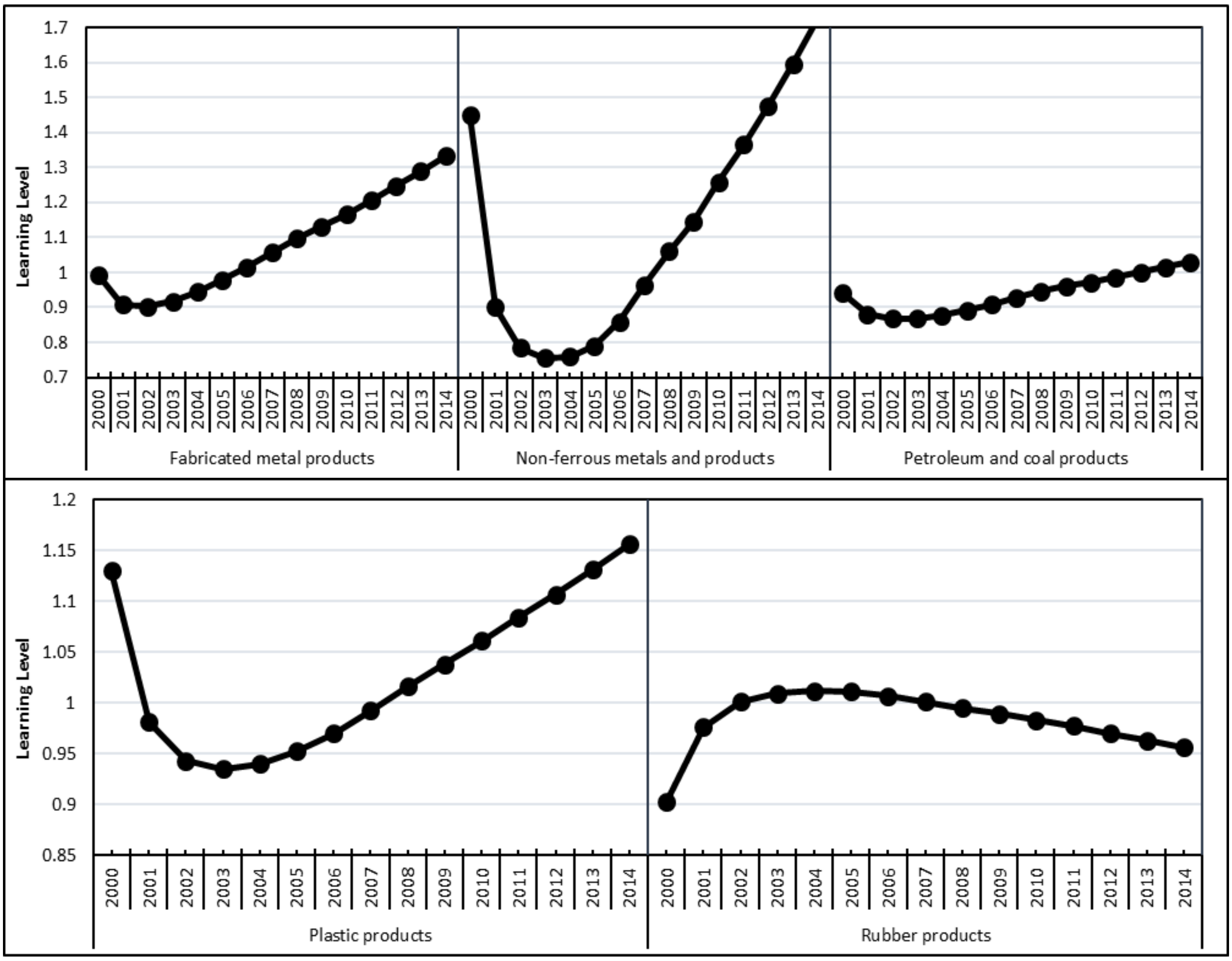


Figure 5.11: Dynamic Learning Curve for Medium-low-tech Industries
Dotted points (lines) below 1.00 on the graph indicates good learning potential

c) Low-tech Industry

For the low-tech industrial group, Food and Furniture showed continuous learning in almost all the years under review (Figure 5.12). This suggests that these two industries showed a continuous and dynamic learning potentials which enable them to cut down their unit production cost over each previous year for each doubling of cumulative production through the period under study. Some low-tech industries such as Beverages & Tobacco, Printing, Leather Tanning, Pulp & Paper and Miscellaneous industries showed learning potentials at some beginning period and are only considered to be cost efficient at this period. These industries, however, lost their unit cost efficiency gain in the greater part of the time under review.

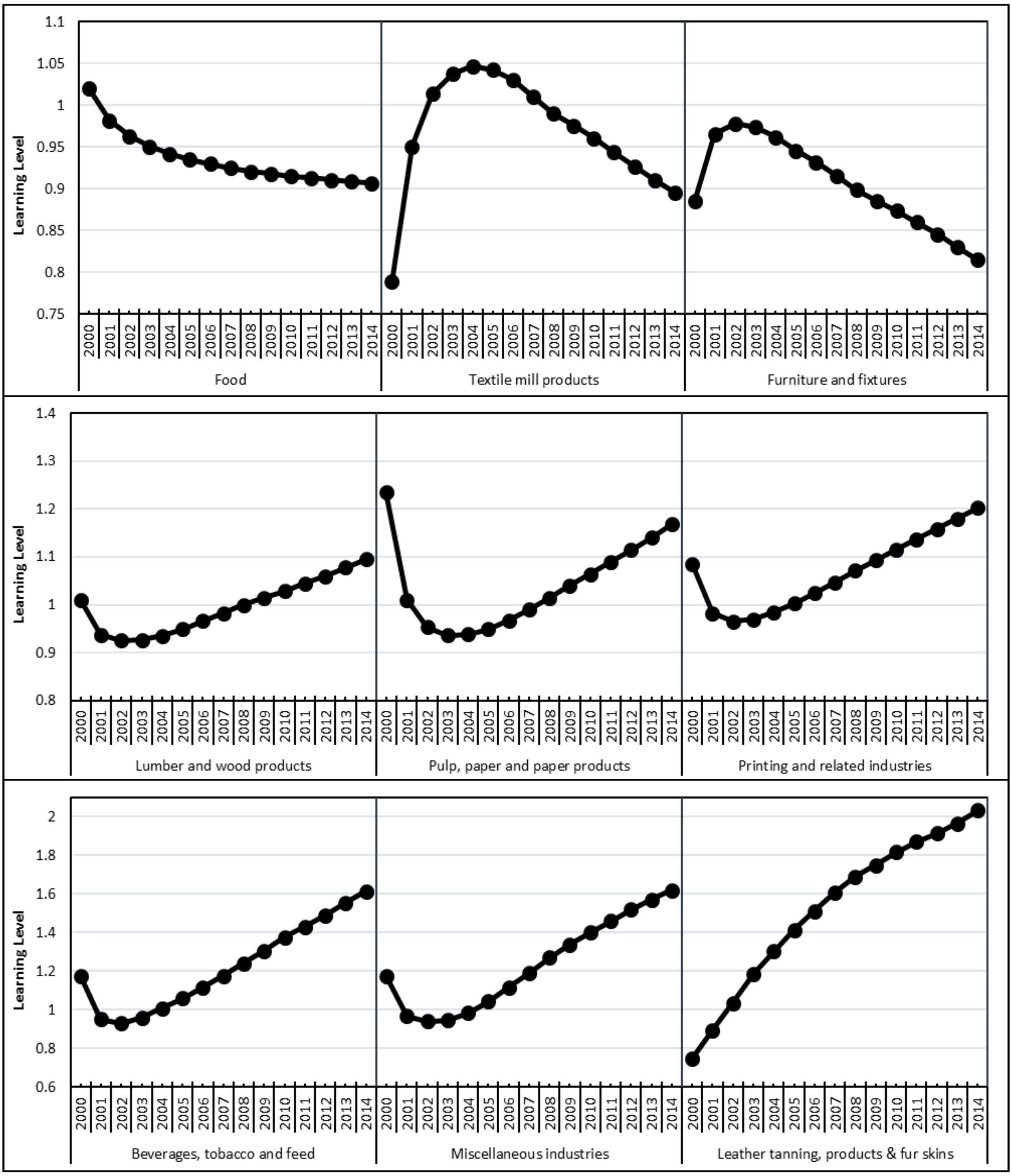


Figure 5.12: Dynamic Learning Curve for Low-tech Industries
Dotted points (lines) below 1.00 on the graph indicates good learning potential

Textile Mill products had huge cost saving at the beginning (200 & 2001) and most part of the years under review (2008 to 2014 and perhaps beyond, Figure 5.12). This suggests that Textile Mill industry showed a progressive learning potential that extend to the most recent years. Lumber & Wood industry showed learning potentials from 2001 through to 2008 and thereafter lost its unit cost efficiency gain for the remainder of the years under review. This again shows that this industry experiences technological forgetting at some end period.

5.3.3 Summary of Path to Technological Learning in Japanese Manufacturing Industries

The dynamic technological learning in Japanese manufacturing industries is summarized in Table 5.4. Three paths to technological learning can be derived from the pattern of industrial learning in Japanese manufacturing industries.

a) Convex Learning Path with a Minimum

Industries showing convex learning path with minimum show either *(1) forgetting at some beginning and end period, (2) forgetting at some end period only, or (3) forgetting at some beginning period only.* Industries in the category (1) started learning after some beginning period but unfortunately did not sustain the learning potential and thereafter lost it. Industries under category (2) demonstrated learning potentials from the beginning period and after a while lost this ability to save cost from technological learning. And lastly, industry under category (3) learned-by-doing and this led them to huge cost saving after the beginning period. Once started, learning for these industries is continuous.

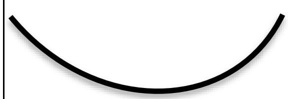
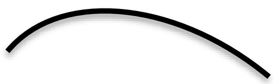
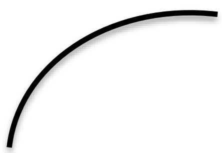
b) Concave Learning Path with a Maximum.

Industries in this category also demonstrated three learning characteristics; *(1) With forgetting at some midpoint, (2) With forgetting at some beginning period and (3) No forgetting at any period.* Industries under category (1) had learning potentials all along but lost it at some midpoint. They, however, recover and established learning thereafter (i.e. return to course). Industry exhibiting characteristic (3) showed continuous learning potentials during out the period under review.

c) Concave Learning Path with No Maximum

This path had only one characteristic as far as industrial learning in Japanese manufacturing industry is concerned. Industry(ies) in this category demonstrated continuous forgetting and never recovered during the period under review.

Table 5.4: Paths of Industrial Technological learning Levels Over Time

Paths of Industrial Learning in Japanese Manufacturing Industry from 2000-2014		Forgetting	Industry
Convex learning path with a minimum		With forgetting at some beginning & end period	Business Oriented Machinery, General Purpose Machiner, Information Com. & Elect. Eqp, Ceramic & Clay, Chemical & Pharmaceutical, Non-Ferrous Metal, Platic, Pulp & Paper, Printing, Beverages & Feed & Miscellaneous
		With forgetting at some end period only	Fabricated Metal, Petroleum & Coal, & Leather Tanning
		With forgetting at some beginning period only	Production Machinery, Food* & Electronic Parts…
Concave learning path with a maximum		With forgetting at some mid periods	Textile Mill & Rubber
		With forgetting at some beginning period	Electrical Machinery
		No forgetting in any period	Furnitures & Fixtures
Concave learning path that either have not reached or have no maximum		With forgetting after beginning period	Leather Tanning

**Food industry exhibit convex learning path with no minimum*

5.3.4 Conclusion on Technological Learning

Technological learning has been found to lower production cost considerably and ensure industrial competitiveness. As demonstrated in this study, different industries exhibit different technological learning. Few industries such as Production Machinery industry, Electrical Parts & Circuit industry, Chemical & Pharmaceutical industry, Petroleum & Coal industry, Rubber industry, Food industry, Furniture & Fixtures industry, and Textile Mills industry demonstrated good learning potentials in almost all the years of the study. Most industries are at the forgetting stage which implies lost in cost efficiency in the production /manufacturing processes. It is noteworthy to mention that about 60 % of the industry showed poor learning potentials in recent times (2010-2014).

Chapter Six

6.0 Conclusion and Policy Implications

This study empirically measured the technical efficiency, total factor productivity (TFP) and technological learning in Japanese manufacturing industries from 2000 to 2014. The study used constant return to technology assumption (CRS) for the estimation of technical efficiency and TFP. A total of 24 manufacturing industries were individually analyzed and discussed in line with the objectives of the study.

In our analysis of the result of Technical efficiency based on CRS, we found that the overall efficiency of Japanese manufacturing industries declined from 65% in 2000 to 42% in 2014. The analysis of technical efficiency for individual industries showed that only Petroleum & Coal industry was 100 percent efficient. Electrical Machinery, Business Oriented Machinery industry, Information Communication industry, Food industry, Furniture & Fixtures, Leather Tanning, and Lumber & Wood industry was on average 62%, 52%, 51%, 61%, 61%, 62% and 65% efficient respectively. Other industries were less than 50% efficient on average throughout the period under review. Further, we found in the slack analysis that, while capital was adequately utilized, labour was needlessly in excess of what is currently required given the returns on sales.

In the TFP analysis, the overall result showed that TFP grew at a constant rate of -0.6% during the period under review (2000-2014) which suggests that there was regress in TFP. This result agrees with the prevailing economic reality of Japan. At the annual level, we found that TFP shock was particularly low in the years marked by financial crisis such as 2001, and 2008-2009. We also found that TFP regress occurred in recent years (2011, 2012 & 2014). Nevertheless, positive TFP was observed in other years, which were a result of technological change and efficiency improvement. We further decomposed the result into industry level in order to understand the contribution of individual industry to the overall TFP. We found that all industries showed a similar trend in comparison with the annual mean result.

This study also estimated the dynamic technological learning in Japanese manufacturing industry. We found that different industry had different learning rates/levels. While some industries had better learning after some beginning period, others showed good learning potentials at some beginning and end period implying forgetting at some mid-period. Specifically, Production machinery, Electrical Devices & Circuit, Chemical & Pharmaceutical, Food, and Furniture & Fixtures industries showed good learning potentials for most part of the study period. Nevertheless, the overall result showed that learning was getting worse and worse in recent years. In other words, Japanese manufacturing industry as a whole is at forgetting stage. The implication of this result is two-fold; (1) Japanese manufacturing industries have not regained its competitiveness and (2) technological progress/accumulation or innovation is at the expense of huge cost.

Policy Implication

Productivity is key to economic development and technological learning implies cost saving. Although the Japanese Government has tried a number of expansionary policies aimed at revitalizing the economy. This effort has probably yielded some results as evident in the positive TFP observed in some years, however, why the overall productivity remains low is somewhat a puzzle and remains a subject of debate. We recommend on the basis of this study that more robust policy that will enhance technological learning in Japanese manufacturing industry should be in the forefront of the ABENOMICS agenda as this is capable of improving productivity in manufacturing and non-manufacturing sector of the economy.

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Appendix A: Summary of the Manufacturing Industries Considered for the Study*

Industry	Sales	Value Added	Asset	Labour
Food	34,587,478	6,525,969	14,519,640	1,098,039
Beverages, Tobacco & Feed	19,097,518	2,973,691	11,122,034	184,050
Textile mill products	5,089,322	1,216,767	3,878,564	195,533
Lumber and wood products	2,094,150	380,606	819,295	53,552
Furniture and fixtures	1,140,473	254,165	473,633	34,915
Pulp, paper and paper products	10,421,035	2,259,119	8,518,865	208,883
Printing and allied industries	5,229,474	1,287,220	2,937,972	146,300
Chemical and allied products	56,937,799	14,551,342	41,154,989	935,776
Petroleum and coal products	29,937,317	1,322,630	7,474,989	50,900
Plastic products	6,726,423	1,526,342	3,638,768	173,982
Rubber products	5,366,916	1,538,852	4,515,917	139,101
Leather tanning, leather products & fur skins	94,733	20,594	41,754	3,959
Ceramic, stone & clay products	9,037,559	2,379,952	7,822,900	222,449
Iron and steel	26,019,903	5,643,834	21,018,209	335,270
Non-ferrous metals & products	17,641,744	2,924,980	13,954,046	249,251
Fabricated metal and products	14,962,068	3,770,124	8,171,582	465,692
General-purpose machinery	13,279,348	3,433,341	7,344,412	326,001
Production machinery	8,911,352	2,238,652	4,765,755	226,105
Business oriented machinery	9,640,601	2,424,046	4,848,845	184,043
Electronic parts, devices and electronic circuits	15,256,477	3,815,214	8,564,686	349,308
Electrical machinery, equipment & supplies	33,906,122	6,861,157	14,540,850	698,023
Information & comm. Electronic equipment	49,087,480	7,676,022	24,887,186	680,108
Transport equipment	111,420,540	21,221,690	57,999,980	1,805,412
Miscellaneous manufacturing industries	4,439,413	970,203	2,173,791	94,987
Total Manufacturing	20,430,219	4,050,688	11,466,194	369,235

*Amount are in millions of yen

Appendix B: Output from Maximum Likelihood Estimate of Cobb-Douglass Production Function

MLE	Coefficient	Standard Error	t-ratio
beta 0	1.98919	0.99848	1.99222
Beta 1	0.70271	0.14174	4.95772
Beta 2	0.27759	0.14462	1.91948
sigma-squared	0.23844	0.94711	0.25176
gamma	0.94453	0.26329	3.58743
mu	0.01178	0.99987	0.01178
eta	-0.00804	0.01133	-0.70976
log likelihood function	172.389		
LR test (one-sided error	509.501		
OLS Estimate	coefficient	standard-error	t-ratio
beta 0	1.6263	0.1671	9.7346
Beta 1	0.9313	0.0274	34.0375
Beta 2	0.0024	0.0327	0.0741
sigma-squared	0.0933		
log likelihood function	-82.362		

Appendix C: Comparing CRS and VRS Technical Efficiencies

	2000		2001		2002		2003		2004		2005		2006		2007		2008		2009		2010		2011		2012		2013		2014	
Manufacturing Industry	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
Business oriented machinery	77	77	76	76	67	68	63	64	64	64	53	53	54	54	46	46	42	42	50	50	49	49	39	39	36	36	34	34	37	37
Ceramic, stone & clay products	43	43	40	40	38	38	35	35	29	34	25	27	28	28	26	26	26	26	31	31	29	30	23	25	25	26	24	25	26	27
Chemical and allied products	47	84	45	83	43	81	37	75	36	80	31	72	32	75	31	75	31	78	41	85	36	89	29	87	31	81	29	81	32	79
Electrical machinery, equipment & supplies	100	100	96	100	91	100	100	100	85	100	44	63	52	72	47	64	43	59	57	69	50	70	37	64	41	66	42	69	47	74
Electronic parts, devices and electronic circuits	75	75	64	64	65	65	59	59	58	58	43	43	45	45	39	44	40	40	50	50	42	48	32	46	33	47	32	44	36	49
General-purpose machinery	67	67	63	66	57	62	54	60	55	64	36	36	40	40	37	37	39	39	44	44	40	40	36	36	36	36	32	32	37	37
Information & comm. Electronic equipment	93	93	66	99	60	96	54	99	56	94	48	86	49	89	48	87	46	90	54	97	46	95	38	65	38	61	34	57	34	51
Iron and steel	35	60	32	57	31	54	29	52	33	57	29	54	29	59	31	62	36	70	33	63	33	74	29	68	27	55	28	56	31	62
Production machinery	64	64	57	57	51	51	54	54	58	58	47	47	51	51	48	48	45	45	43	43	45	45	39	39	39	39	35	35	43	43
Transport equipment	62	100	63	100	63	100	56	100	53	100	43	100	46	100	45	100	43	100	56	100	49	100	41	100	44	100	38	100	38	100
Beverages, Tobacco & Feed	63	75	60	75	54	69	53	70	53	65	40	47	39	46	34	41	38	46	54	60	46	61	31	42	34	43	31	41	36	43
Food	75	75	79	83	75	83	64	77	61	76	49	69	51	72	48	68	55	75	73	94	64	92	54	85	57	86	51	83	56	88
Furniture and fixtures	75	75	72	77	68	74	66	71	66	66	52	54	57	60	51	52	54	56	66	68	58	59	56	58	61	62	55	56	58	59
Leather tanning, leather products & fur skins	95	100	52	100	50	100	49	100	88	100	69	100	54	100	61	100	48	100	63	100	62	100	53	100	54	100	52	100	73	100
Lumber and wood products	79	79	77	80	83	88	72	76	68	69	59	59	70	72	52	53	54	55	66	66	59	60	57	58	59	60	58	59	61	62
Miscellaneous manufacturing industries	71	71	77	79	64	66	62	63	51	51	41	41	48	48	50	50	54	54	63	63	49	49	39	39	44	44	37	37	39	39
Printing and allied industries	62	63	64	65	58	58	50	51	49	49	39	39	41	41	37	37	39	39	54	54	45	45	38	38	40	40	36	36	35	35
Pulp, paper and paper products	41	41	39	40	39	39	34	36	32	34	25	27	28	29	26	28	28	29	37	38	31	35	26	30	28	30	28	30	31	32
Textile mill products	45	45	43	43	39	39	37	37	37	37	25	25	30	30	27	27	28	29	53	53	45	45	27	27	29	29	26	26	27	27
Fabricated metal and products	53	53	53	54	52	53	45	45	49	51	43	43	45	45	44	44	44	44	56	56	49	51	39	45	43	48	40	44	44	48
Non-ferrous metals & products	38	43	32	42	29	38	26	36	27	37	27	36	37	51	39	53	35	46	39	49	36	59	28	49	27	45	25	43	30	46
Petroleum and coal products	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Plastic products	71	71	67	67	57	57	51	52	55	55	46	46	47	48	42	42	41	41	46	46	40	41	37	37	41	41	38	38	40	40
Ruber products	39	39	45	46	40	40	32	33	32	32	25	26	28	28	27	27	29	29	31	31	30	30	26	26	27	27	23	23	25	25
Industry Average	**65**	**70**	**61**	**70**	**57**	**67**	**53**	**64**	**54**	**64**	**43**	**54**	**46**	**58**	**43**	**55**	**43**	**55**	**52**	**63**	**47**	**61**	**40**	**54**	**41**	**54**	**39**	**52**	**42**	**54**

Appendix D: Slack Analysis for Labour and Capital (0'000)

	2000		2001		2002		2003		2004		2005		2006		2007		2008		2009		2010		2011		2012		2013		2014	
Firm	K	L	K	L	K	L	K	L	K	L	K	L	K	L	K	L	K	L	K	L	K	L	K	L	K	L	K	L	K	L
Food	0	34	0	42	0	46	0	14	0	39	0	44	0	48	0	47	0	54	0	77	0	76	0	67	0	70	0	67	0	77
Beverages, Tobacco & Feed	0	0	0	6	0	8	0	0	0	6	0	4	0	3	0	3	0	3	0	4	0	4	0	3	0	3	0	3	0	4
Textile mill products	0	2	0	7	0	6	0	0	0	5	0	5	0	5	0	5	0	5	0	9	0	7	0	4	0	5	0	4	0	4
Lumber and wood products	0	1	0	4	0	4	0	1	0	3	0	3	0	3	0	2	0	2	0	3	0	3	0	2	0	3	0	3	0	3
Furniture and fixtures	0	1	0	2	0	2	0	1	0	2	0	1	0	1	0	1	0	2	0	2	0	1	0	1	0	2	0	2	0	2
Pulp & paper products	0	0	0	6	0	6	0	0	0	5	0	4	0	4	0	3	0	4	0	5	0	4	0	4	0	4	0	4	0	5
Printing and allied industries	0	1	0	8	0	7	0	0	0	6	0	4	0	5	0	5	0	5	0	7	0	5	0	4	0	5	0	5	0	4
Chemical and allied products	1223	0	342	0	382	0	284	0	397	0	0	1	169	0	183	0	192	0	484	0	741	0	921	0	548	0	405	0	102	0
Petroleum and coal products	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Plastic products	0	2	0	9	0	7	0	0	0	7	0	6	0	7	0	6	0	6	0	7	0	6	0	6	0	7	0	6	0	6
Rubber products	0	0	0	5	0	4	0	0	0	3	0	2	0	3	0	3	0	3	0	3	0	3	0	3	0	3	0	2	0	2
Leather tanning & fur skins	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ceramic, stone & clay products	0	0	0	8	0	7	0	0	0	6	0	4	0	4	0	4	0	4	0	4	0	4	0	3	0	4	0	4	0	4
Iron and steel	0	0	0	6	0	5	0	0	0	6	0	5	0	5	0	6	0	7	0	6	0	2	0	5	0	5	0	6	0	7
Non-ferrous metals & products	0	0	0	5	0	4	0	0	0	4	0	3	0	6	0	6	0	5	0	6	0	6	0	4	0	4	0	4	0	5
Fabricated metal and products	0	3	0	23	0	20	0	0	0	20	0	17	0	18	0	18	0	18	0	22	0	19	0	16	0	19	0	17	0	19
General-purpose machinery	0	2	0	26	0	27	0	0	0	26	0	8	0	8	0	7	0	7	0	7	0	7	0	6	0	6	0	5	0	5
Production machinery	0	1	0	9	0	8	0	0	0	9	0	7	0	8	0	10	0	10	0	8	0	10	0	9	0	9	0	8	0	10
Business oriented machinery	0	1	0	12	0	10	0	0	0	10	0	7	0	7	0	7	0	6	0	7	0	8	0	6	0	5	0	5	0	5
Electronic devices and circuits	0	4	0	18	0	17	0	0	0	15	0	11	0	12	0	12	0	12	0	15	0	12	0	10	0	11	0	9	0	10
Electrical machinery & equipment	0	0	0	0	0	0	0	0	0	0	0	26	0	33	0	29	0	25	0	34	0	30	0	22	0	27	0	28	0	31
Information & Elect. equipment	0	0	41	0	168	0	301	0	0	0	0	12	0	6	0	4	0	2	333	0	382	0	0	14	0	14	0	11	0	8
Transport equipment	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Miscellaneous manuf.	0	0	0	5	0	4	0	0	0	4	0	3	0	4	0	4	0	5	0	6	0	4	0	3	0	4	0	3	0	3