Estimating Technical Change and Total Factor Productivity: A Comparative Study of Countries*

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Abstract

This study estimates the change in technology and productivity over the years, namely, technical change and total factor productivity (TFP), in 40 countries during the time period from 1995 to 2007. Using the Socio-Economic Accounts (SEAs) from the World Input-Output Database (WIOD) and building on a translog production function with a quadratic time trend and fixed effects, estimation results reveal that technical change and TFP growth vary depending on an economy's average labor product and regional characteristics. Focusing on Japan in particular and comparing it with other countries, this study elucidates Japan's lost decades. Japan's productivity growth has actually been stagnating since the late 1990s, compared to other economies, especially its Asian peers. Japan has been suffering from its low productivity growth, however, technical change in Japan has not been as low. Eastern Europe is high both in technical change and productivity growth, while the Americas and Australia are low in both. Although productivity growth in Asia has been strikingly high, Asia has had a lower technical change rate. Moreover, high average labor product countries tend to have a higher technical change rate while their TFP growth is the lowest compared to other economies.

JEL: D24, O33, O47, O50

Keywords: technical change, total factor productivity (TFP), production function, lost decades

1. Introduction

Economic growth has been lackluster for more than a decade now. Figure 1

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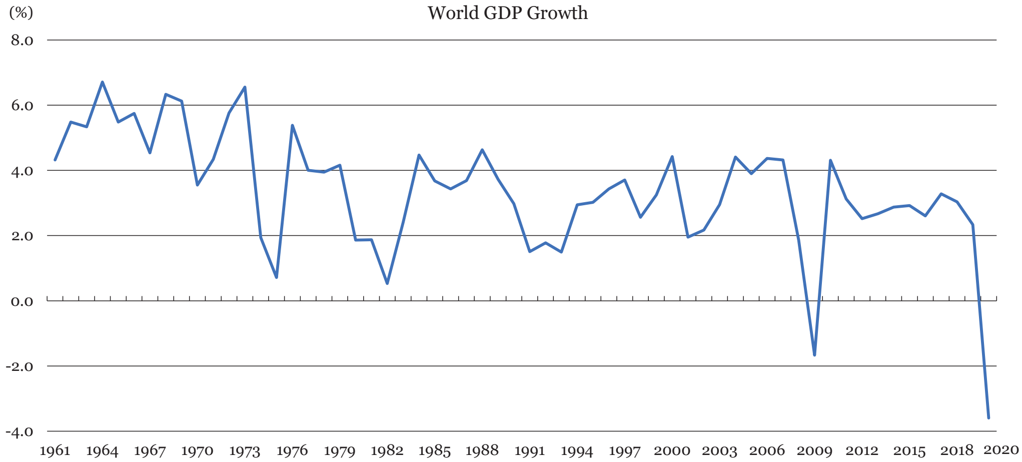
Figure 1: World GDP Growth Over the Years



Source: The World Bank.

shows the world GDP growth over the years, and average growth during the past decade has been 2.2%. One of the greatest issues that the world faces is improving productivity and innovating technology. IMF (2021) describes raising productivity growth and inducing technological change as basic key ingredients to drive economic growth.

It has become increasingly important to capture the factors behind the economic growth or lack thereof we have been observing over the recent years. Clarifying these attributes would pave way for future economic growth. Therefore, the aim of this study is to measure the change in productivity and technology over the years. In order to do so, this study constructs and estimates a production function that takes technical change into account and then, further calculates total factor productivity (TFP) as a residual.

First, *TFP* is a typical indicator for measuring the efficiency and technological progress of a firm or an economy. This concept, proposed by Solow (1957), is based on the idea that efficiency and technological progress can be captured as “residuals” by subtracting the contribution of known available factor inputs in the production function. Second, different technologies may be available in different time periods due to technological change. I will be referring to this change as *technical change* in this paper.

Estimation results reveal that technical change and TFP growth vary depending on an economy’s average labor product and regional characteristics. Eastern Europe is high both in technical change and productivity growth, while the

Americas and Australia are low in both. Although productivity growth in Asia has been strikingly high, compared to other regions, Asia has had a lower technical change rate. Moreover, high average labor product countries tend to have a higher technical change rate while their TFP growth is the lowest compared to other economies. Japan has been suffering from its low productivity growth, however, technical change in Japan has not been as low.

The remainder of this paper is organized as follows. Section 2 presents an overview of relevant literature. Section 3 briefly describes the data used in this study. Section 4 explains the results for technical change. TFP estimation results are discussed in Section 5. Section 6 concludes.

2. Literature Review

Measuring and analyzing technical change and TFP growth have been the subject of investigations in many empirical studies. These literature are comprehensive and diverse in that they cover a wide range of research questions regarding the concept, modeling, estimation and effects of technical change and TFP. For example, Syverson (2011) surveys and evaluates recent empirical work on TFP, addressing the question of why businesses differ in their measured productivity levels.

Heshmati and Kumbhakar (2011) model technical change via a time trend and other exogenous factors. They use balanced panel data for Chinese provinces for the period 1993 to 2003. In their study, technology indices were defined based on external economic factors and time trend. Results show that technical change varies significantly across the provinces and regions and its impacts on TFP steadily declines over time.

In another study, Heshmati and Kumbhakar (2014) consider estimation of technical change and TFP growth by utilizing both observable internal and external determinants of technical change. Results are based on an unbalanced panel data for 40 OECD member, accession and enhanced agreement countries observed for the period 1980 to 2006. Their focus in modeling technical change is on key technology shifters associated with it. Estimates of TFP growth and its components are found to vary greatly.

Covering 13 manufacturing industries in 12 OECD countries between 1970 and 1992, Griffith et al. (2004) examine whether research and development (R&D) has a direct effect on a country's rate of TFP growth through innovation, and whether R&D's effect on TFP growth depend on a country's level of TFP relative to the technology frontier. According to their results, R&D has a positive and statistically significant effect on both innovation and technology transfer rates. They also find that educational attainment is an important and conditional element for TFP growth through both innovation and technology transfer. Trade with a country on the world technology frontier shows a slight positive effect on TFP growth.

Speaking of trade, using data from 83 countries between 1960 and 1989, Miller and Upadhyay (2002) find that trade is positively associated with TFP growth. A positive and statistically significant effect of trade on TFP growth was detected, although its effects are negative for low per capita income countries. They also find that at low levels of income the interaction term between human capital and trade is positive. This means that for low-income countries a certain level of human capital is necessary to enjoy the benefits of trade.

Tugcu and Tiwari (2016) investigate the causal relationship between different types of energy consumption and TFP growth in Brazil, Russia, India, China and South Africa (BRICS) from 1992 to 2012. Their results indicate no remarkable causal link between renewable energy consumption and TFP growth in BRICS. However, in the case of non-renewables, energy consumption creates a positive externality that contributes to economic development in Brazil and South Africa by a growth in TFP and energy use itself.

This study contributes to the literature in that it attempts to measure both technical change and TFP of 40 countries. By doing so, not only does this study conduct a comparative study of countries, but also reveals the differences in effects between technical change and TFP. Moreover, focusing on Japan, specifically, this study measures both technical change and TFP from the late 90s until most of the 00s, which covers the period of Japan's lost decades.

3. Data

This study uses data from the Socio-Economic Accounts (SEAs) from the World Input-Output Database (WIOD)[1], which was released for the general public in April 2012, and later updated in 2016. The international supply and use table covers annual time-series data from 1995 to 2014 for 40 countries. Table 1 lists the country coverage.

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1. This database is available at http://www.wiod.org/home.

The core of the database is a set of harmonized national supply and use tables, linked together with bilateral trade data in goods and services. These two sets of data are then integrated into a world input-output table. See Timmer (2012) for the detailed framework and calculations.

Table 1: Country Coverage by Region

Americas and Australia		Eastern Europe		Western Europe	
Australia	AUS	Austria	AUT	Belgium	BEL
Brazil	BRA	Bulgaria	BGR	Germany	DEU
Canada	CAN	Cyprus	CYP	Denmark	DNK
Mexico	MEX	Czech Republic	CZE	Finland	FIN
United States	USA	Estonia	EST	France	FRA
Asia		Greece	GRC	United Kingdom	GBR
China	CHN	Hungary	HUN	Ireland	IRL
Indonesia	IDN	Lithuania	LTU	Italy	ITA
India	IND	Latvia	LVA	Luxembourg	LUX
Japan	JPN	Poland	POL	Malta	MLT
South Korea	KOR	Romania	ROU	Netherlands	NLD
Taiwan	TWN	Russia	RUS	Spain	ESP
		Slovak Republic	SVK	Portugal	PRT
		Slovenia	SVN	Sweden	SWE
		Turkey	TUR		

The SEAs contain annual data from 1995 to 2009 on industry output and value added, capital stock and investment, and wages and employment.[2] The variables used in this study are gross value added at current basic prices, nominal gross fixed capital formation, and total hours worked by persons engaged. Unfortunately, data on nominal gross capital formation is available only until 2007, so observations for years 2008 and 2009 are dropped from this study. All values are adjusted to real values using 1995 prices.

Thus, the real sectoral output (value-added output) is the dependent variable and gross fixed capital formation and labor hours are the independent variables or

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
lmY	520	-4.692	3.2457	-10.95	2.9026
lmK	520	-4.697	3.2386	-11.83	2.9377
lmL	520	-1.826	1.9294	-5.957	2.7622
mYear	520	0	3.7453	-6	6

2. Further details on the SEA database can be found in Erumban et al. (2012).

inputs in this study. Following Coelli et al. (2005), logarithmic mean-scaled quantities are used.[3] In other words, all variables are mean-scaled, and converted into logarithm values. The descriptive statistics are shown in Table 2.

Table 3: Average Labor Product by Group

High	Medium	Low
AUS	AUT	BGR
BEL	CYP	BRA
CAN	DEU	CHN
CZE	ESP	EST
DNK	FIN	GRC
FRA	GBR	LVA
HUN	IND	MLT
IDN	IRL	PRT
JPN	ITA	ROU
KOR	LTU	RUS
LUX	MEX	SVK
SWE	NLD	SVN
TWN	POL	TUR
USA		

Source: Author's calculations based on SEAs.

Table 4: Average Capital Product by Group

High	Medium	Low
BEL	AUT	AUS
BGR	BRA	CHN
CAN	DEU	CZE
CYP	ESP	DNK
FIN	GRC	EST
FRA	IND	HUN
GBR	ITA	IRL
IDN	JPN	KOR
MEX	LUX	LTU
RUS	MLT	LVA
SWE	NLD	PRT
TUR	POL	SVK
TWN	ROU	SVN
USA		

Source: Author's calculations based on SEAs.

3. This study uses the mean-scaled input quantities to enable interpreting the first-order coefficients of the logarithmic input quantities as output elasticities at the sample mean.

Furthermore, dividing the value-added output by labor hours gives us average labor product. Likewise, by dividing the value-added output with gross fixed capital formation, average capital product is also calculated. Countries are then classified into high, medium, and low average product groups. The lists of countries in the average labor product and average capital product groups are shown in Tables 3 and 4, respectively.

A good number of countries remain in the same category for both average labor product and average capital product, which is visible in Table 5, a cross table. However, Japan, for example, is grouped into high average labor product category whereas for average capital product it is classified in the medium group. There are also countries like Bulgaria, which is grouped in low average labor product group but is classified as high average capital product.

Table 5: Cross Table of Average Labor Product and Average Capital Product

group_lab group_cap	High		Medium		Low		Total	
High	7	50.0%	4	28.6%	3	21.4%	14	100%
Medium	2	15.4%	7	53.8%	4	30.8%	13	100%
Low	5	38.5%	2	15.4%	6	46.2%	13	100%
Total	14	35.0%	13	32.5%	13	32.5%	40	100%

Using a cross table enables us to further see the geographical distribution of the three average labor product groups, shown in Table 6. The majority of the Americas and Australia (presented as As & A) and Asian countries belong to the high average labor product group. Most countries in the Eastern European region are classified as low average labor product. Half of the Western European region are grouped in the medium average labor product category.

Table 6: Cross Table of Average Labor Product and Region

group_lab region2	High		Medium		Low		Total	
As&A	3	60.0%	1	20.0%	1	20.0%	5	100%
Asia	4	66.7%	1	16.7%	1	16.7%	6	100%
E.Europe	2	13.3%	4	26.7%	9	60.0%	15	100%
W.Europe	5	35.7%	7	50.0%	2	14.3%	14	100%
Total	14	35.0%	13	32.5%	13	32.5%	40	100%

4. Technical Change and Output Elasticities

Different technologies may be available in different time periods due to technical change. Solow (1957) defines the phrase "technical change" as a short-hand expression for any kind of shift in the production function. The state of the available "technologies" should be included as an explanatory variable in order to conduct a reasonable production analysis. A time trend can be used as a proxy for a gradually changing state of available "technologies." Therefore, time (t) is included as an additional explanatory variable in the production function:

$$y = f(x, t) \tag{1}$$

where y is output, x is input and t is time. This function can be used to analyze how the time (t) affects the available production technology. The average production technology can be estimated from panel datasets.

For example, in case of a Cobb-Douglas production function, a linear time trend can be added to account for technical change:

$$\ln y = \alpha_0 + \sum_i \alpha_i \ln x_i + \alpha_t t \tag{2}$$

where the subscript i denotes the different kinds of input. Given this specification, the coefficient of the linear time trend can be interpreted as the rate of technical change per unit of the time variable t:

$$\frac{\partial \ln y}{\partial t} = \alpha_t \tag{3}$$

In contrast, a Translog production function that accounts for constant and neutral technical change has the following specification:

$$\ln y = \alpha_0 + \sum_i \alpha_i \ln x_i + \frac{1}{2}\sum_i \sum_j \alpha_{ij} \ln x_i \ln x_j + \alpha_t t \tag{4}$$

Here, in regard to our model in this study, input x_1 is capital and input x_2 is labor.[4]

Now that we have constructed our production functions, a set of conventional tests are conducted in order to check the consistency of the different estimators and to determine which specification fits better.[5] Conducting a Hausman test, it shows

4. Details on these variables are explained in Section 3.

5. Here, I only present test results and statistics that are more relevant to this current study, which adopts the Translog production function with non-constant and non-neutral technical

that the random effects estimator is inconsistent for both Cobb-Douglas and Translog production functions, due to correlation between the individual effects and the explanatory variables. The calculated χ^2 test statistic is 1355 for the Translog model, which resulted in a p-value of 0.00. Testing the poolability of the model, the F-statistic is 237.11 with a p-value of 0.00. Thus, the pooled model is rejected in favor of the model with fixed individual effects. This also means that the individual effects are statistically significant at the 0.1% level.[6] Further running a Wald test, the calculated χ^2 test statistic is 24.04, which resulted in a p-value of 0.00. Thus, the Cobb-Douglas specification is rejected in favor of the Translog specification.

Technical change is not always constant and is not always neutral. In other words, technical change may have either increasing or decreasing rates or may be non-neutral, or biased. A production function accounting for this can be constructed by including a quadratic time trend and interaction terms between time and input quantities:

$$\ln y = \alpha_0 + \sum_i \alpha_i \ln x_i + \frac{1}{2}\sum_i \sum_j \alpha_{ij} \ln x_i \ln x_j + \alpha_t t + \sum_i \alpha_{it}\, t \ln x_i + \frac{1}{2}\alpha_{tt}\, t^2 \tag{5}$$

We will call this a Translog production function with non-constant and non-neutral technical change. In this specification, the rate of technical change depends on the input quantities and the time period:

$$\frac{\partial \ln y}{\partial t} = \alpha_t + \sum_i \alpha_{it} \ln x_i + \alpha_{tt}\, t \tag{6}$$

and output elasticities may change over time:

$$\epsilon_i = \frac{\partial \ln y}{\partial \ln x_i} = \alpha_i + \sum_j \alpha_{ij} \ln x_j + \alpha_{it}\, t \tag{7}$$

Now a Wald test can be conducted to test whether this Translog production

change of a fixed effects model. This specification and model selection was selected after thoroughly running all tests necessary.

6. The implications of the possibility of time-invariant individual effects existing are important. To note, Yane (2021) attempts to construct a global production function, and consecutively estimates technical efficiencies in the world. However, we see that in this current study that there appears to be time-invariant individual effects. This suggests that in Yane (2021)'s cross-sectional model, there may have been unobserved time-invariant individual effects that affect the output quantity and are correlated with some of the input quantities. The fixed effects estimation in this current study gives unbiased results because the effects of the unobserved time-invariant variables are absorbed in the fixed effects.

function with non-constant and non-neutral technical change outperforms the Translog production function with constant and neutral technical change. The calculated χ^2 test statistic is 8.36, statistically significant at the 5% level. As a result, the fit of the Translog specification with non-constant and non-neutral technical change is better than the fit of the Translog production function with constant and neutral technical change.

Hence, we use the following Translog production function in order to measure the technical changes:

$$\ln y_{kt} = \beta_0 + \sum_i \beta_i \ln X_{ikt} + \frac{1}{2}\sum_i \sum_j \beta_{ij} \ln X_{ikt} \ln X_{jkt} + \beta_t T_t + \sum_i \beta_{it} \ln X_{ikt} T_t + \frac{1}{2}\beta_{tt} T_t^2 + \varepsilon_{kt} \tag{8}$$

Table 7: Estimation Results for Translog Production Function with Non-constant and Non-neutral Technical Change

	Model 1	**Model 2**	Model 3
(Intercept)	0.047		-0.439***
	(0.027)		(0.096)
lmK	0.986***	**0.387*****	0.877***
	(0.007)	**(0.028)**	(0.028)
lmL	0.036*	**0.088**	0.247***
	(0.016)	**(0.074)**	(0.055)
I(0.5 * lmK^2)	-0.003	**0.002**	0.013
	(0.003)	**(0.005)**	(0.008)
I(0.5 * lmL^2)	-0.033**	**-0.045**	-0.103**
	(0.012)	**(0.030)**	(0.034)
I(lmK * lmL)	0.011	**0.035****	0.036*
	(0.006)	**(0.011)**	(0.016)
myear	-0.007	**0.019*****	-0.003
	(0.005)	**(0.002)**	(0.002)
I(myear * lmK)	0.004**	**0.000**	0.002***
	(0.001)	**(0.000)**	(0.001)
I(myear * lmL)	-0.003	**-0.002****	-0.004**
	(0.002)	**(0.001)**	(0.001)
I(0.5 * myear^2)	-0.002	**0.000**	-0.002*
	(0.002)	**(0.000)**	(0.001)
Obs.	520	**520**	520
R2	0.995	**0.898**	0.907
R2 Adj.	0.995	**0.887**	0.905

Notes: Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Estimation Results for Cobb-Douglas and Translog Production Functions with Constant and Neutral Technical Change

	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
(Intercept)	0.002		-0.894***	0.031		-0.730***
	(0.019)		(0.097)	(0.024)		(0.102)
lmK	0.985***	0.292***	0.688***	0.987***	0.373***	0.833***
	(0.005)	(0.017)	(0.020)	(0.007)	(0.026)	(0.029)
lmL	0.036***	0.034	0.311***	0.034*	-0.010	0.218***
	(0.008)	(0.050)	(0.037)	(0.016)	(0.065)	(0.052)
myear	-0.020***	0.021***	-0.005**	-0.020***	0.021***	-0.003*
	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)
I(0.5 * lmK^2)				-0.002	0.007	0.031***
				(0.003)	(0.004)	(0.006)
I(0.5 * lmL^2)				-0.032**	-0.047	-0.057
				(0.012)	(0.030)	(0.032)
I(lmK * lmL)				0.010	0.016*	0.004
				(0.006)	(0.008)	(0.012)
Obs.	520	520	520	520	520	520
R2	0.995	0.890	0.877	0.995	0.896	0.886
R2 Adj.	0.994	0.881	0.876	0.995	0.886	0.884

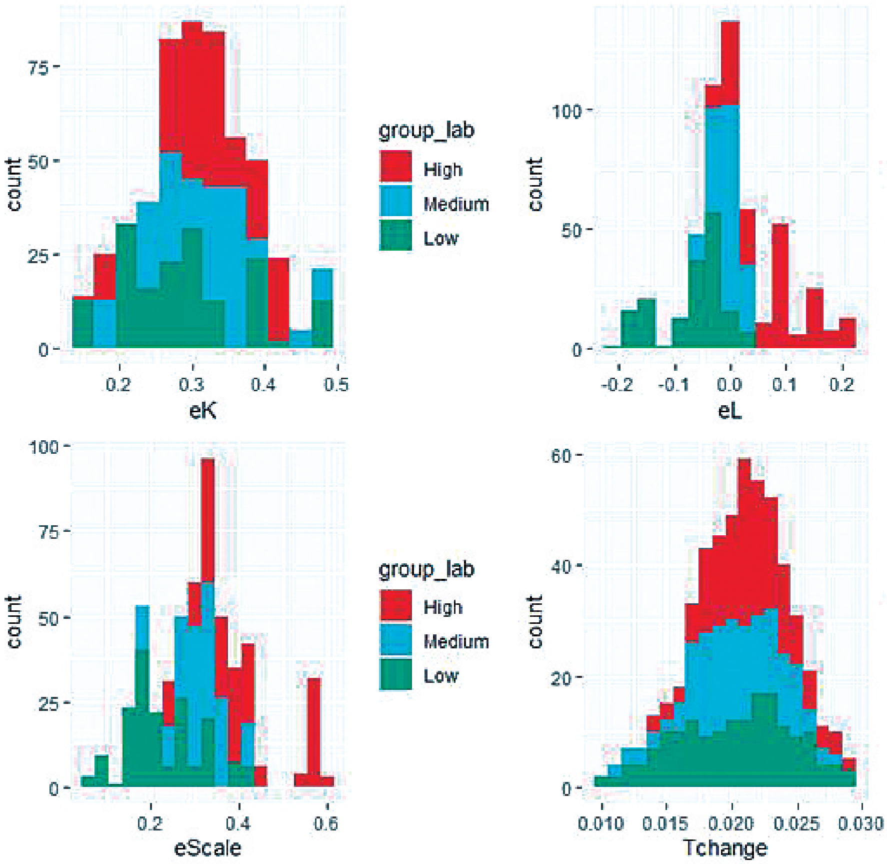
Notes: Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

where $\ln y_{kt}$ is the logarithm of output measure of total value-added output of country k (k = 1,2,…,N) in period t (t = 1,2,…,T) and $\ln X_{ikt}$ is a vector of logarithm of i (i = 1,…,I) inputs. T is a time trend and βs are unknown parameters to be estimated. The estimation results are shown in Table 7. The different columns show results for the different estimations. Models 1, 2, 3 refer to pooled, fixed effects and random effects models, respectively. Table 8 shows the estimation results for the Cobb-Douglas and Translog production functions with constant and neutral technical change.

Results reveal that the estimated annual rate of technical change is around 1.9% and is statistically significant at the 0.1% level. This indicates that technical change is labor saving. The coefficient for capital input is 0.387 and statistically significant at the 0.1% level, however, the coefficient for labor input 0.088 and is not statistically significant at the 5% level.

Furthermore, histograms of the estimated output elasticities of capital, *eK*, labor, *eL*, and elasticity of scale, *eScale*, are shown in Figure 2. The graphs indicate that the higher average labor product groups tend to be more left skewed than lower ones. If the high average labor product countries increase their capital input by one percent, the output of most of these countries will increase by about 0.3%.

Figure 2: Histograms of Output Elasticities, Elasticity of Scale and Technical Change



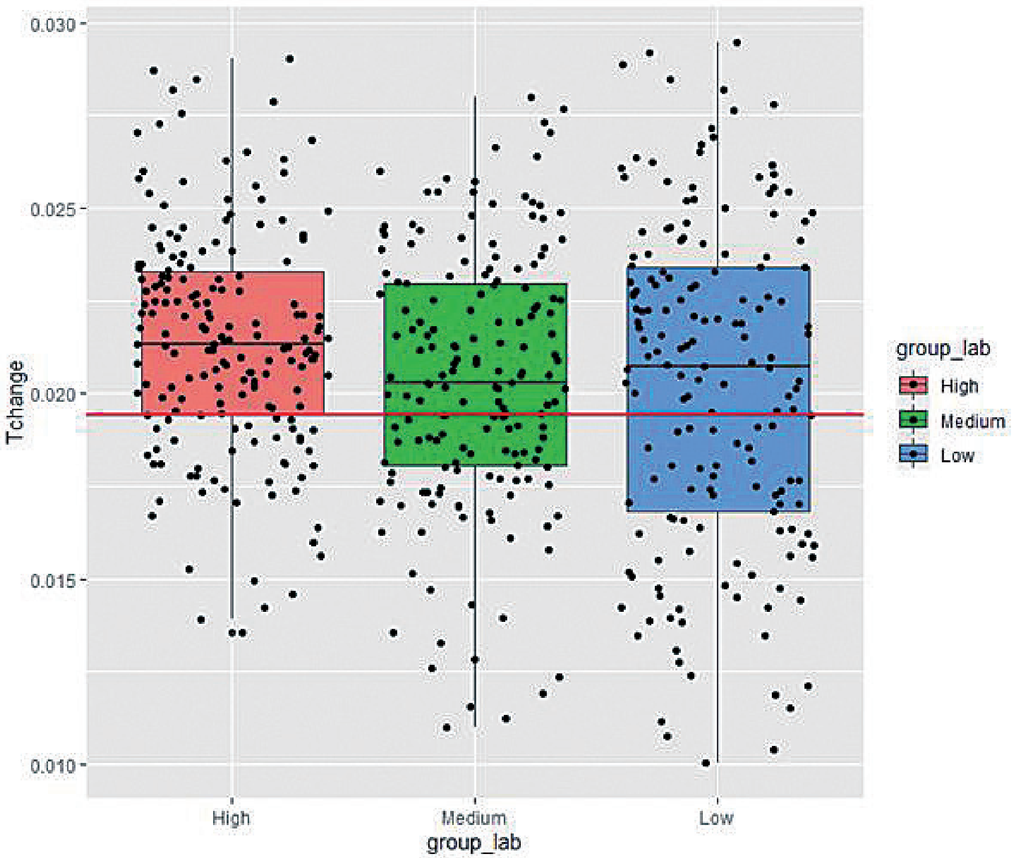
Source: Author's calculations.

For lower average labor product economies, the output increase tends to be smaller. As for labor input, the output elasticity becomes smaller the lower the average labor product is. If the high average labor product countries increase all input quantities by one percent, the output of most countries in this category will increase by approximately 0.33%. This suggests that there are decreasing returns to scale.

Figure 2 visualizes the variation of the annual rates of technical change, *Tchange*, as well. The resulting histogram seems to indicate that technical change tends to be higher as average labor product becomes lower. Let us investigate further using box plots.

Figure 3 depicts the box plots of technical change for high, medium and low average labor product groups. The red line shows the *mean* of Japan's technical

Figure 3: Box Plot by Average Labor Product Group



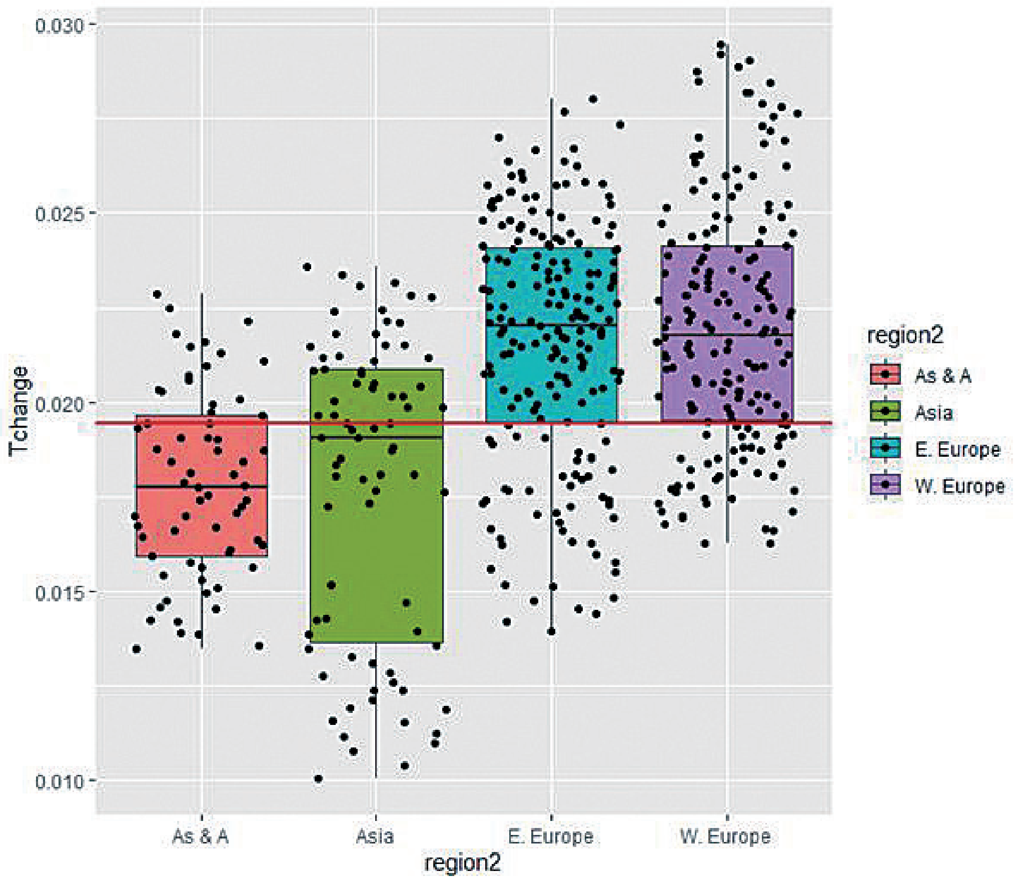
Source: Author's calculations.

change, which is approximately 1.9%.[7] Medium average labor product group sits relatively lower than the high average labor product group. Low average labor product group has the greatest variance, with its median in between the high and medium groups. Japan's mean technical change rate is lower than the medians of all three average labor product groups.

Next, Figure 4 shows the box plots of technical change for the different regional groups defined in Table 1. Again, here, the red line shows the *mean* of Japan's technical change. Europe's median technical change ranks the highest, with the East fairing higher than the West. Next comes Asia and then the Americas and Australia group, albeit Asia has the widest range of variance. The minimum

7. Note that box plots show the median, not the mean.

Figure 4: Box Plot by Regional Group



Source: Author's calculations.

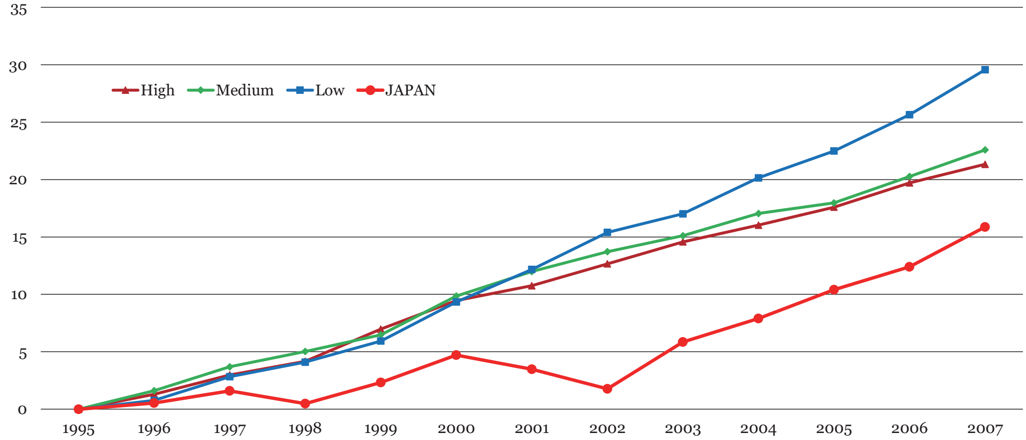
technical change belongs to the Asian region. Japan's mean technical change rate falls in between the box plots of the European group and the Americas and Australia group.

5. Total Factor Productivity (TFP)

Since TFP is defined as "residuals" obtained by estimation of the production function:

$$\ln TFP_{kt} \equiv \ln y_{kt} - \sum_i \beta_i \ln X_{ikt} - \frac{1}{2}\sum_i \sum_j \beta_{ij} \ln X_{ikt} \ln X_{jkt} \tag{9}$$

Figure 5: TFP Growth by Average Labor Product Group

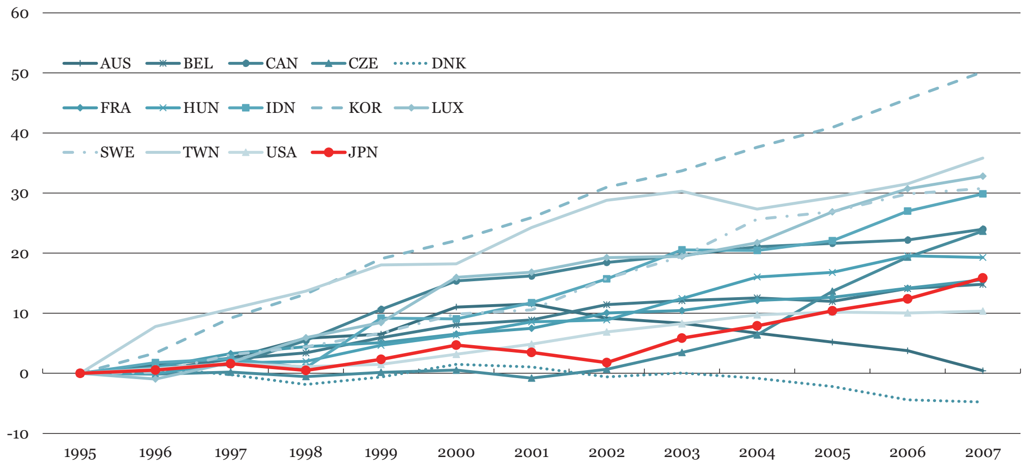


Source: Author's calculations.

Figures 5 – 8 illustrate the results of the resulting TFP estimates. First of all, Figure 5 depicts TFP growth by average labor product group. The low average labor product group has caught up and surpassed the higher average labor product groups in terms of productivity growth. As of 2007, the high average labor product group has the lowest productivity growth. What is also striking is the productivity growth of Japan. It is far below all three groups.

Figure 6 enables us to investigate further, focusing on high average labor product group, to which Japan belongs. It suggests that even among the high

Figure 6: TFP Growth in High Average Labor Product Group

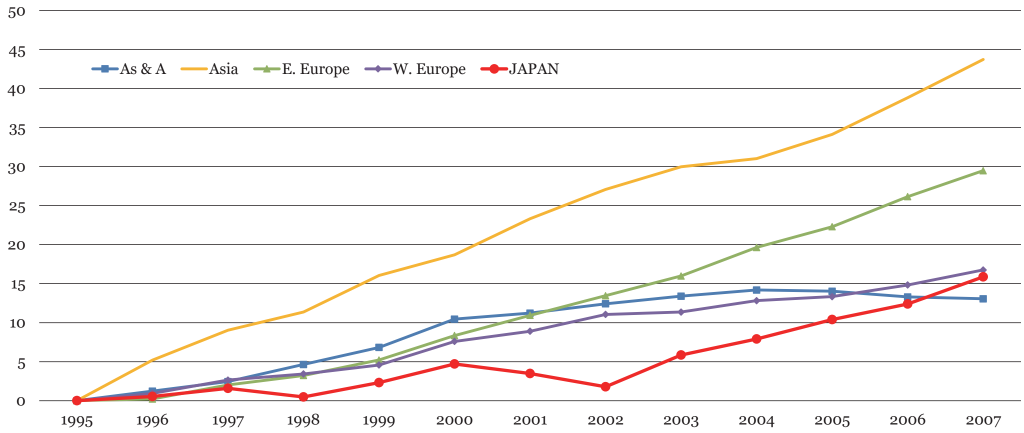


Source: Author's calculations.

average labor product group, Japan's productivity has been very low. After dropping in 2000, it starts to increase again in 2002, and outpaces Australia, the US, Belgium and France. The only country with productivity growth lower than that of Japan from start to finish of our data is Denmark. Another country that boosted its productivity growth is the Czech Republic.

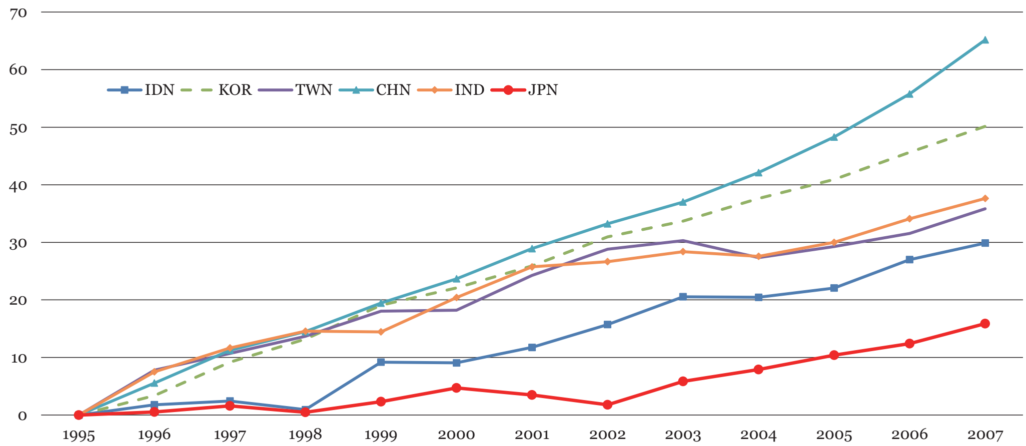
Figure 7 shows TFP growth by region. Asia has always had the highest productivity growth throughout 1995 to 2007. Japan, however, has lagged behind, only catching up and surpassing the Americas and Australia in the final year of our observation, 2007. While all other regions' overall productivity has an upward and

Figure 7: TFP Growth by Region



Source: Author's calculations.

Figure 8: TFP Growth in Asia



Source: Author's calculations.

increasing trend, productivity in the Americas and Australia started to decline after 2004.

Finally, Figure 8 presents TFP growth among Asian countries. It clearly shows the staggering productivity growth of Japan. Japan has the lowest productivity growth in Asia. In contrast, China and South Korea show the highest, resilient productivity growth.

6. Conclusion

This study contributes to the literature in that it attempts to measure both technical change and TFP of 40 countries. By doing so, not only does this study conduct a comparative study of countries, but also reveals the differences in effects between technical change and TFP. Moreover, focusing on Japan, specifically, this study measures both technical change and TFP from the late 90s until most of the 00s, which covers the period of Japan's lost decades.

Estimation results based on a Translog production function with a quadratic time trend reveal that technical change varies depending on an economy's average labor product as well as regional characteristics. First, technical change of the high average labor product group is higher than that of the medium average labor product group. Low average labor product group has the greatest variance, with its median in between the high and medium groups. Second, Europe's median technical change ranks the highest, with the East fairing higher than the West. Asia and then the Americas and Australia group follow. Third, Japan's mean technical change rate is lower than the medians of all three average labor product groups. Japan's mean technical change rate falls in between the medians of the European group and the Americas and Australia group.

The estimated TFP reveals that the low average labor product group has caught up and surpassed the higher average labor product groups in terms of productivity growth. Asia has always had the highest productivity growth throughout 1995 to 2007. China and South Korea lead the trend, showcasing the highest, resilient productivity growth. While all other regions' overall productivity has an upward and increasing trend, productivity in the Americas and Australia started to decline after 2004.

What is also striking is the TFP growth of Japan. The results suggest that even among the high average labor product group, Japan's productivity has been very low, and clearly show the staggering productivity growth of Japan. In addition, Japan has the lowest productivity growth in Asia. These findings elucidate Japan's lost decades. Japan's technology and productivity growth has actually been stagnating since the late 1990s, compared to its peers.

In conclusion, the effects of technical change and TFP growth vary depending on an economy's average labor product and regional characteristics. Eastern Europe is high both in technical change and productivity growth, while the Americas and Australia are low in both. Although productivity growth in Asia has been strikingly high, compared to other regions, Asia has had a lower technical change rate. Moreover, high average labor product group tends to have a higher technical change rate while its TFP growth is the lowest among the average labor product groups. Japan has been suffering from its low productivity growth, however, technical change in Japan has not been as low.

Policy implications for this study are mainly a note of precaution: it is important to accurately measure and capture technical change and TFP growth, as well as distinguishing them. For example, in the case of Japan, building policies focusing on productivity deems more crucial than trying to increase technical change.

Possible future research includes measuring technical efficiencies, which will further help elucidate the change in TFP growth. Doing so should help us understand the reasons for reduced or improved productivity and competitiveness. Furthermore, investigating further by dividing countries into groups based on income will be beneficial since there may be effects depending on different levels of income of an economy.

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