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Efficiency and Productivity of Singapore's Manufacturing Sector 2001-2010: An analysis using Simar and Wilson's (2007) bootstrapped truncated approach

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Efficiency and Productivity of Singapore's Manufacturing Sector 2001-2010: An analysis using Simar and Wilson's (2007) bootstrapped truncated approach

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1. Introduction

Manufacturing has been a key growth driver of Singapore's economy. In the 1970s and 1980s, great strides in Singapore's economic development were achieved through development of manufacturing. By the late 1980s, services had grown to become a significant contributor to growth and with increased economic integration, the economic landscape of Singapore was reshaped. To maintain Singapore's industrial competitiveness, the *Strategic Economic Plan 1991* was introduced to develop a manufacturing-service nexus based on Porter's cluster model (Chia and Lim 2003). In 1999, *Industry 21* was launched to develop Singapore into a robust global hub of knowledge industries to develop its manufacturing and services with emphasis on technology, innovation and capabilities. Coinciding with *Industry 21* in 1999 was the launch of *Technopreneurship 21* by the National Science and Technology Board (NSTB) aimed at developing Singapore as a hub for foreign-based technology businesses and promoting local technopreneurial enterprises. By creating a manufacturing-service nexus in a knowledge-based global hub, Singapore provides abundance of opportunities for foreign investment, development of new technologies, innovation and creativity to raise productivity growth and remain internationally competitive.

Singapore still remains dependent on its manufacturing sector for growth. Statistics drawn from the *Yearbook of Statistics 2011* show manufacturing contributing approximately 24-26 percent of GDP between 2001 and 2010. But when labour productivity growth in manufacturing regressed between 2006 and 2008; from 3.1 percent in 2006 to -10.9 percent in 2008, this raised concerns especially with regards to Singapore's ability to remain internationally competitive.[1] Consequently, the Economic Strategies Committee (henceforth ESC) was formed in 2010 and subsequently released the ESC 2010 report. The ESC 2010 reported that Singapore's manufacturing productivity between 2006 and 2008 was well below

[1] Statistics drawn from *Yearbook of Statistics Singapore 2011*.

levels of the United States, Sweden, Japan and Finland. The major concern for the ESC was that negative productivity would lower its international competitiveness and negatively impact on Singapore's growth, income and employment.

Anecdotal comments suggested that incessant use of foreign workers attributed to declining productivity performance. While influx of foreign workers may influence labour productivity, partial productivity measures reported in the ESC 2010 do not truly reflect a country's productivity performance. It is more meaningful to measure productivity based on total factor productivity (TFP) since TFP is the portion of output not explained by the amount of inputs used in production. As such, its level is determined by how efficiently and intensely the inputs are utilised in production.

There are many extant studies on productivity studies on Singapore's manufacturing (Tsao 1985; Kim and Lau 1994; Wong and Gan 1994; Young 1994; Rao and Lee 1995; Leung 1998; Bloch and Tang (1999); Mahadevan 2000; Mahadevan and Kalirajan 2000; Thangavelu and Owyong 2003; Kong and Tongzon 2006; Tan 2006; Sun 2007; Thangavelu et al. 2008). However most of these studies cover the period before the turn of the century, except for Thangavelu et al. (2008) which goes up to 2004. As far as the author is aware of, there are no studies on Singapore's manufacturing productivity beyond 2004. The current study contributes to the current literature by filling this void with a focus on the manufacturing sector for the period 2001-2010 motivated by the findings of ESC 2010. The study also contributes to the literature by employing Simar and Wilson's (2007) bootstrapped truncated approach which has gained wide-recognition in its theoretical exposition to generate results that are more reliable than pervious two-stage methods. In the first stage, bootstrapped DEA-variable returns to scale (VRS) model is employed to estimate the technical efficiency of manufacturing industries. In the second stage, the bootstrap DEA scores are regressed against a set of environmental variables using a truncated regression analysis based on maximum likelihood method. Determining how these explanatory variables impact on efficiency estimates helps to shed light on the sources of inefficiency. The objective of the paper is twofold: first, to measure productivity change and technical efficiency of the industries in the manufacturing sector; and second, to seek out and determine sources of inefficiencies.

The paper is divided into five sections. Following the introduction in Section 1, Section 2 describes the methodologies employed; Malmquist productivity change index, DEA model and bootstrapped truncated regression approach. Section 3 describes the inputs and output employed as well as the environmental variables. Section 4 discusses the results based on Malmquist productivity change index, DEA and regression analysis. The paper concludes with some brief remarks.

2. Methodology

Data envelopment analysis (DEA), as developed by Charnes, Cooper, and Rhodes (CCR) in 1978 and later modified by Banker, Charnes and Cooper (BCC) in 1984, builds on the frontier efficiency concept first elucidated in Farrell (1957). It is a nonparametric method that measures the efficiency of decision making units (DMUs) and does not require the specification of a specific functional form relating inputs to outputs or the setting of weights for the various factors. DEA thus optimises for each observation an efficient frontier—the maximum outputs empirically obtainable for any DMU in the observed population given its level of inputs. For a general overview of DEA, see Coelli et al. (2005).

However, DEA has several limitations. There is no error term in DEA indicating that the errors in variables are included in the efficient estimates. DEA scores have no statistical significance due to its non-parametric nature and its inability to explain sources for inefficiency. To address this problem, Ray (1991) and Coelli et al. (2005) suggested the use of a two-stage analysis whereby the second stage employs a regression analysis. Simar and Wilson (2007) noted that many studies adopted such two-stage approach whereby DEA scores in the first stage are regressed on covariates (i.e. environmental variables) in the second stage to help handle environmental variables.[2] However, Simar and Wilson (2007) argued that many of these studies in regressing DEA estimates on environmental variables in a two-stage analysis face a key problem in that the DEA efficiency estimates are, by construction, serially correlated. To address this problem, Simar and Wilson (2007) proposed an alternative estimation and statistical inference procedure based on a double-bootstrap approach. We employ this approach in our analysis.

2.1 Stage 1 — Data envelopment analysis

We use the Farrell/Debreu-type output-oriented variable returns-to-scale (VRS) model to derive efficiency scores. We do not consider a constant returns-to-scale (CRS) assumption since it is only appropriate when industries are operating at their optimal scale. This is an unlikely situation in the context of Singapore whereby Thangavelu et al. (2008) noted considerable evidence of ongoing structural change in Singapore's manufacturing in terms of cross-border sourcing and production sharing between 2000 and 2004. Furthermore, imperfect competition and volatility in the business cycle are additional factors associated with firms/industries not operating at their optimal scale. The assumption of VRS also appears appropriate given that our study focuses on manufacturers of varying sizes. The output-oriented VRS DEA model is expressed as:

$$\hat{\theta}_i = \max_{\hat{\theta},\lambda}\left\{\theta_{i0} > 0 \,\middle|\, \hat{\theta}_i y_i \sum_{i=1}^{n} y_i\lambda\,; x_i \geq \sum_{i=1}^{n} x_i\lambda\,;\ \sum_{i=1}^{n}\lambda = 1\,;\ \lambda \geq 0\right\},$$

i = 1, ...n firms (1)

[2] Due to the long list of studies, we omit them from the paper and direct readers to Simar and Wilson (2007) for this list.

where y_i is a vector of outputs, x_i is a vector of inputs, and λ is a I x 1 vector of constants. The value obtained for $\hat{\theta}_i$ is the technical efficiency score for the i-th industry. A measure of $\hat{\theta}_i = 1$ indicates that the industry is technically efficient, whereas it is inefficient if $\hat{\theta}_i > 1$. This linear programming problem must be solved *n* times, once for each industry in the sample.

As DEA is sometimes criticised for the potential bias in efficiency estimates and the omission of random error, we employ algorithm #2 bootstrap approach outlined in Simar and Wilson (2007). By combining DEA with bootstrapping technique, we successfully generate a set of bias-corrected estimates of DEA efficiency scores (denoted $\hat{\hat{\theta}}_i$) and confidence intervals that help resolve this problem.

2.2 Stage 2 — Truncated regression

The bias-corrected efficiency scores derived from the bootstrap algorithm are then regressed on a set of hypothesised environmental factors using the following regression model:

$$\hat{\hat{\theta}}_i = a + Z_i\delta + \varepsilon_i, \quad i = 1, \ldots, n \tag{2}$$

where $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$ with left-truncation at $1\text{-}Z_i\delta$; a is a constant term and Z_i is a vector of specific environmental variables for industry *i* that is expected to affect the efficiency of industry performance. The double-bootstrapping truncated regression algorithm #2 step-by-step description is outlined in several studies (Alfonso and Aubyn 2006; Simar and Wilson 2007; Barros and Assaf 2009; Alexander et al. 2010; Barros and Garcia-del-Barrio 2011). We omit the description here and direct readers to these papers.

2.3 Malmquist Productivity Change Index

The study also employs the Malmquist productivity change index (MPI) for the period 2001-2010. The objective of using this model is two-fold; first, to generate MPI estimates which are more reliable than the partial productivity estimates reported in ESC 2010; second, to decompose MPI productivity change between two periods into technical change and efficiency change to provide further insights of laggards within Singapore's manufacturing. As illustrated by Färe et al. (1994), the component distance functions of MPI can be estimated using DEA-like methods. An output-oriented DEA is used to compute the output distance function while an input-oriented DEA is used to compute the input distance function. We assume an output-orientation on the basis that industries are motivated to maximise profits by maximising output while constrained by fixed inputs. As Tan (2006) points out, if each industry group is a proponent of its characteristic type of industrial activity, then it is in the interest of each group to manage and utilise its resources efficiently to maximise output.

The MPI has been adopted by many studies that analyse productivity change at the industry level. These include Färe et al. (1992) in the pharmaceutical industry, Hjalmarsson and Veiderpass (1992) in electricity retail distribution, Price and Weyman-Jones (1996) in the gas industry, Leung (1998), Mahadevan (2002) and Tan (2006) in manufacturing, Rezitis (2006), Jaffry et al. (2007), Guzmán and Reverte (2008), Chiu et al. (2010), Lee et al. (2010) and Fadzlan (2011) in banking and finance services, Worthington and Lee (2008) and Kempkes and Pohl (2010) in higher education, Luh et al. (2008) and Balcombe et al. (2008) in agriculture and Reichmann and Sommersguter-Reichmann (2010) in university library.

The framework shown in Figure 1 is based on Coelli et al. (2005). Figure 1 shows a production frontier which represents the efficient level of output (y) produced from a given level of input (x) under the assumption that the frontier can shift over time.

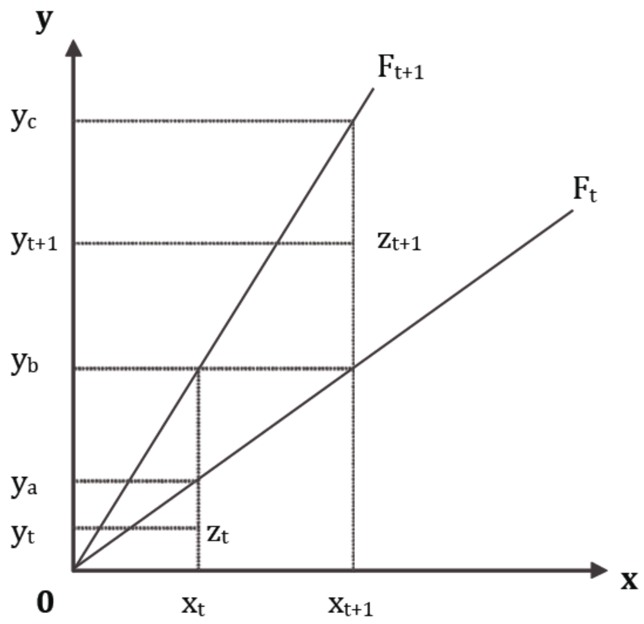

Figure 1: Efficiency, technical and productivity change

The frontiers (F) obtained in the current (t) and future (t +1) time periods are labeled accordingly. If inefficiency exist, the relative movement of any given industry over time will therefore depend on both its position relative to the corresponding frontier (efficiency change) and the position of the frontier itself (technical change). If inefficiency is ignored, then productivity growth over time will be unable to distinguish between improvements that derive from an industry 'catching up' to the frontier, or those that result from the frontier itself shifting up over time.

For any given industry in period *t*, the bundle z_t is based on inputs x_t producing output y_t. But this is technically inefficient since the industry lies below the production frontier F_t. With the available technology and the same level of inputs, the industry could have produced output y_a. In the next period, there is technology increase such that more outputs can be produced for any given level of inputs; thus the frontier moves upward to F_{t+1}. With technology increase, assume that the industry's inputs increases to x_{t+1}, hence its output will now be y_{t+1} and move to output/input bundle z_{t+1}. Once again the industry is inefficient in reference to the new technology since it could be producing output y_c with the given inputs. The challenge for productivity assessment is to sort these increases in output relative to the level of inputs into that associated with the change in efficiency and that associated with the change in technology. This is solved using the MPI to decompose this productivity change between the two periods into technical change and efficiency change. Following Coelli et al. (2005), the output-based MPI is expressed as:

$$M_o^{t+1}(y_t, x_t, y_{t+1}, x_{t+1}) = [(D_o^t(y_{t+1}, x_{t+1})/D_o^t(y_t, x_t)) \times (D_o^{t+1}(y_{t+1}, x_{t+1})/D_o^{t+1}(y_t, x_t))]^{1/2} \quad (3)$$

where the superscript *O* indicates an output-orientation, *M* is the productivity of the most recent production point (x_{t+1}, y_{t+1}) (using period t + 1 technology) relative to the earlier production point (x_t, y_t) (using period t technology), *D* are output distance functions, and all other variables are as previously defined. Values greater than 1.00 indicate total factor productivity (TFP) growth between the two periods. Equation (3) can be further re-expressed as:

$$M_o^{t+1}(y_t, x_t, y_{t+1}, x_{t+1}) = \underbrace{[D_o^{t+1}(y_{t+1}, x_{t+1})/D_o^t(y_t, x_t)]}_{E} \times \underbrace{[(D_o^t(y_{t+1}, x_{t+1})/D_o^{t+1}(y_{t+1}, x_{t+1})) \times (D_o^t(y_t, x_t)/D_o^{t+1}(y_t, x_t))]^{1/2}}_{T} \quad (4)$$

where *M* (Malmquist TFP) is the product of technical change (T) and efficiency change (E). T (‘frontier-shift’ effect which comes from innovation and diffusion of new technology) is measured by shifts in the frontier between period t + 1 and period t which corresponds to y_c/y_b and y_b/y_a in Figure 1. E (‘catch-up’ effect) which corresponds to $(y_{t+1}/y_c)/(y_t/y_a)$ in Figure 1 is the efficiency change over the same period which measures how much closer to the frontier the firm/industry is by capturing the extent of knowledge of technology use either from changes in improved resource allocation or reduction in organisational slack.

3. Data and Input/Output Specification

To estimate our production frontier, we used balanced panel data on twenty manufacturing industries for the period 2001 to 2010 (20 industries x 10 years = 200 observations), drawn from the Singapore Economic Development Board (EDB), *Report on the Census of Manufacturing Activities* (CMA). The CMA identifies twenty industries which make up the manufacturing sector. We employ a capital-labour-energy-materials-output (KLEMQ) framework similar to Tan (2006) whereby one output (value added) and four inputs are identified. The inputs and outputs employed follow a production approach to modeling manufacturing industry behaviour, that is, manufacturers combine labour and non-labour factors of production and produce outputs measured in terms of value added. Capital is represented by gross fixed assets which is defined as the accumulated cost of acquiring the fixed assets. Labour is in terms of total number of hours worked (average number of paid hours per week × 52 weeks) which are drawn from the *Singapore Yearbook of Manpower Statistics 2010.* This measure of labour input is more accurate than 'number of workers' since the former measures labour intensity more adequately. Energy here refers to expenditure cost on utilities. Materials, reported in monetary values, comprise of raw materials, chemicals and packing materials consumed in the production process. All monetary variables are converted into 2006 prices to account for inflationary effect. Value added was deflated using manufactured products price index; gross fixed assets were deflated by gross fixed capital formation deflators; utilities were deflated using the price indices of electricity tariff; and materials were deflated using the domestic supply price index. All deflators and price indices were drawn from the *Yearbook of Statistics 2011*. Table 1 presents the descriptive statistics of the data used in both stage 1 and stage 2 analyses.

Second stage analysis consists of five environmental variables deemed to have some influence on efficiency. These are export-orientation, capital intensity, quality of worker, flexible work arrangements and foreign workers. This section of analysis only focuses on the year 2009 since there were no data available for flexible work arrangements and foreign workers for most of the years.

Table 1: Descriptive statistics of inputs and output (all monetary values in 2005 thousand dollars)

Variables	Minimum	Maximum	Mean	Std. dev.
Output (2001-2010)				
Value Added	20,671	26,517,443	2,361,326	4,058,116
Inputs (2001-2010)				
Gross fixed assets	38,591	57,808,118	5,541,677	10,138,559
Total hours worked	1,338,043	273,559,104	49,646,694	67,941,594
Utilities	760	821,872	113,075	166,152
Materials	27,471	62,330,555	6,147,543	11,509,854
Second stage variables (2009)				
Export-orientation (EO) (%)	12	95	53	23
Capital intensity (KL)	54,177	3,634,250	563,332	1,029,902
Quality of worker (RPW)	20,074	112,626	41,874	24,719
Flexible work arrangements (Flex) (%)	0.1	7.7	1.8	1.9
Foreign workers (Foreign)	291	1,232	800	290

EO is the ratio of direct exports to sales which measures the level of export orientation. The more export-oriented an industry is, the more incentive it has to be efficient in order to remain internationally competitive. *KL* is the capital-labour ratio which is the ratio of capital expenditure (gross fixed assets) to the number of workers employed. As noted by Mahadevan (2000), *KL* measures capital intensity of an industry suggesting that industries with higher capital intensities are likely to use resources more efficiently and avoid underutilization with incentive to economise on the cost of capital. *RPW* (remuneration per worker) follows Leung (1998) which assumes to be a proxy for quality of labour. *Flex* refers to the proportion of workers on flexible working arrangements. Studies from Shepard et al. (1996), Clifton and Shepard (2004) and Ang et al. (2005) showed that adoption of flexible work arrangements improved productivity and employee performance. Hence, we include this variable into our regression model. *Foreign* is a measure to reflect the intensive use of foreign workers on technical efficiency. For this measure, the number of foreign workers by manufacturing industry is not available. We thus use levy rates as a proxy to measure the intensity of foreign worker utilisation. Levy is a pricing mechanism aimed to control the number of foreign workers in Singapore. According to the Ministry of Manpower Singapore (MOM), if a firm has a high dependency ratio of foreign workers, it faces higher levy rates than firms with low dependency ratio. This is based on a three-tier system whereby Tier 1 (up to 30 percent of total workforce) faces a monthly levy ranging from SGD$190 to SGD$290; Tier 2 (30-50 percent of total workforce) levy ranging from SGD$270 to SGD$370 and Tier 3 (50-65 percent of total workforce) levy of SGD$450. Hence there is a positive correlation between more foreign workers hired and levy rates which justifies the use of levy rates as a proxy to measure the intensity of foreign worker utilisation. Sources of data for stage 2 analysis are as follows: Data for direct exports, total sales, gross fixed assets, number of workers and remuneration are drawn from CMA 2009; data for flexible working arrangements and levy rates are drawn from the *Singapore Yearbook of Manpower Statistics 2010.*

4. Empirical results

4.1 Total factor productivity

This section examines the productivity change of Singapore's manufacturing for the 2001-2010 period. The estimates of TFP growth, technical change and efficiency change based on equation (4) are reported in Table 2.

Table 2: TFP, Technical Change and Efficiency Change of Singapore's Manufacturing Sector, 2001-2010

	TFP change	Technical Change (T)	Efficiency Change (E)	Pure Technical Efficiency (PTE)	Scale Efficiency (SE)
2001-02	1.073	1.378	0.778	0.810	0.961
2002-03	0.986	0.977	1.009	0.965	1.046
2003-04	1.245	1.298	0.959	0.986	0.973
2004-05	0.908	0.889	1.021	1.070	0.955
2005-06	0.986	1.269	0.777	0.829	0.938
2006-07	1.012	1.026	0.987	1.012	0.975
2007-08	0.781	0.608	1.284	1.070	1.200
2008-09	1.126	0.831	1.355	1.323	1.024

2009-10	1.128	0.832	1.356	1.279	1.060
Mean	1.019	0.982	1.037	1.025	1.012

Table 2 shows manufacturing exhibiting a mean TFP of 1.9 percent attributed by gains in efficiency change (E) of 3.7 percent while technical change regressed by -1.8 percent suggesting that productivity growth came only from ‘catch-up’ and not from ‘frontier-shift’. Decomposing E, we note that both PTE (2.5 percent) and to a lesser extent, SE (1.2 percent), contributed to growth in E.

On annual basis, it is observed that there is a negative relationship between T and E. Our findings are in line with Leung (1998), but for different time-periods, which suggest that whenever T rises from better use of technology and equipment, E lags behind due to increase organisational slack and vice-versa. Since 2007-08, TFP growth came only from E while T declined suggesting that manufacturing had been undergoing major restructuring to improve efficient use of resources and improvements in best-practice management. This is evident from the estimates of PTE whereby growth in PTE since 2007-08 suggest that workers are becoming well-equipped with the appropriate skills to reach their full potential and that firms are becoming more efficient in capital utilisation.

Due to the heterogeneous nature of manufacturing and to better understand the TFP and its decomposed components, we look at the growth rates of each component by industry level. Table 3 presents the mean TFP scores for each manufacturing industry. Of the twenty industries, fourteen posted positive TFP growth mainly attributed to improved E indicating ‘catch-up’ towards the frontier. Eighteen of the twenty industries performed well in E largely due to improvements in SE and to a lesser extent in PTE.

Table 3: TFP by Manufacturing industry (annual mean), 2001-2010

	TFP	Technical Change (T)	Efficiency Change (E)	Pure Technical Efficiency (PTE)	Scale Efficiency (SE)
Food, Beverage and Tobacco	0.996	0.980	1.016	1.004	1.012
Textiles and Textile Manufactures	1.069	0.975	1.097	1.154	0.950
Wearing Apparel Except Footwear	1.008	0.983	1.025	1.029	0.996
Leather, Leather Products and Footwear	0.966	0.986	0.980	1.000	0.980
Wood and Wood Products Except Furniture	1.009	0.978	1.032	1.036	0.996
Paper and Paper Products	1.021	0.980	1.042	1.043	0.999
Printing and Reproduction of Recorded Media	1.037	0.961	1.079	1.081	0.998
Refined Petroleum Products	0.891	1.016	0.878	0.866	1.013
Petrochemicals and Petrochemical Products	1.059	1.016	1.042	0.982	1.061
Other Chemicals and Chemical Products	0.990	0.967	1.023	0.959	1.066
Pharmaceutical Products	0.964	0.964	1.000	1.000	1.000
Rubber and Plastic Products	0.985	0.975	1.011	1.011	0.999
Non-Metallic Mineral Products	1.052	0.966	1.088	1.089	0.999
Basic Metal	1.038	0.990	1.048	1.053	0.996
Fabricated Metal Products	1.015	0.982	1.034	0.989	1.045
Computer, Electronic and Optical Products	1.043	0.980	1.064	1.000	1.064
Electrical Equipment	1.080	0.985	1.095	1.097	0.999
Machinery and Equipment	1.077	0.993	1.084	1.038	1.044
Transport Equipment	1.016	0.987	1.029	1.000	1.029
Other Manufacturing Industries	1.087	0.981	1.108	1.107	1.000
Mean	1.019	0.982	1.037	1.025	1.012

Table 3 however shows most industries regressing in T. This raises the following question: "Did the quest for efficiency gains result in falling technical change?" It is important to remind ourselves that the motivation to raise efficiency stemmed from comments made by Krugman (1994) that Singapore's growth was largely driven by factor accumulation.

4.2 Technical efficiency

Table 4 presents technical efficiency scores of the twenty manufacturing industries based on equation (1).

Measures of scale efficiency are also included using the ratio of efficiency scores of CCR/BCC (Banker 1984). As pointed out by Golany and Roll (1989), CCR under CRS measures overall efficiency which is made up of pure technical efficiency and scale efficiency, while BCC under VRS measures only pure technical efficiency and excludes scale effects.

Table 4: Technical Efficiency BCC DEA estimates, 2001-2010

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	CCR Average	BCC Average	Scale	Position in frontier (a)
Food, Beverage and Tobacco	2.490	4.166	4.358	5.059	5.006	6.207	6.427	3.738	2.612	2.405	4.062	4.009	1.013	irs
Textiles and Textile Manufactures	3.633	2.775	3.503	1.000	1.000	1.000	1.000	1.000	1.739	1.000	4.153	1.509	2.751	irs
Wearing Apparel Except Footwear	1.296	2.044	2.161	2.206	1.992	2.655	2.498	1.962	1.476	1.000	2.047	1.855	1.103	irs
Leather, Leather Products and Footwear	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.841	1.000	1.841	irs
Wood and Wood Products Except Furniture	2.601	3.181	2.523	2.904	2.137	2.753	1.000	3.782	2.793	1.890	4.160	2.428	1.713	irs
Paper and Paper Products	3.984	4.264	5.513	6.518	4.977	6.445	6.932	4.283	3.486	2.719	4.857	4.722	1.029	irs
Printing and Reproduction of Recorded Media	2.189	3.126	2.966	3.537	2.872	2.914	2.672	2.161	1.908	1.086	2.512	2.430	1.033	irs
Refined Petroleum Products	1.132	1.475	1.796	1.767	2.291	3.510	5.505	10.987	4.533	4.114	3.228	2.939	1.098	irs
Petrochemicals and Petrochemical Products	1.943	2.725	2.759	3.083	3.223	5.962	4.619	61.464	4.798	2.282	5.244	4.395	1.193	drs
Other Chemicals and Chemical Products	1.945	2.539	3.001	4.538	4.717	6.636	7.329	4.885	4.188	2.823	4.780	3.935	1.215	drs
Pharmaceutical Products	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	crs
Rubber and Plastic Products	2.517	3.361	3.025	4.024	3.703	4.548	5.397	3.514	2.950	2.274	3.447	3.423	1.007	irs
Non-Metallic Mineral Products	5.368	6.142	4.836	6.156	6.977	7.431	9.355	3.758	3.135	2.486	5.305	5.181	1.024	irs
Basic Metal	3.011	3.909	4.677	1.960	1.075	1.525	1.945	1.930	1.830	1.893	2.407	2.169	1.110	irs
Fabricated Metal Products	1.692	2.375	2.783	4.014	3.482	4.335	4.455	2.912	2.297	1.862	3.107	2.868	1.084	irs
Computer, Electronic and Optical Products	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	3.358	1.000	3.358	drs
Electrical Equipment	3.180	3.516	3.260	3.823	3.140	3.277	2.763	1.878	1.731	1.384	2.693	2.661	1.012	irs
Machinery and Equipment	1.401	1.980	2.080	2.540	2.072	2.436	2.437	1.359	1.099	1.000	1.901	1.750	1.087	irs
Transport Equipment	1.000	1.470	1.821	1.264	2.006	2.511	2.528	1.356	1.246	1.000	1.636	1.535	1.066	drs
Other Manufacturing Industries	2.853	3.339	2.895	4.171	3.579	3.870	3.907	1.910	1.470	1.138	2.771	2.691	1.030	irs
Number of efficient industries	4	3	3	4	4	4	5	4	3	7	1	3	1	
Mean	2.262	2.769	2.848	3.078	2.862	3.551	3.688	5.794	2.315	1.768	3.225	2.675	1.338	
Median	2.067	2.750	2.839	2.993	2.582	3.095	2.717	2.061	1.869	1.623	3.167	2.546	1.085	
Standard deviation	1.177	1.308	1.276	1.712	1.643	2.076	2.476	13.298	1.207	0.863	1.261	1.266	0.636	

(a) irs: increasing returns to scale; crs: constant returns to scale; drs: decreasing returns to scale

This rationale also assumes that BCC scores may be interpreted as management skills. Results show that manufacturing, on average, was operating at 50 percent efficiency with only three industries at efficient levels for the entire period – ‘Leather, Leather Products and Footwear’, ‘Pharmaceutical Products’ and ‘Computer, Electronic and Optical Products’. The industries ‘Pharmaceutical Products’ and ‘Computer, Electronic and Optical Products’ have in the last ten years been the main drive of Singapore’s focus - to become a knowledge-based, technological and innovative hub. In 2001, ‘One-North’, a business park development of Jurong Town Corporation houses the twin research and development hubs of ‘Biopolis’ and ‘Fusionopolis’. ‘Biopolis’ focuses on biomedical sciences which would have influenced the ‘Pharmaceutical Products’ industry while ‘Fusionopolis’ which focuses on Infocomm Technology, Media, Physical Sciences & Engineering industries would have influenced the ‘Computer, Electronic and Optical Products’ industry. Hence, we observe their efficient scores. However, when scale effects are considered, only ‘Pharmaceutical Products’ remained efficient and at optimal size.

‘Computer, Electronic and Optical Products’ industry had been the largest contributor in manufacturing output. This industry plays a significant role in terms of foreign investment as well as value-added, output and employment. It is a key supplier of semiconductors, infocomm products and other computer peripherals to major companies like Hewlett Packard, Dell, Lenovo and Apple and is home to over 14 Semiconductor wafer fabrication plants, 20 assembly and test operations, and 40 integrated circuit design centres (Chan 2010). Although technically efficient, this industry is not operating at optimal size and needs to reduce its scale of operations indicated by its decreasing returns to scale (drs) dimension. On annual basis, the number of efficient industries hovered around four before peaking at seven in 2010 which suggest that best-practice management only occurred then.

4.3 Sources of technical efficiency

Drivers of efficiency were quantified using Simar and Wilson's (2007) bootstrap truncated regression algorithm #2. Bias-corrected efficiency scores derived using equation (2) are regressed against a set of explanatory variables described in Section 3. Computations of estimations were done using MATLAB.

The estimated coefficients and 95% confidence intervals are presented in Table 5.

Table 5: Truncated regression results

Variable	Coefficient	95% Confidence interval	
		Lower bound	Upper bound
Constant	8.92041*	6.29294	13.35467
Export-orientation (*EO*)	-0.06041*	-0.08816	-0.04318
Capital intensity (*KL*)	-0.0000006*	-0.0000011	-0.0000005
Quality of worker (*RPW*)	0.0000345*	0.0000243	0.0000477
Flexible work arrangements (*Flex*)	0.33180*	0.20359	0.46948
Foreign workers (*Foreign*)	-0.00541*	-0.00805	-0.00358

* Significance at the 5% level. All bias-adjusted coefficients that are significant at the 5% levels are also significant at the 1% level; total number of iterations = 2,000.

EO is statistically significant and negatively impacts on efficiency. We observe that two of the three efficient industries ('Pharmaceutical Products' and 'Computer, Electronic and Optical Products') have the two highest exports to sales value, 95.2 and 80.2 percent, respectively. This suggests that these industries are export-oriented and have an incentive to be efficient to remain competitive against foreign competition. On the other hand, we observe that the export to sales value for all other industries averaged around 49.4 percent (excluding 'Pharmaceutical Products' and 'Computer, Electronic and Optical Products') and most were operating inefficiently. This suggests that these industries are relatively not export-oriented and thus have little incentive to operate efficiently since there is lack of foreign competition. *KL* is significant and negatively influences efficiency which is in-line with Mahadevan's (2000) findings. This suggest that gains from use of high value added capital have not been fully realised due to mismatch of skills with capital or that diffusion of technology is yet to be realised thus improvements in technical efficiency did not occur. *RPW* is statistically significant and impacts positively on efficiency which is expected since quality workers are inherently more efficient. *Flex* is statistically significant and has a positive influence on efficiency which suggests that flexible work arrangements actually improve workers performance. This finding is consistent with Shepard et al. (1996), Clifton and Shepard (2004) and Ang et al. (2005) suggesting that flexibility in work arrangements creates better work-life arrangement, which produces a more efficient workforce. Similar findings were also reported in a recent media release in Channel News Asia that Singapore companies offering flexible and home-based work arrangements reported a 10 per cent increase in productivity (Chan 2011). The most significant result from the regression analysis is that *Foreign* is statistically significant and negatively influences efficiency. MOM acknowledges that low-skilled foreign workers made up eighty percent of total foreign workers which further suggest that low-skilled foreign workers attributed to the low efficiency in 2009. Nonetheless, there seems to be signs of improvement in efficiency as noted in Table 4. The number of efficient industries in 2009 was three and increased to seven in 2010. This suggest that skill programmes introduced throughout the 2000's may have finally had some influence on efficiency but at a relatively slow rate since upgrading of skills and the ability to harness the new skills and become proficient in takes time.[3]

MOM recognises that the key drivers for productivity growth is not only in skill upgrading but also in the adoption of technology and innovation. However, this will open up new challenges for the future. As shown in Table 2 there is potential to raise T since 2007-08. If technology and innovation are appropriately adopted, T should improve but at the expense of E since newly attained skills may no longer be valid. This leads to the conundrum on whether to adopt new technology and innovation and if so when should it be adopted. Since 2001, Singapore's economic landscape has been changing at a rapid rate so-much-so that the pace of

[3] In 1998, MOM released the *Manpower 21* blueprint which focused on talent capital and constant upgrading of employee skills and knowledge (Osman-Gani, 2004). This was followed up with various upgrading skills programmes such as the Continuing Education and Training (CET) system in 2003, the Singapore Workforce Skills Qualifications (WSQ) launched in 2005 and the Institute for Adult Learning in 2008.

technology change requires workers to continually upgrade their skills to remain relevant. There is no doubt that skills of workers need to be upgraded and fast otherwise inefficiencies will quickly build-up which will lower Singapore's international competitiveness and stagnate low-skilled wages which is a current issue.

5. Concluding Remarks

This paper analysed productivity growth and technical efficiency in Singapore's manufacturing sector for the period 2001 to 2010. MPI was employed to estimate TFP growth, technical change and efficiency change and DEA was used to measure technical efficiency estimates. A second stage analysis using Simar and Wilson's (2007) bootstrap truncated regression approach was conducted to quantify sources of efficiency for 2009. Two outcomes were revealed in our findings. First, the TFP results showed that any productivity growth was only attributed to efficiency change. We observed no improvements in technical change which suggests the lack in innovation and diffusion of new technologies. Gains made in efficiency change further suggest that skills programs initiated in the 2000s had some positive impact on it. Second, technical efficiency estimates over the study period showed that most industries were operating below efficiency except for 'Pharmaceutical Products' which was technically efficient and operating at the optimal size. Sources of efficiency were estimated using Simar and Wilson's (2007) bootstrap truncated regression. Using maximum likelihood to regress environmental variables against the bias-corrected efficiency scores, we determined that quality of workers and flexible work arrangements contributed positively to efficiency while export-orientation, capital intensity and foreign workers contributed negatively to efficiency.

Whilst the study provides interesting results, it should be noted that one of the main limitations of the current study was the use of a small sample size. In terms of sample size, dependent on availability of disaggregated data, a larger sample size would have provided more robust results. In terms of time-series, if levy rates and flexible working arrangements data were available for all years, this would have generated more robust results in determining sources of efficiency over time. Other areas in improving the analysis includes the addition of more explanatory variables such as the amount of funding provided by the government at industry level to measure the impact skills programs and initiatives had on efficiency. Another variable worth considering is the degree of foreign ownership impacting on efficiency. However, these data are not available at the industry level and thus omitted from our study. Nonetheless, the current findings provide useful information for policymakers to implement appropriate measures to help address the laggard efficiency and productivity of Singapore's manufacturing sector.

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