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WHAT INFORMATION TECHNOLOGY MEANT FOR ECONOMIC PROSPERITY OF USA, JAPAN AND GERMANY?

Abstract

Technological progress and economic growth are deep related. It is primarily through technological improvements that humankind has been able to progress to the extent it has since the First Industrial Revolution. Technological advances have displaced existing economic structures and laid down fundaments for new economic forces and opportunities, all of which had a widespread welfare effect. Growth theory indeed assumes that changes in real output and productivity are result of technological shocks within the economy. By focusing on computer and information techonology, using ARIMA models and Beveridge-Nelson univariate decomposition this paper estimates the impact of technological shocks on GDP, GDP per capita and labour productivity growth of three world's strongest economies: USA, Japan and Germany. The paper confirms the thesis that information technology has been the key factor of improved productivity and growth performance of these economies.

Keywords

'Third' Industrial Revolution technologies, productivity and growth, ARIMA models, Beveridge-Nelson decomposition, USA, Japan, Germany

1. Introduction

Historical pattern of technological progress strongly suggests that innovations that sprouted from technological developments, which are independent of society initiatives, have been an indispensable part of economic growth of developed countries. These technological improvements displaced existing economic structures and laid down fundaments for new economic forces and opportunities, all of which had a widespread welfare effect. Innovations have long been recognized as one of the key elements of economic development, though some scholars believe that its direct link to the concept of economic growth is rather controversial. Economic historians have stressed the role of technological innovations (together with other important factors such as institutional, political and economic climate, education, lower population growth, as well as efficient investment policy) as an underlying determinant of the process that designs economic growth path (Dosi, Freeman and Fabiani, 1994). Dichotomy between technological changes and technology adoption also explains the persistent productivity difference across countries and time (Gancia and Zilibott, 2009). Developed countries have recognized technology as the dominant factor influencing productivity growth, which enabled them to adequately generate and diffuse new knowledge into productive structures (helping the economic actors on other social levels in much broader sense). As a result, macro and microeconomic coordination, greater productivity and greater consumption were achieved in modern developed societies. In some developed countries, the impact of technological progress on economic growth has been estimated at 60-70% as compared with other growth factors. Growth theory indeed assumes that changes in real output are result of technological shocks within the economy. These shocks embodied in technological innovations have permanent effect on real output and productivity growth, raising the standard of living over the time as the economy moves to an improved equilibrium point (Falatoon and Safarzadeh, 2006).

For the number of years economists were sceptical about effects of computer and information technology on aggregate productivity and economic growth, however new studies have shown that the surge of productivity (especially in the USA in the 1990s) has been largely the result of the adoption of new technologies (Edwards, 2001). The computer equipment manufacturing industry comprised only 0,30% of USA's value added in the period 1960-2007, but has generated 2,70% of economic growth and 25,0% of productivity growth (Jorgenson, Ho and Samuels, 2010). Since the 1960s and 1970s slogan 'Made in Japan' has been a synonym for high quality and high technology for consumers all around the globe, especially in the field of electronics (Fan and Watanabe, 2006). Germany's tryouts in high technology are as instructive as any lessons learned from that constitute the more closely studied success stories, from Silicon Valley and Route 128 to Japan, Taiwan and South Korea (Siebert and Stolpe, 2001). The so-called 'New Economy' associated with advances in computer, information and communication technology is often related to transformation of economies from industrial to information societies. Good examples include government promotion and regulation of technology development and information industries, information infrastructure, as well as prevailing development of information based talent and cultures. However, some state that the advances made by using these new industries are far from the benefits associated with the two industrial revolutions. Up until the end of the 1980s economists had trouble to distinguish actual benefits from such technologies. The potential of computer, information and communication prospect, however, was made clear in the 1990s. (Šimurina and Tolić, 2008).

This paper analyzes the impact of major technological innovations within the 'Third Industrial Revolution technologies (i.e. computer and information technology) on the real GDP, GDPpc and labour productivity growth of three developed countries (USA, Japan and Germany) by using the data for the years 1950-2013. Data are collected from the Conference Board *Total Economy Database*. The results are an indispensible part of a much larger study conducted by the author thus represents an analytical extent (comparison, reasoning, deliberation, etc.) on the conclusions drawn from Tomić (2012) and Škare and Tomić (2014).

2. Theoretical background and main empirical facts

Technological change is composed of many socio-economic relationships and therefore it is inevitably tied up with historical factors. The objective of this paper is not only to measure the implications of technological innovations on mankind well-being, but to observe and analyze them in a form that will provide distinctive international comparison. While on one hand we have to recognise the fact that though, generally speaking, technological progress increases productivity gains and welfare of people, it is, however, not an easy task to quantify and assess a precise contribution of technological progress; on the other hand, the non-rivalry of technology, as modelled in most of endogenous growth literature, implies that higher population growth spurs technological change (Kremer, 1993). Thus, technological progress must be observed within economic (output and productivity growth) and social (population growth) domain.

The main question that dwells upon the economists is whether economic growth can be sustained in the long run. If it can then: what determines the long-run growth-rate; in what socio-economic environment can it be fostered; and which economic policy can be used to accelerate it. Naturally, macroeconomic management faces difficult question as to how best to promote rapid and sustainable economic growth in face of depleting non-renewable natural resources. As many scholars point out, advances in technology are the best chance mankind has to overcome the apparent limits to growth. By citing Schumpeter (1934), Sollow (1970), Romer (1990), Aghion and Howit (1992) and many others, Grossman and Helpman (1993) concluded that improvements in technology have been the real force behind perpetually rising standards of living. Technology has been widely identified as contributor to economic growth beginning from the empirical study by Denison in 1967, showing that it has been responsible for over 40% of economic growth in the USA and the UK. Simon Kuznets work (1966) too identifies the significance of technological change i.e. that productivity and economic growth are broadly assigned to technology development (Cypher and Dietz, 2004). Following the Neo-Classical growth models and pioneering work of Robert Solow (1956; 1957) we could conclude that technological change, is indeed expressed in relatively large 'residual factor' (Dosi, Freeman and Fabiani, 1994). But until recently, little progress was made in the formal modelling of technical change itself. As Gancia and Zilibott (2009) point out, despite the obvious importance of technology in explaining modern growth, quantifying the exact contribution of technical progress is not really easy, considering that technological progress is hard to observe and measure directly. New-Growth theory (Romer; 1986; Grossman and Helpman, 1991; Aghion and Howitt, 1992) does attempt to incorporate some measures of technological innovation, however it also provides some limitations on the ways the technology is represented (Dosi, Freeman and Fabiani, 1994). Furthermore, since innovative activity and technological progress have a positive effect on productivity growth, it means that Schumpeterian growth hypothesis which predicts that productivity growth is driven by the levels of research intensity in the economy, in fact holds (Rajabrata, 2011). Following endogenous technological approach some second-generation Schumpeterian growth models were developed (Aghion and Howitt, 1998; Howitt, 1999; Peretto and Smulders, 2002; Ha and Howitt, 2007).

Advancement in computer and information (plus communication) technology, often referred as ICT sector, is regularly labelled as 'Third Industrial Revolution'. Though there is no compelling evidence that these technological improvements constitute the next industrial revolution, its full potential is being revealed and materialised in the lower prices of information technology, reduction in the cost of capital, rapid productivity growth and significant improvement in organisational techniques. From new innovations like software, robotics, biotechnology and nanotechnology to improvements in manufacturing systems, technology has made economies and more efficient and productive (Škare and Tomić, 2014). Computer and information technology has been an important element of growth dynamics of the most of the developed countries in last few decades. Furthermore, computer derived technology became an important element in explaining cross-country income differences. Considering that technological progress is the fundamental force underlying long-run GDP growth, we can conclude that it can also explain why some countries have been so much more productive than the others (Tomić, 2012). For example, Cypher and Dietz (2004) by following various studies concluded that the level of technological capability of information technology was positively correlated with the pace of economic expansion of OECD countries over the period 1965-1990. The share of GDP devoted to the research and development in the private sector in less developed countries lags far behind what is spent in the OECD developed economies, suggesting that there remains a gap in technological effort and capability between even the highest tier less developed economies and the developed countries. In following pages we conclude that focus on technological entrepreneurship enabled USA to pioneer new technical advances. USA's approach comprised new and tight industrial networks of small and larger firms, research universities, venture capital etc. that concentrated around high-tech districts like Silicon Valley in California and Route 128 around Boston (Florida and Kenney, 1990). Most research suggests that levels of information technology investments by companies did contribute substantially to the increased labour productivity growth in Japan. Jorgenson and Motohashi (2003) point out that the contribution of information technology to economic growth was strikingly similar in the USA and Japan in the second half of 1990s. Several empirical studies have suggested that the research productivity of the German innovation system is much higher in comparison with most European countries (Siebert and Stolpe, 2001). Again, we have to acknowledge that USA and Japan have been exchanging on the first and second place of the annual list of countries with most inventions for a long time, with Germany being always in the top behind these two economic giants.

3. Methodology and data

In order to test effects of technological progress on growth and productivity of selected countries we have applied methodology used by Falatoon and Safarzadeh (2006). Similar methodology was used by Škare and Tomić (2014). Their approach is based on Neo-Classical growth models of Solow (1956) and Swan (1956) who assume that real GDP per unit of labour is a function of capital per unit of labour and technology:

$$Y/N = f(A, K/N) \tag{1}$$

where Y is real GDP, N is labour unit, K is capital input and A is technological improvement. Since growth theory assumes that in equilibrium real GDP of unit of labour grows at the rate of technological growth, it means that with technological innovation of A, at the so-called steady-state, real GDP will grow at the rate of innovation growth ($\acute{A}$). If we consider technological innovations as supply shocks which have a permanent effect on the trend of GDP, a decomposition of such variable on its permanent and irregular components could reveal impact of technological improvement on the growth rate of real GDP between two 'path breaking' innovations. As to ensure appropriate decomposition of the deviations of the real GDP growth from its long-run growth into its deviations due to demand shocks and technological improvement within time, Falatoon and Safarzadeh based their modelling on the equation:

$$\acute{Y}_t = \acute{A}_t + \acute{N}_t \tag{2}$$

such that the trait represents the rate of change of the respective variable. If $\acute{Y}^*$ and $\acute{N}^*$ represent potential values, equation (2) can be reformulated to interpret both, deviation of real GDP growth from its long run and growth rate of potential real GDP per unit of growth for effective labour so we get:

$$(\acute{Y}_t^* - \acute{Y}_t) = \alpha\, [\acute{Y}_t^* - (\acute{A}_t + \acute{N}_t^*)] \tag{3}$$

$$(\acute{N}_t^* - \acute{N}_t) = (1 - \alpha)\, [\acute{Y}_t^* - (\acute{A}_t + \acute{N}_t^*)] \tag{4}$$

Equations (1) and (2) should be interpreted as follows; an increase in the growth rate of technological improvement depending on the value of α will accelerate the rate of real GDP while positively impacting on the rate of growth of real output; but with the time passing by, the excess output gap will become smaller so the effect of the technology shock will eventually fade away, pushing the rate of growth to its long-rung potential (Falatoon and Safarzadeh, 2006).

In order to evaluate the permanent trend in the growth and productivity variables we have to extract conditional expectation of the limiting value of the forecast function derived from ARIMA models, similar to the above mentioned authors. An ARIMA model is appropriate for this kind of analysis since it predicts a value in a response time series as a linear combination of its own past values, past errors (shock or innovations) and current and past values of other time series. Besides, ARIMA procedure provides a comprehensive set of tools for univariate time series model identification, parameter estimation and forecasting, and in that way it offers great flexibility. To identify appropriate ARIMA models we have to recognize its elements *p*, *d* and *q*. Lags of the differenced series in the forecasting equation are called auto-regressive terms (*p*), lags of the forecast errors are called moving average terms (*q*), and a time series which needs to be differenced to be made stationary is said to be an integrated version (*d*) of a stationary series. Based on those elements we can estimate proper ARIMA model. In the literature on trend/cycle decomposition, Beveridge and Nelson (BN) approach was recognized as a model based method for decomposing a univariate or multivariate time series into permanent and transitory components. Beveridge and Nelson (1981) showed how to decompose ARIMA (*p*,*1*,*q*) i.e. proposed a definition of the permanent component of an *I*(*1*) time series y_t with drift μ as the limiting forecast as horizon goes to infinity, adjusted for the mean rate of growth over the forecast horizon,

$$TD_t + BN_t = \lim_{h \to \infty} y_{t+h|t} - \delta h \tag{5}$$

where TD_t represents deterministic trend. The stochastic part of permanent component (*7*), BN_t is referred as the *BN* trend. The implied cycle (*C*) at the time *t* is then

$$C_t = y_t - TD_t - BN_t \tag{6}$$

so Beveridge and Nelson suggested that if Δy_t has Wold representation $\Delta y_t = \delta + \psi^*(L)\varepsilon_t$ then BN_t follows a pure random walk without drift (Zivot, 2005, pp. 5):

$$BN_t = BN_t - 1 + \psi^*(1)\varepsilon_t \tag{7}$$

To conclude, the long-horizon conditional forecast used to calculate the BN trend corresponds to an estimate of the permanent component of an integrated time series. This forecast will be different at each period as additional information becomes available.

Data on growth and productivity variables (real GDP, real GDPpc, real labour productivity (LP) per person and per hour) for mentioned countries has been collected from the Conference Board *Total Economy Database* for the period 1950-2013. Variables are converted to 2013 price level with 2005 EKS PPPs in order to obtain real category. Data span is chosen based on the assumption that commercial usage of computer and subsequent technologies started immediately after the II World War. Likewise Falatoon and Safarzadeh (2006), we also divided the sample periods into sub-periods based on the major technological improvements in computer and subsequent industries over the last 60 years, with classification being selected by the *rule-of-thumb*. In order to evaluate trend perspective, we estimated growth rates for all the variables and for all sub-periods. To estimate adequate ARIMA models we performed logarithmic transformation on the variables and tested the presence of a unit root. For this purpose we used Augmented Dickey Fuller test (1979), Phillips-Perron test (1988) and Kwiatkowski-Phillips-Schmidt-Shin test (1992). Generally (though with some exceptions), all tests confirmed the presence of unit root for all the variables and for all the countries in a whole and in its sub-periods. Graphical displays of the observed variables also suggest that they are not stationary in levels. In conclusion, variables reveal a non-stationary behaviour. This means that we have to apply appropriate degree of integration before we run ARIMA models.

Now that we know all the characteristics of our variables, we can estimate ARIMA models for all the countries. Due to several facts (small sample, loss of degrees of freedom, similar results in whole period and when divided in sub-periods), ARIMA models were estimated for a whole period and then divided into its sub-periods (as growth rates). The model selection was based on Schwartz Bayesian Criterion being the most restrictive one. For each model we checked for serial correlation in residuals. ARCH tests indicated no problem of autocorrelation and there were no problems of normality in residuals. Since all the variables had to be differenced in order to obtain stationarity and we wanted to gain some flexibility in moving average terms so we can filter out the noise and more accurately estimate local mean, ARIMA (1,1,1) models were estimated for all the countries[1]. The permanent trend in the variable (as a measure of economic prosperity impact of technological progress) was presented as the conditional expectation of the limiting value of the forecast function derived from the obtained ARIMA models. For each sub-period growth rates were calculated so that the economic prosperity impact of innovation could be measured as a geometric mean[2] of the permanent trend component of the decomposed series for that sub-period. Systematisation of the results by the country can be found in the Appendix[3].

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[1] Except for the USA when assessing the lnGDP: ARIMA (1,1,2) and lnGDPpc: ARIMA (2,1,1).

[2] Geometric mean is an important tool for calculating portfolio performance for many reasons, but one of the most significant is it takes into account the effects of compounding.

[3] For detailed insight into data analysis, tests and results please contact the author.

4. Economic growth and the ICT

Since the adaptation of new technologies, ICT is being credited for relatively strong acceleration in productivity and output growth in the USA, Japan and Germany. Producers and users of computers, semiconductors and other ICT equipment have been making sizeable efficiency gains, boosting aggregate total factor productivity growth. That has happened in the period when many other developed industrial economies have not experienced a pickup in productivity growth (Gust and Marquez, 2002). Namely the delay in the adaptation of new high-tech principles in those countries was translated into slower output and productivity growth in comparison to these three economic pillars. During the observed period, inclined by the commercial usage of computer and subsequent industries, average GDP growth was well over 3% and average GDPpc growth above 2%. After the II World War, Japan had an incredible growth path (in average GDP growth 4,80%, GDPpc growth 4,06%) whereat Computer and information related industries contributed the most to the positive co-movements of other economic indicators (aggregate income effect, investment, research and development, employment etc.). Therefore, Japan had benefited the most from these industries. Interestingly, Computer and subsequent industries had a stronger long-term impact effect on the European economies, than on the US economy. We also evaluated the effects of the increase in labour productivity over the observed period (which was followed by the fall in hours engaged in the production process). Labour productivity increase per person and per hour was ranging from 1,68% to 1,87% in the USA, from 3,80% to 4,11% in Japan and from 2,61% to 3,54% in Germany. However, we must not ignore the fact that there has been a slowdown in growth and productivity since 1970s due to a decrease in the rate of technological development. Labour productivity per hour and per person (as well as total employment) grew, however hours employed in production fell substantially which also contributed to that fact. This is especially noticeable in Japan and Germany where both real output and productivity growth was falling over the years. The proximate reason for the decline in the rate of technological development can be found in a decline in fertility of R&D and limited reach of technological improvements in the service sector (Blanchard, 2003). This statement is not so much true for the US that relied on the role of regulatory practices in influencing the diffusion of ICT. As Gust and Marquez (2002) noticed, European countries and Japan have participated in recent wave of invention and innovation thus having full access to the newer technologies. However, they have arguably been slower in applying them due to relatively inflexible and more costly labour markets. The decline of growth rates can be seen in *Figure 1*, pointing slowdown in labour productivity in Japan, relative deceleration of output and productivity growth rates in Germany and stable dynamics in the USA. Non-the-less, ICT sector proved to be an important source of new growth paths.

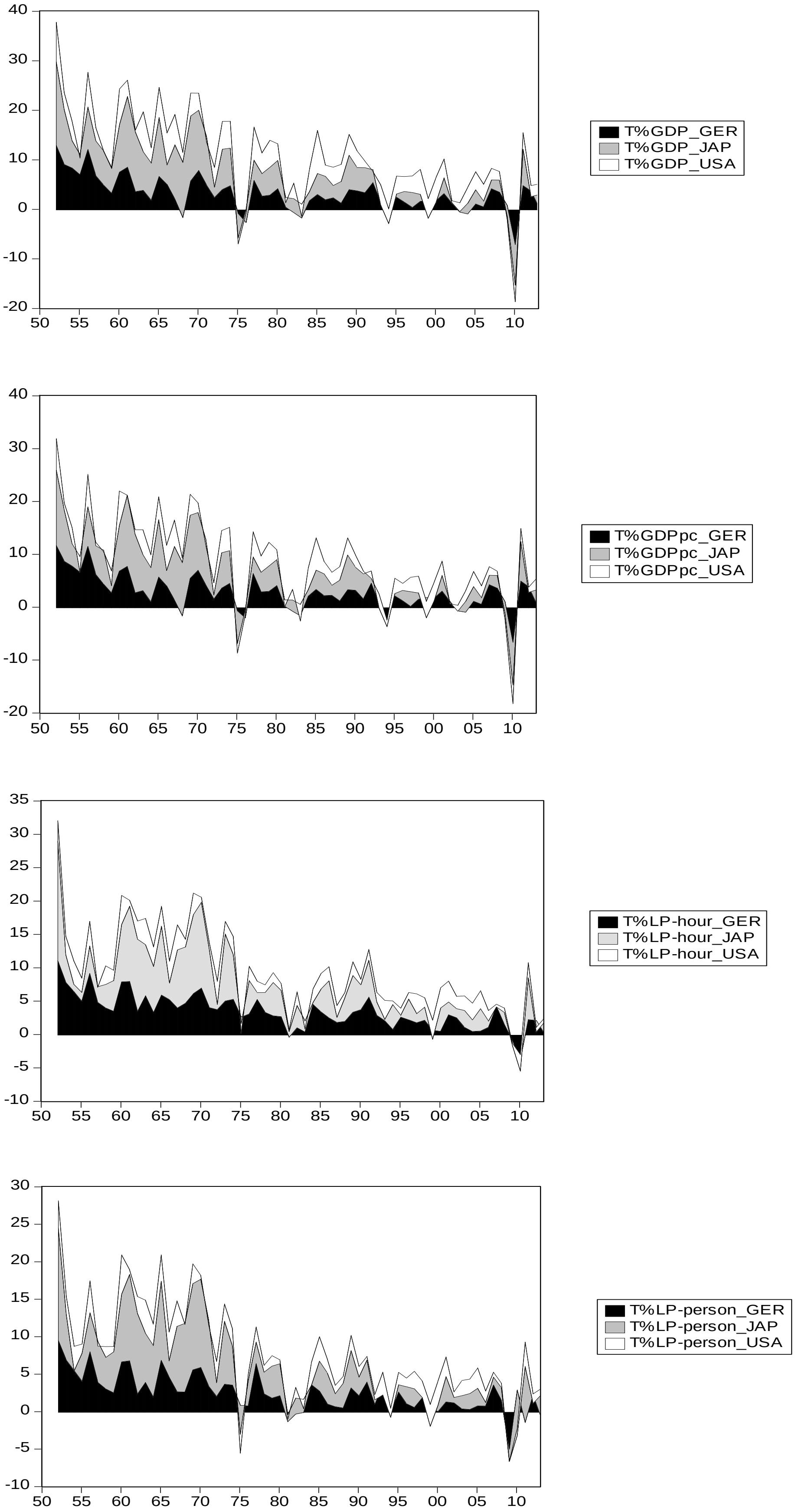

Figure 1. *Real output and productivity growth due to technological progress*
Source: Author's calculations

Results suggest that the technological progress in main innovation industries was the highest contributing part of the long-run growth of GDP and GDPpc, as well of labour productivity in the observed period. The industry that gave the highest relative contribution to the average output growth in the 20th century was the Computer industry with an average GDP growth rate of 3,51%, average GDPpc growth of 2,09,%, LP per person growth of 2,15% and LP per hour of 2,45% for the USA (estimated by technological improvements), meaning that technological progress of that industry was in fact entirely integrated in improved standard of living. This was even more so true for Germany (average GDP growth rate of 5,62%, average GDPpc growth of 4,99,%, LP per person growth of 4,52% and LP per hour of 5,55%) and especially Japan (average GDP growth rate of 8,62%, average GDPpc growth of 7,54,%, LP per person growth of 6,95% and LP per hour of 6,64%). Subsequent industries, closely related to the Computer Industry, likewise showed significant influence. Together, their average and cumulative impact effect on the GDP growth within technological domain was 3,06% and 9,16% for USA, 4,50% and 13,49% for Japan, and 3,08% and 9,24% for Germany. Interestingly, we find weak correlation between GDP and productivity growth rates among these countries over the time and variables, meaning that the growth paths were piebald (see *Table 3*).

The contribution of new technologies to GDP and productivity growth in Japan conspicuously increased up until the 1980s, but then dramatically decreased in the 1990s. Though it played essential role in sustaining growth, in the 1990s technological progress made a marginal contribution to the economy (Fan and Watanabe, 2006), as Japan entered its post-bubble and economic recession period as its growth rate dropped to around 1% in the period 1990-2013. Despite that fact, Japan’s success in exporting high-tech products has been impressive. There are few basic reasons why Japan was so powerful in ICT development: (1) patent system was designed to promote technological catch-up and diffusion through incremental innovation, (2) large companies are active in multiple high-tech industries, (3) close internal linkages between innovation and manufacturing i.e. strong technological synergy and (4) important role of government in promoting technological capability and capacity. Many scholars have attributed the strong economic performance of the USA in the 1900s and 2000s to intense productivity growth. Most of studies support the view that the productivity gains after 1990 were linked to ICT developments, although this effect was somewhat weaker than in earlier period when GDP and productivity growth was much higher. Established climate of entrepreneurship plus development of technological and managerial talent, networks of new small and some old larger firms as well as research facilities enabled works, firms and business complexes to respond quickly to ever changing market conditions which generated a constant flow of innovations putting USA in such manner in the centre of technological advances that provided stable output and productivity growth over time. Germany on the other hand remained content with maintaining comparative advantages in its traditional industries - engineering based in the after war period with growth rates exceeding 5%, both in real GDP and labour productivity. As new development opportunities concentrated around high-tech sectors, Germany as a country endowed with capital and skilled labour force (scientists, researchers, engineers, etc.) needed to focus on the new scope: diffusion of ICT knowledge and equipment from public sector to private industry and back. As Lehrer (2000) pointed, reorientation of the German economy towards high-tech has come to be widely regarded as a condition *sine qua non* for prosperity, economic growth and even the preservation of its traditional industries. The results showed up quickly in the patent statistics, favourable conditions for high-tech entrepreneurship which was harmonized with competitiveness in the traditional industries and followed with reallocation of major resources from old industries to new ones and so on. Furthermore, Siebert and Stolpe (2001) argue that not only German, but European income elasticity as well, in relation to employment of additional R&D scientists and engineers is high, if employed in Germany, because the technological innovation in Germany tends to create the maximum knowledge spill-over effect for other European economies. Indeed, Germany has fully participated in the upsurge of patenting since the mid-1990s. We can conclude that technological progress by all main contributing (computer and subsequent) industries assured permanent welfare effect that generated political, social and economic power of the USA, Japan and Germany worldwide. These countries developed certain line of technological advancement by investing in complementary inputs such as knowledge, science and research that contributed over the time to each country’s specific capability to effectively facilitate growth. Thus we agree with Cypher and Dietz (2004) in their conclusion that precisely these areas of social investment that can spell the difference between successful and failed development and are the necessary precondition for future economic prosperity.

5. Beyond conclusion

The significance of technological improvement to economic growth and development has been empirically verified over and over again. Each theoretical model, even the neoclassical growth model, has confirmed that basic factor of production cannot explain all of economic growth and that the ‘residual’ which often constitutes technology is the factor that can explain the differing development paths of nations. Technological advancement reduces costs and increase productive efficiency and thus rejects the Malthusian thesis of deprivation and hunger. Therein, we have showed that technological progress in the observed period was in fact entirely incorporated in the improved living standard of selected countries, thereby having enormous welfare effect which conceptually has designed subsequent growth. But technological change was a historically ephemeral event which went through the phase of discovery, implementation and obsolescence. Having that in mind, we can be sure that a new maiden technology will soon arise as a part of new post-modern period of economic growth.

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Appendix

Table 1. Agregate results

USA	Industry	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1950 - 1972	Computer	3,86	2,35	2,30	2,56	3,51	2,09	2,15	2,45
1973 - 1989	Silicon Chips	3,19	2,19	1,11	1,32	3,20	2,23	1,14	1,33
1990 - 2013	Information	2,46	1,41	1,63	1,72	2,45	1,49	1,64	1,70
Average		**3,17**	**1,98**	**1,68**	**1,87**	**3,06**	**1,93**	**1,64**	**1,83**

JAP	Industry	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1950 - 1972	Computer	9,35	8,14	7,53	7,31	8,62	7,54	6,95	6,64
1973 - 1989	Silicon Chips	3,91	3,07	2,87	3,31	3,82	3,00	2,93	3,41
1990 - 2013	Information	1,13	0,99	1,01	1,71	1,05	0,92	0,96	1,69
Average		**4,80**	**4,06**	**3,80**	**4,11**	**4,50**	**3,82**	**3,61**	**3,91**

GER	Industry	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1950 - 1972	Computer	6,04	5,36	4,79	5,92	5,62	4,99	4,52	5,55
1973 - 1989	Silicon Chips	2,16	2,18	1,97	3,03	2,04	2,09	1,91	2,93
1990 - 2013	Information	1,53	1,37	1,08	1,67	1,58	1,41	1,07	1,70
Average		**3,24**	**2,97**	**2,61**	**3,54**	**3,08**	**2,83**	**2,50**	**3,40**

1 GDP growth, **2** GDPpc growth, **3** LP per person growth, **4** LP per hour growth, **5** GDP growth due to technological progress, **6** GDPpc growth due to technological progress, **7** LP per person growth due to technological progress, **8** LP per hour growth due to technological progress

** average growth rates*

*** possible slight differences in aggregation due to a rounding-up problem*

Source: **Author's calculation. Systematization based on Falatoon and Safarzahed (2006).**

Table 2. Results of ARIMA models

USA

lnGDP ARIMA (1,1,2)

```
          coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const       0,0310011    0,00333871    9,285    1,61e-020 ***
  phi_1      -0,799968     0,299147     -2,674    0,0075    ***
  theta_1     0,969718     0,300267      3,230    0,0012    ***
  theta_2     0,234266     0,137865      1,699    0,0893    *
Mean dependent var   0,030946   S.D. dependent var   0,022351
Mean of innovations -0,000043   S.D. of innovations  0,021708
Log-likelihood       151,8360   Akaike criterion    -293,6719
Schwarz criterion   -282,9563   Hannan-Quinn        -289,4574
Test for ARCH of order 1 -  with p-value = P(Chi-Square(1) > 0,0133012) = 0,908183
Test for normality of residual -  with p-value = 0,812486
```

lnGDPpc ARIMA (2,1,1)

```
          coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const       0,0199494    0,00110639   18,03     1,11e-072 ***
  phi_1       0,887680     0,0871895    10,18     2,41e-024 ***
```

```
  theta_1    -0,841838     0,137640     -6,116    9,58e-010 ***
  theta_2    -0,158162     0,127676     -1,239    0,2154
Mean dependent var   0,019291   S.D. dependent var   0,022116
Mean of innovations  0,001259   S.D. of innovations  0,021240
Log-likelihood       152,4964   Akaike criterion    -294,9929
Schwarz criterion   -284,2772   Hannan-Quinn        -290,7784
Test for normality of residual -  with p-value = 0,217295
Test for ARCH of order 1 -  with p-value = P(Chi-Square(1) > 0,471082) = 0,49249
```

lnLPperson ARIMA (1,1,1)

```
          coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const       0,0172063    0,00243942    7,053    1,75e-012 ***
  phi_1       0,816590     0,215287      3,793    0,0001    ***
  theta_1    -0,716790     0,248260     -2,887    0,0039    ***
Mean dependent var   0,017085   S.D. dependent var   0,013170
Mean of innovations -0,000206   S.D. of innovations  0,012881
Log-likelihood       184,7527   Akaike criterion    -361,5054
Schwarz criterion   -352,9328   Hannan-Quinn        -358,1337
Test for ARCH of order 1 -  with p-value = P(Chi-Square(1) > 0,386182) = 0,534313
Test for normality of residual -  with p-value = 0,329251
```

lnLPhour ARIMA (1,1,1)

```
          coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const       0,0189272    0,00286726    6,601    4,08e-011 ***
  phi_1       0,898841     0,100843      8,913    4,95e-019 ***
  theta_1    -0,752320     0,132178     -5,692    1,26e-08  ***
Mean dependent var   0,018857   S.D. dependent var   0,010674
Mean of innovations -0,000380   S.D. of innovations  0,010106
Log-likelihood       199,9536   Akaike criterion    -391,9071
Schwarz criterion   -383,3346   Hannan-Quinn        -388,5355
Test for normality of residual -  with p-value = 0,128183
Test for ARCH of order 1 -  with p-value = P(Chi-Square(1) > 0,709967) = 0,399455
```

JAP

lnGDP ARIMA (1,1,1)

```
          coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const       0,0501978    0,0244337     2,054    0,0399    **
  phi_1       0,954164     0,0472648    20,19     1,26e-090 ***
  theta_1    -0,547281     0,155980     -3,509    0,0005    ***
Mean dependent var   0,045837   S.D. dependent var   0,040171
Mean of innovations -0,002429   S.D. of innovations  0,024898
Log-likelihood       142,6179   Akaike criterion    -277,2358
Schwarz criterion   -268,6632   Hannan-Quinn        -273,8641
Test for normality of residual -  with p-value = 0,00164531
Test for ARCH of order 1 -  with p-value = P(Chi-Square(1) > 0,190018) = 0,662902
```

lnGDPpc ARIMA (1,1,1)

```
          coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const       0,0426046    0,0189774     2,245    0,0248    **
  phi_1       0,935271     0,0606922    15,41     1,40e-053 ***
  theta_1    -0,533612     0,167429     -3,187    0,0014    ***
Mean dependent var   0,039207   S.D. dependent var   0,036888
Mean of innovations -0,001901   S.D. of innovations  0,024814
Log-likelihood       142,9607   Akaike criterion    -277,9213
Schwarz criterion   -269,3488   Hannan-Quinn        -274,5497
```

```
Test for normality of residual -  with p-value = 0,00396876
Test for ARCH of order 1 - with p-value = P(Chi-Square(1) > 0,264912) = 0,606765
```

lnLPperson ARIMA (1,1,1)

```
          coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      0,0392079    0,0171020     2,293    0,0219    **
  phi_1       0,934035    0,0582016    16,05     5,88e-058 ***
  theta_1   -0,529493     0,162314     -3,262    0,0011    ***
Mean dependent var   0,036809   S.D. dependent var   0,033765
Mean of innovations -0,001685   S.D. of innovations  0,022553
Log-likelihood       148,9845   Akaike criterion    -289,9690
Schwarz criterion   -281,3965   Hannan-Quinn        -286,5974
Test for normality of residual -  with p-value = 0,00913348
Test for ARCH of order 1 -  with p-value = P(Chi-Square(1) > 0,254406) = 0,613989
```

lnLPhour ARIMA (1,1,1)

```
          coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      0,0429885    0,0149627     2,873    0,0041    ***
  phi_1       0,893557    0,0745403    11,99     4,13e-033 ***
  theta_1   -0,288445     0,160191     -1,801    0,0718    *
Mean dependent var   0,039904   S.D. dependent var   0,030923
Mean of innovations -0,001414   S.D. of innovations  0,019772
Log-likelihood       157,2401   Akaike criterion    -306,4801
Schwarz criterion   -297,9076   Hannan-Quinn        -303,1085
Test for normality of residual -  with p-value = 0,013269
Test for ARCH of order 1 -  with p-value = P(Chi-Square(1) > 3,61074) = 0,0574077
```

GER

lnGDP ARIMA (1,1,1)

```
          coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      0,0412113    0,0246512     1,672    0,0946    *
  phi_1       0,981020    0,0259469    37,81     0,0000    ***
  theta_1   -0,739453     0,0873928    -8,461    2,65e-017 ***
Mean dependent var   0,032023   S.D. dependent var   0,029703
Mean of innovations -0,003953   S.D. of innovations  0,022339
Log-likelihood       149,3537   Akaike criterion    -290,7075
Schwarz criterion   -282,1349   Hannan-Quinn        -287,3359
Test for normality of residual -  with p-value = 0,25527
Test for ARCH of order 1 -  with p-value = P(Chi-Square(1) > 1,00041) = 0,317212
```

lnGDPpc ARIMA (1,1,1)

```
          coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      0,0382826    0,0217035     1,764    0,0778    *
  phi_1       0,979730    0,0273508    35,82     5,23e-281 ***
  theta_1   -0,757927     0,0837825    -9,046    1,48e-019 ***
Mean dependent var   0,029253   S.D. dependent var   0,027855
Mean of innovations -0,003805   S.D. of innovations  0,021946
Log-likelihood       150,5353   Akaike criterion    -293,0706
Schwarz criterion   -284,4981   Hannan-Quinn        -289,6990
Test for normality of residual -  with p-value = 0,416945
Test for ARCH of order 1 -  with p-value = P(Chi-Square(1) > 1,04107) = 0,307573
```

lnLPperson ARIMA (1,1,1)

```
          coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
```

```
  const      0,0292974    0,0201097    1,457    0,1451
  phi_1      0,987377     0,0178799    55,22    0,0000    ***
  theta_1    -0,743160    0,0804514    -9,237   2,53e-020 ***
  Dummy      -0,0439401   0,00901468   -4,874   1,09e-06  ***
Mean dependent var   0,025662   S.D. dependent var   0,022588
Mean of innovations -0,002962   S.D. of innovations  0,014410
Log-likelihood       176,7951   Akaike criterion    -343,5901
Schwarz criterion   -332,8744   Hannan-Quinn        -339,3756
Test for normality of residual  - with p-value = 0,0560599
Test for ARCH of order 1 -  with p-value = P(Chi-Square(1) > 0,0021587) = 0,962942
```

lnLPhour ARIMA (1,1,1)

```
             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      0,0376084    0,0230648    1,631    0,1030
  phi_1      0,987078     0,0184424    53,52    0,0000    ***
  theta_1    -0,674729    0,101086     -6,675   2,48e-011 ***
Mean dependent var   0,034473   S.D. dependent var   0,022390
Mean of innovations -0,002618   S.D. of innovations  0,013311
Log-likelihood       181,6775   Akaike criterion    -355,3550
Schwarz criterion   -346,7824   Hannan-Quinn        -351,9834
Test for normality of residual -  with p-value = 0,247082
Test for ARCH of order 1 -  with p-value = P(Chi-Square(1) > 0,376163) = 0,539664
```

Source: **Author's calculation.**

Table 3. Correlations between the countries by variables

Correlation	T%GDP_GER	T%GDP_JAP	T%GDP_USA
T%GDP_GER	**1**	0.69	0.48
T%GDP_JAP	0.69	**1**	0.41
T%GDP_USA	0.48	0.41	**1**

Correlation	T%GDPpc_GER	T%GDPpcJAP	T%GDPpc_USA
T%GDPpc_GER	**1**	0.65	0.41
T%GDPpc_JAP	0.65	**1**	0.36
T%GDPpc_USA	0.41	0.36	**1**

Correlation	T%LP-hour_GER	T%LP-hour_JAP	T%LP-hour_USA
T%LP-hour_GER	**1**	0.64	0.35
T%LP-hour_JAP	0.64	**1**	0.29
T%LP-hour_USA	0.35	0.29	**1**

Correlation	T%LP-person_GER	T%LP-person_JAP	T%LP-person_USA
T%LP-person_GER	**1**	0.55	0.40
T%LP-person_JAP	0.55	**1**	0.27
T%LP-person_USA	0.40	0.27	**1**

Source: **Author's calculation.**