

Department of Economics

Issn 1441-5429

Discussion paper 13/09

R&D Intensity, Technology Transfer and Absorptive Capacity

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Abstract

In the line of Schumpeterian fully endogenous growth theory, this study attempts to investigate whether differences in research intensity as well as absorptive capacity help to explain cross-country differences in productivity growth in a panel of 55 sample countries including 23 OECD and 32 developing economies over the period 1970 to 2004. Using several indicators of innovative activity and product variety empirical results from system GMM estimator confirm that research intensity has significant positive effect on productivity growth in both the OECD and developing countries. TFP growth is also found to be enhanced by the distance to technology frontier in both the group of countries. R&D based absorptive capacity seems to have significant positive impact on productivity growth in both the groups though strong in OECD countries. Human capital based technology transfer is found significant and robust in both the OECD and developing countries. Absorptive capacity appears to be sensitive to the model specification and measurement of innovative activity as well as product variety.

JEL Classifications: O10, O30, O47

Keywords: Schumpeterian growth theory, R&D intensity, TFP growth, technology transfer, human capital, absorptive capacity, system GMM, OECD, developing countries

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^{*} I thank Professor Jakob B. Madsen and Dr. James B. Ang for their invaluable guidance and motivation. Helpful comments and suggestions from participants at 14th Australasian Macroeconomics Workshop 2009 at Deakin University and 2009 Higher Degree Research (HDR) Student Workshop at Monash University are gratefully acknowledged. Any remaining errors are the sole responsibility of mine.

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1. Introduction

Whether the differences in factor accumulation or technological knowledge can explain the wide variations in the level as well as growth rate of per capita output across countries has been hotly debated for many decades. The debate started after the emergence of the neoclassical growth model of Solow (1956) and Swan (1956) which considers technological progress as an exogenous process. The neoclassical 'Solow residual' or, total factor productivity (TFP) is considered as a measure for technological progress since it captures the impact of technical change and other factors that raise output beyond the measured contribution of inputs of labour and capital (Solow, 1957). The standard neoclassical model assumes that all countries face a common rate of technological advancement and thus it predicts the existence of beta convergence where poor countries tend to grow faster than the rich ones due to diminishing returns to capital and thereby the poor countries tend to catch up to the rich countries in terms of per capita output (Barro and Sala-i-Martin, 1995). However, significant technology differences across countries are well documented in empirical research and hence per capita income across countries differs not only because of differences in capital stocks per worker but also because of differences in productivity (Howitt, 2000).

Mankiw et al. (1992) argue that the differences in physical and human capital in an augmented Solow model can account for roughly 80% variation of the cross-country income differences, whereas Klenow and Rodriguez-Claire (1997) state that total factor productivity accounts for about 90% of the cross-country disparities in the growth rates. Prescott (1998) shows that capital per worker cannot account for the huge observed differences in output per worker, instead technological changes or, total factor productivity increases labor productivity in the long run. Hall and Jones (1999) argue that the differences in physical capital and educational attainment can only partially explain the variation in output per worker, rather a large amount of variation is driven by differences in the level of the Solow residual across countries. Easterly and Levine (2001) observe that the 'residual' rather than factor accumulation accounts for most of the income and growth differences (about 60%) across nations. Mahadevan (2003) argues that the concept of TFP gained importance for sustaining output growth in the long run as input growth, which is subject to diminishing returns, is insufficient to generate more and more output growth and thus TFP growth has become the engine behind long run economic growth. The current consensus is that efficiency is at least as important as capital in explaining income differences (Caselli, 2005).

The emergence of the endogenous growth models has made it possible to account for the endogeneity of the technological change and therefore balanced growth results exclusively from the technological progress (Romer, 1986; Lucas, 1988). Competition among research firms generates innovation which in turn facilitates technological development (Aghion and Howitt, 1992). Now it is well established in the endogenous growth literature that research and development (R&D) has significant positive effect on productivity growth, which in turn drives output growth. R&D does not only stimulate innovation but also promote R&D based absorptive capacity by easing the imitation of already existed discoveries. Technological knowledge is often implicit and circumstantially specific and therefore it is difficult to codify in manuals and books and also hard to understand without having proper knowledge (Polanyi, 1962; Arrow, 1969; Evenson and Westphal, 1995). Active engagement in R&D in technological field can facilitate absorbing the discoveries of others and thereby technology transfer requires the receiving countries to invest resources in order to master the foreign technology so that they can be adapted more appropriately in the local condition (Griffith *et al.*, 2003, 2004; Aghion and Howitt, 2005).

The earliest version of endogenous growth theory is the so called AK theory where both physical capital accumulated from savings and intellectual capital accumulated from technological progress are lumped together (Uzawa, 1965; Lucas, 1988). Since technology is a part of the aggregate capital, it will not allow marginal product of total capital to drag down to zero by counteracting diminishing returns. Schumpeterian growth theory goes beyond AK theory by distinguishing explicitly between physical capital and intellectual capital where the former grows from savings and the latter grows from innovation (Aghion and Howitt, 2006). Research firms receive monopoly rent when a successful innovation is patented. A new innovation renders existing innovations obsolete by destroying their monopoly rent and hence technological development follows so-called Schumpeterian process of 'creative destruction' (Aghion and Howitt, 1992). Focusing on the quality improving innovations through the process of 'creative destruction', the most recent Schumpeterian fully endogenous growth theory assumes that the rate of technological progress in one country depends on domestic research intensity in that country. In other words, sustained productivity growth requires a sustained fraction of labor force (GDP) to be employed (spent) on R&D (Aghion and Howitt, 1998; Dinopoulos and Thomson 1998; Ha and Howitt, 2007; Madsen, 2008a).

Countries that are technologically backward may have potential to generate rapid growth than that of more advanced countries (Gerschenkron, 1962). Because of this 'advantage of backwardness', recent endogenous growth theories also focus on convergence through technology transfer (Griffith et al., 2003, 2004). Absorptive capacity captures the idea that countries may differ in their effort and ability to adopt new technologies (Arrow, 1969; Kneller, 2005; Kneller and Stevens, 2006). Investment in domestic R&D may increase the capacity to absorb foreign technology more appropriately (Verspagen, 1991). To catch up with the developed countries, semi-industrialist countries should not rely only on a combination of technology imports and investment, but have to increase their national technological activities (Fagerberg, 1994). The more backward a country's technology, the greater is the potential for that country to grow rapidly than the technologically leading countries, provided that the former has sufficient social capabilities to exploit latter's technology (Abromovitz, 1986). Human capital may contribute to productivity growth through the channel of technological catch-up and thereby absorptive capacity depends on the level of human capital (Nelson and Phelps, 1966; Benhabib and Spiegel, 1994; Engelbrecht, 1997). Therefore, investment in domestic R&D as well as human capital are essential for upgrading technologies, moving up the development ladder and catching up with the forefront countries.

Almost all of the empirical studies based on Schumpeterian growth theories have been conducted for high income OECD countries (Griffith *et al.*, 2003, 2004; Zachariadis, 2004; Ha and Howitt, 2007; Madsen, 2008a). About 80% of the total world R&D expenditures were performed by the seven developed countries (G7) in 1998 (National Science Foundation, 2002). Technology investments in the forms of R&D expenditures are found to be important to exploit technology transfer in OECD countries (Cohen and Levinthal, 1989). Although developing countries do not conduct R&D on a significant scale, Schumpeterian growth theories could have important implications for developing countries as they consider domestic expenditure on R&D, which can augment locally appropriate technologies that might lead to faster economic growth. There are two important grounds which concern the relevance of Schumpeterian theories in developing countries. First, the theory considers that the differences in growth rates in developing countries can be explained by the differences in productivity growth, rather than the differences in the rate of factor accumulation. Second, developing countries need to undertake domestic investment to adapt and implement foreign technology properly and thereby technology transfer and absorptive capacity could be of

importance to those economies (Howitt, 2005). In addition, Schumpeterian theory can allow for technology enhancing expenditures in developed countries which might have positive impact on developing countries through the flow of goods and ideas (Coe *et al.*, 1997; Zachariadis, 2004).

Ulku (2007a) provides most probably the only macro-level empirical attempt to test Schumpeterian theory in developing countries along with their developed counterparts. However, her study is limited to 26 OECD and only 15 non-OECD countries and as a measure for innovation she uses utility patent applications in manufacturing sectors made in the US patent and Trademark office, which may not represent the true extent of patenting in different countries. Patent is an output of R&D and therefore it cannot capture the whole range of innovations irrespective of their success. Only successful innovations are patented and therefore, R&D inputs such as R&D Scientists and Engineers as well as R&D expenditures can be more effective measure for innovations. Again the trouble of using patents for developing countries is that they do not innovate much but imitate. Therefore, it is better to use alternative measures for innovation to investigate the applicability of Schumpeterian theory. Again she uses yearly macro data and hence her results are highly likely to be affected by business cycle and transitional dynamics. 5 or 10 year differences may correct this problem. In addition, she obtains her empirical results especially for non-OECD countries based on a very small sample size (15 countries) and hence her findings may not be conclusive for those economies. Finally, she does not examine the effect of technology transfer as well as absorptive capacity across sample countries. Therefore, the major contributions of this study include: (a) examining the importance of R&D intensity in explaining differences in cross-country productivity growth by using four alternative R&D indicators such as, number of scientists and engineers engaged in R&D, domestic expenditures on R&D, patent application by residents and patent granted to residents, (b) comparing the effectiveness of Schumpeterian growth theory between 23 high income OECD and 32 developing countries by using three alternative estimators such as, pooled OLS, fixed effects and system GMM, and (c) investigating cross-country technology transfer and absorptive capacity by applying different specifications and measurement of innovative activity and product variety.

Therefore, this study attempts to investigate the empirical evidence of Schumpeterian fully endogenous growth theory, using a large panel of 55 sample countries including 23 high

income OECD and 32 low and medium income developing countries over the period of 1970 to 2004. Using different econometric estimators and various indicators of innovative activity and product variety for both the OECD and developing countries, this paper examines whether R&D intensity has direct effect on TFP growth and whether the impact of R&D intensity on TFP growth depends on the distance to the technology frontier. In addition to R&D Scientists and Engineers and R&D expenditures, it uses the flow of patents applications and patent granted to residents as a direct measure of innovative activity whether testing Schumpeterian growth theories. Being the technology leader as well as the major trading partner of most of the countries in the world, the US technology is assumed to be the technological frontier of the world. Finally, it estimates the effect of human capital based absorptive capacity on productivity growth.

1.1. Research Questions

There are four different research questions to be addressed in this study, namely:

1. Is there any relationship between R&D intensity and TFP growth?

2. Is there any association between distance to technological frontier and TFP growth?

3. Does the effect of R&D intensity on TFP growth depend on the distance to technological frontier?

4. Is there any significant impact of human capital based absorptive capacity on TFP growth?

The paper is structured as follows. Section II briefly discusses the evolution of Schumpeterian growth theories. It will help one to understand why this study is applying Schumpeterian fully endogenous growth theory in its empirical study. Section III explains empirical literature review on Schumpeterian theory and absorptive capacity. Section IV presents hypothesis development. Research design is illustrated in section V. Section VI reports empirical results with necessary interpretations. Section VII concludes.

II. Evolution of Schumpeterian Growth Theories

The basic idea behind endogenous growth theories is that technological progress is the driving force for long-run economic growth. The earliest version of the endogenous growth theory is so called AK theory that combines capital accumulation and technological progress together. Since technology is a part of the aggregate capital, it will not allow marginal product of total capital to drag down to zero by counteracting diminishing returns. Schumpeterian growth theory goes beyond AK theory by distinguishing explicitly between

physical capital and intellectual capital where the former grows from savings and the latter grows from innovation (Aghion and Howitt, 2006). The first-generation endogenous growth theory captures the endogenous technological movement by assuming a significant positive relationship between the level of R&D and the TFP growth (Romer, 1990; Aghion and Howitt, 1992). The proportional relation between them indicates that an increase in the size of the population, other things remain unchanged, on an average could raise the number of R&D personnel and thus activities in R&D might increase, which may lead to increase TFP and output growth. Hence, the critical scale effect assumption of these first generation models became problematic as it considered population growth should lead to accelerating per capita output growth.²

Jones (1995a,b) observed that the number of scientists and engineers in the US grew more than five times without increasing the TFP growth since 1950s. Also, he found scale effect inconsistency in time series analysis of several developed countries, such as France, Germany, Japan and the USA. All these evidences point out that the R&D activities are increasing exponentially, but the TFP growth rate and per capita output growth rate remain roughly constant over time. Afterwards he came up with the semi-endogenous version of the second generation R&D model with an argument that the TFP growth is associated with the R&D growth, not with the level of R&D. Later Kortum (1997) and Segerstrom (1998) support semi-endogenous growth models. Relaxing the assumption of the constant returns to knowledge of the first generation model, these semi endogenous growth models assume diminishing returns to knowledge. Therefore, a positive growth in R&D input is required to maintain sustained TFP growth.

Schumpeterian version of the second generation endogenous (or, fully endogenous) growth theory is in fact a response to the Jones critique by modifying the scale effect of the first generation models. Instead of considering the impact of the level of R&D expenditures, these growth models without scale effect predict a positive relation between the TFP growth and the R&D intensity, the latter is measured by the ratio of R&D expenditures to output (Young, 1998; Aghion and Howitt, 1998 ; Dinopoulos and Thomson 1998 ; Peretto, 1998 ; Howitt, 2000; Zachariadis, 2004 ; Ha and Howitt, 2007, Madsen, 2008a). Therefore, they have

² First generation endogenous growth theory is also known as Schumpeterian growth theory with scale effect. Earlier Schumpeterian endogenous growth theory with scale effect started with the publication of four important articles (Romer, 1990; Segerstrom *et al.*, 1990; Grossman and Helpman, 1991a, and Aghion and Howitt, 1992) and its rapid development has followed the general evolutionary process of creative destruction (Dinopoulos and Sener, 2007). Romer (1994) provides an excellent overview on the origin of the earlier Schumpeterian models.

responded against Jones critique by arguing that the US TFP growth was roughly remained constant since 1950s as the R&D intensities were roughly constant during that period. These Schumpeterian versions of the fully endogenous growth models assume the constant returns to knowledge as in the first generation model, but with an assumption of increasing complexity of the new innovation, i.e. product proliferation with the increasing population. Along with the productivity growth in the advanced economies, these second generation endogenous growth models may place profit making entrepreneurial activities at the centre to drive technological progress and output growth in developing countries (Zachariadis, 2004).

III. Literature Review

Most of the empirical studies on R&D and TFP growth have been investigated in micro-level and across the developed OECD countries. A number of empirical studies conclude that foreign sources of technology are one of the important contributors of TFP growth in developed countries (Coe and Helpman, 1995; Keller, 2002). Since developing countries carry out little or, insignificant R&D activities, the degree of technological diffusion from countries close to the frontier is likely to be one of the key drivers to accelerate the TFP growth in those developing economies (Savvides and Zachariadis, 2005). Despite the importance of this issue, very few studies have been undertaken to examine the significance of technological diffusion in developing countries. Coe et al. (1997) argue that total factor productivity in developing countries is positively and significantly related to R&D in their industrial country trade partners and to their imports of machinery and equipment from the industrial countries. Mayer (2001) points out that machinery imports by developing countries have been higher over the past few years and that such imports from technologically more advanced developing countries remains small compared to such imports from industrially developed countries. Machinery imports combined with human capital stocks have a positive and statistically significant impact on cross country growth differences in the transition to the steady state in developing countries.

Employing a panel of manufacturing industries in 14 OECD countries over the period of 1970 to 1995, Keller (2002) observes that international R&D spillovers are responsible for only 20% of the total impact of R&D stocks on productivity, while the remaining 80% are attributable to domestic R&D stocks. Using data from 10 US manufacturing industries during 1963 to 1988, Zachariadis (2003) demonstrates a positive impact of R&D intensity on innovation, technological progress, and economic growth. He observes that in steady state

there is a positive effect of R&D intensity on the rate of patenting, of the rate of patenting on the rate of technological change, and of the rate of technological change on the growth rate of output per worker. Therefore, his results reject the null hypothesis that growth is not induced by R&D intensity rather he found the evidence in favour of Schumpeterian fully endogenous growth model. Using data from four manufacturing sectors from 17 OECD countries over the period of 1981 to 1997, Ulku (2007b) argues that the knowledge stock is the prime determinant of innovation in all four manufacturing sectors and that R&D intensity increases the rate of innovation in the chemicals, electrical and electronics, and drugs and medicine sectors. She also finds that the rate of innovation has consistent positive and significant impact on the output growth rates in all those manufacturing sectors. Therefore, all these findings lend support to the evidence of Schumpeterian fully endogenous growth theories.

Griffith *et al.* (2003, 2004) show the evidence of R&D induced innovation, technology transfer and R&D based absorptive capacity using a panel of industries across twelve OECD countries for the period of 1974 to 1990. They found that the R&D intensity is statistically significant in both technological catch up and innovation. They conclude that the existing US based studies may underestimate the returns to R&D if they fail to consider the R&D based absorptive capacity. Using aggregate and manufacturing sector data across 10 OECD countries from 1971 to 1995, Zachariadis (2004) exhibits a strong positive and significant relationship between R&D intensity and productivity growth. He also suggests that R&D-induced growth models are consistent with the experience of countries close to the technology frontier. To the extent, the technologies developed in the R&D-intensive countries could flow across national borders and thus R&D induced growth models will also have important implications about growth policy in developing countries that do not perform intensive R&D.

The macro level analysis of the Schumpeterian version of the second generation endogenous (or, fully endogenous) growth models are limited to few studies and small number of OECD countries, where it is commonly found that the relationship between R&D intensity and TFP growth is positive and significant (Zachariadis , 2004; Ulku, 2007a ; Ha and Howitt, 2007 and Madsen, 2008a). Using data from 10 OECD countries over the period of 1971 to 1995, Zachariadis (2004) finds the evidence for a positive effect of aggregate R&D intensity on the output growth rate which is the underlying focus of Schumpeterian framework without scale effect. He observes that the impact of R&D is much higher for the aggregate economy as

compared to the manufacturing sector and its industries. Finally he concludes that the use of aggregate data in studying the R&D effect has a clear advantage over industry-level data because it can potentially captures the overall R&D spillovers. Applying data from 41 OECD and non-OECD countries from the period of 1981 to 1997, Ulku (2007a) argues that an increase in the share of researchers in labor force increases innovation only in large market OECD countries. An increase in innovation raises per labor GDP in all non-OECD countries except for low income countries, while raising it only in the high-income OECD countries and thereby suggesting that despite the large markets OECD countries is the world leader in innovation, non-OECD countries benefit more from it in improving their economic growth.

To best of knowledge of the author, Ha and Howitt (2007) conduct probably the first macro level empirical study to investigate the applicability of Schumpeterian fully endogenous as well as semi-endogenous growth models. Taking aggregate R&D data from the USA over the period of 1953 to 2000, they observe strong support for the Schumpeterian model but fail to establish any evidence for the semi-endogenous growth models. Using cointegration tests and forecasting exercises, they conclude that sustained TFP growth requires sustained fraction of GDP to be spent on R&D. Using data from 21 OECD countries for the period of 1870 to 2004, Madsen (2008a) obtains time series evidence of Schumpeterian fully endogenous growth model. He concludes that domestic and foreign researches are, to a large extent, able to account for TFP growth. In addition, he observes a positive significant relationship between TFP growth and the distance to the technological frontier, which is consistent with the assumption of the Schumpeterian second generation endogenous growth model. Lastly, he observes consistent positive influence of research intensity spillovers on TFP growth. However, he does not find any evidence of the Schumpeterian growth theory in his crosscountry analysis.

The history of cross-country income differences demonstrates mixed patterns of convergence and divergence (Howitt and Mayer-Foulkes, 2005). The proportional gap in living standard between the richest and the poorest countries grew more than five folds over the period of 1870 to 1990 (Pritchett, 1997). According to Maddison (2001) the gap grew from 3 in 1820 to 19 in 1998. However, after the World War II, this income gap seems to have halted at least among a number of industrially developed countries, who have shown convergence to parallel growth path and thus become the members of so called convergence club. Barro and Sala-i-Martin (1992), Mankiw *et al.* (1992) and Evans (1996) also find the evidence that most

countries tend to converge to parallel growth over the postwar era. Convergence may occur from two different sources-diminishing returns to capital and technological diffusion (Barro, 1997). Convergence may be restricted to a group of countries that engage in R&D and hence they will grow at the same rate in the long run (Howitt, 2000). However, this recent pattern on convergence is not universal because as a whole the gap between the leading and poorest countries is widening overtime. The poorest countries, mostly situated in Sub-Saharan Africa and South Asia have been falling behind due to low level of industrialization, education and social capital (Baumol, 1986 ; Abromovitz, 1986; Dowrick and Gemmel, 1991; Shin, 1996). Hence empirically observed convergence is nothing but the club convergences within OECD countries (Durlauf and Johnson, 1995 ; Quah 1993,1997; Mayer-Foulkes, 2002).³ Using data from 16 OECD countries (G16) over the period of 1883 to 2004, Madsen (2008b) finds the evidence of sigma convergence among the G16 countries and this convergence is attributed to international patents and knowledge spillovers through the channel of imports.

A large number of empirical studies have already established that the large differences in per capita income or output across countries are mostly due to productivity differences, rather than to differences in capital accumulation (Klenow and Rodriguez-Claire, 1997; Dollar and Wolf, 1997; Prescott, 1998; Hall and Jones, 1999 ; Easterly and Levine, 2001; Hendricks, 2002). Therefore, recent endogenous growth literatures also put emphasis on technology transfer and absorptive capacity to explain the observed differences in productivity across countries (Griffith *et al.*, 2003, 2004 ; Eaton and Kortum, 1999 ; Xu, 2000; Keller, 2000, 2001 ; Kneller, 2005). Although Gerschenkron's (1962) 'advantage of backwardness' is a strong force towards convergence of growth rates, the observed divergence between the rich and poor countries suggest that there may be countervailing forces at work on the evolution of the gap. Due to differences in institutions, climate, skills, etc., technology developed in one country cannot be used in another country without further modification. Again new technology increases complexity and often embedded in physical capital that creates large

³ Absolute convergence means poor countries tend to grow faster per capita than the rich countries without conditioning on any other characteristics of those economies and thereby will converge to the same growth path This absolute convergence is not the same as more familiar 'conditional convergence' because the latter states that countries with similar characteristics converge to the same growth path (Galor, 1996). Conditional convergence is also known as 'club convergence'. According to Barro and Sala-i-Martin (1995) there are two different concepts of conditional convergence-beta and sigma. If poor countries tend to grow faster than rich ones then that will be called beta convergence, whereas if the dispersion of per capita income or output across a group of countries decline overtime then that will be termed as sigma convergence.

scale of interdependencies between the leader and the follower nations. Therefore, these factors may create disadvantage of backwardness and thus the follower countries need to undertake local R&D investments to take advantage of technology transfer (Howitt, 2005).

Absorptive capacity may provide important explanations for cross-country productivity differences. There are two different channels that determine the capacity to absorb and implement foreign technology-domestic R&D (Fagerberg, 1994 ; Verspagen, 1991 ; Griffith et al., 2003, 2004) and human capital (Nelson and Phelps, 1966; Abromovitz, 1986; Cohen and Levinthal, 1989; Benhabib and Spiegel, 1994,2005; Engelbrecht, 1997). Using a panel of industries across twelve OECD countries for the period of 1974 to 1990, Griffith et al. (2003, 2004) observe that both R&D and human capital affect the rate of cross-country convergence in productivity growth. Applying data from 9 manufacturing industries in 12 OECD countries over the period of 1973 to 1991, Kneller and Stevens (2006) find the evidence that human capital plays a significant and quantitatively important role in explaining cross-country differences in efficiencies. R&D is found to have insignificant effect on efficiency. There is strong evidence that countries differ in the efficiency with which they use frontier technology. Using the same dataset Kneller (2005) finds that the effect of human capital is quantitatively more important than that of R&D on absorptive capacity, and that the latter matters only for smaller OECD countries. Senhadji (2000) observes a robust positive relation between human capital and cross-country productivity, whereas Miller and Upadhyay (2000) do not find any significant relation between them. Kneller and Stevens (2006) also find the evidence that human capital affects production both directly and indirectly through efficiency, which has sharp contrast to Benhabib and Spiegel's (1994) who do not find direct effect of human capital on production.

Technology diffusion is not costless and therefore differences in knowledge investments may explain a significant portion of income differences across countries. Most of the income above subsistence level is made possible by international diffusion of knowledge (Klenow and Rodriguez-Clare, 2005). Effective cost of innovation and technology adoption falls when a country is further away from the technology frontier (Parente and Prescott, 1994). Quality ladder models feature knowledge spillovers in that each quality innovation is built on the previous leading edge technology (Aghion and Howitt, 1992, 1998; Grossman and Helpman, 1991a). Innovation is usually embodied in capital and intermediate goods and therefore the direct import of these goods is one channel of international technology spillovers (Grossman

and Helpman, 1991b; Coe and Helpman, 1995). Foreign Direct Investment (FDI) by the Multinational Corporations (MNCs) may be another channel for the international transmission of technology (Savvides and Zachariadis, 2005). Geographical distance may also affect international spillovers (Eaton and Kortum, 1996; Kneller, 2005).

Since international technology spillovers exert significant positive impact on TFP growth, Coe and Helpman (1995) argue that the extent to which a country's total TFP depends not only on domestic R&D but also on the foreign R&D efforts of its trade partners. Using data from 22 OECD countries over the period of 1971 to 1990, they find that foreign R&D has beneficial effects on domestic productivity and these effects are stronger the more an economy is open to international trade. Employing data from 77 developing countries and 21 OECD countries for the period of 1971 to 1990, Coe et al. (1997) argue that the R&D spillovers from industrial countries in the north to less developed countries in the south are extensive. On an average, a 1% increase in the R&D capital stock in industrial countries raises output in the developing countries by 0.06%. The spillover effects from the US are the largest because it is the most important trade partner for many developing countries. A 1% increase in the US R&D capital stock raises total factor productivity on an average for all the selected 77 developing countries by 0.03%. Using data from 21 OECD countries from the period of 1983 to 1990, Xu and Wang (1999) demonstrate that about half of the return on R&D investment in a G-7 country spilled over to other OECD countries while considering knowledge spillovers both in embodied and disembodied in trade flows. Using data from 32 developing countries from 1965 to 1992, Savvides and Zachariadis (2005) find that foreign R&D has significant positive impact on domestic productivity and value added growth.

Being technologically backward, developing countries are not necessarily at a disadvantage to more advanced economies. They have some advantage in the catching-up process, deriving from the very fact of their backwardness. Latecomers are able to import and exploit the technologies already developed elsewhere. In addition they can derive extra scale of economies by leapfrogging over some of the earlier stages of technological development (Gerschenkron, 1962). Although R&D activities are important for long term technological growth in an economy, about 80% of the total world R&D expenditures were performed by the seven developed countries (G7) in 1998 (National Science Foundation, 2002). Developing countries, in general, do not engage in significant amounts of R&D activities, rather they rely heavily on the innovation by the advanced economies and mostly play their

role as technological followers. The study of Savvides and Zachariadis (2005) in most of the developing countries finds that international technology transmission happens through imports of intermediate capital goods and inflow of foreign direct investment. These international technology spillovers show significant positive effect on TFP growth. Domestic R&D intensity might help developing countries to innovate new technology as well as absorbing foreign R&D to speed up the process of technological catch up.

IV. Hypothesis Development

4.1. Theories Related to Hypothesis Development

To provide the theoretical background of the proposed study, this paper considers the following homogenous Cobb-Douglas production function:

$$Y = AK^{\alpha}L^{1-\alpha}$$
(a)

where, *Y* is the output, *A* is the level of TFP or, knowledge, *K* is the aggregate capital stock and *L* is the aggregate workforce or, labor, α is the capital share which is assumed to be constant. In the spirit of Romer (1990) and Benhabib and Spiegel (1994), this study does not include human capital as an input factor, rather it treats human capital as affecting domestically produced technological innovation, or productivity. The proponents of the first generation endogenous growth models (Romer, 1986, 1990; Grossman and Helpman, 1991a,b ; Aghion and Howitt, 1992) assumes the following ideas production function (Ha and Howitt, 2007):

$$g_A = \frac{A}{A} = \lambda X^{\sigma}, \qquad 0 < \sigma \le 1$$
 (b)

where, g_A indicates TFP or, knowledge growth, A denotes TFP, A is the change in TFP, λ is a parameter of research productivity, X indicates R&D input, measured by either the flow of R&D labor, or the flow of productivity adjusted R&D expenditure on labor and capital and σ is a duplication parameter. The model assumes constant returns to knowledge in the creation of new knowledge. Therefore, the above model (b) implies that long run growth depends on policies that determine long run level in R&D input. The major drawback of first generation endogenous growth model is the implication of R&D scale effect, which predicts that the higher the level of R&D expenditures, the higher will be the TFP growth.

Jones (1995b) refuted the prediction made in the first generation model and argued that there is no empirical relationship between the level in the R&D input and the TFP growth in

leading industrialist countries such as France, Germany, Japan and the USA. He proposed the semi-endogenous growth model as follows:

$$g_A = \frac{A}{A} = \lambda X^{\sigma} A^{\phi-1} , \qquad \phi < 1$$
 (c)

where, ϕ is the return to knowledge, assuming decreasing returns to knowledge. Thus the model (c) assumes that there is a positive association between R&D growth and TFP growth. Schumpeterian version of the second generation endogenous (or, fully endogenous) growth model is a response to Jones's critique, which corrects the first generation's R&D scale effect by suggesting a positive relation between the R&D intensity and the TFP growth (Young, 1998; Aghion and Howitt, 1998 ; Dinopoulos and Thomson 1998 ; Ha and Howitt, 2007; Madsen, 2008a). As an economy grows, proliferation of product varieties induces R&D to spread more thinly over a large number of different sectors and thus reduces the effectiveness of R&D. Therefore, considering the deleterious effect of the complexity on the productivity on R&D, the functional form of the Schumpeterian version's Knowledge growth becomes,

$$g_A = \frac{\dot{A}}{A} = \lambda \left(\frac{X}{Q}\right)^{\sigma} A^{\phi-1}, \quad 0 < \sigma \le 1, \quad \phi \le 1$$
(d)

$Q \propto L^{\beta}$ in the steady state

where, Q is the product variety, L is employment or population and β is the coefficient of product proliferation. The ratio between X and Q is termed as research intensity. Q is often measured by L. The idea behind equation (d) is that an increasing population increases the number of people who can enter an industry with a new product, thus resulting in more horizontal innovations, which dilutes R&D expenditures over a large number of isolated projects. The first generation endogenous growth models (equation b) assume that $\phi = 1$ and $\beta = 0$, semi endogenous models (equation c) predict that $\phi < 1$ and $\beta = 0$, and finally the recent second generation (or, fully endogenous) growth models (equation d) assume that $\phi = 1$ and $\beta = 1$.

In the light of the above-mentioned Schumpeterian fully endogenous growth model (Eq. d) Howitt (2000) argues that countries those perform R&D will converge to a parallel growth path whereas those that do not will not grow at all in the long run. In this model, TFP growth is determined by the flow rate of innovation time the relative technological gap between and country and world technology leader, as follows:

$$g_A = \frac{\dot{A}_t}{A_t} = \psi \left(\frac{X}{Q}\right)_t \times \left(\frac{A_t^{\max} - A_t}{A_t}\right)$$
(e)

where, ψ is the R&D productivity parameter, (X/Q) is the share of output devoted to R&D, and A^{\max} is the productivity of the technology leader. If the leading edge parameter A_t^{\max} remains unchanged, then according to equation (e) each country's average productivity level converges to A_t^{\max} as long as $\psi(X/Q)_t$ becomes positive. On the other hand if A_t^{\max} constantly increases, then more innovative economies will be more productive because their intermediate products are up to date and thus their average productivity level is permanently closer to the leading edge technology (A_t^{\max}). Therefore, productivity convergence to the global growth rate will occur due to foreign technology transfer.

Human capital is also an important channel to absorb foreign technology. Nelson and Phelps (1966) advocate the complementary relationship between educational attainment (*SCH*) and technology transfer in improving productivity growth. They introduce the concept of theoretical level of technology T_i , which is according to them the best practice level of technology while the technological diffusion takes place instantly. Therefore, realizing theoretical technology into improved technological practice does not only depend on educational attainment or human capital but also on the gap between the level of theoretical technology in practice as follows:

$$g_A = \frac{\dot{A}_t}{A_t} = \phi(SCH) \times \left[\frac{T_t - A_t}{A_t}\right], \qquad \phi(0) = 0, \qquad \phi'(SCH) > 0$$
(f)

Thus, according to Nelson and Phelps (1966) hypothesis, the rate of increase in technology in practice (not the level) is an increasing function of educational attainment or, human capital, (*SCH*) and proportional to the technology gap, $(T_t - A_t)/A_t$. In other words, the rate at which the technological gap is closed will depend on the level of human capital.

More recently, in the light of the Schumpeterian fully endogenous growth theory, Griffith *et al.* (2003, 2004) present a theoretical model which reconciles empirical evidence of R&D based innovation as well as R&D's role in promoting absorptive capacity and productivity convergence. Therefore, R&D does not only stimulate TFP growth but also facilitate technology transfer. They tested the two faces of R&D by the following specification:

$$g_{A} = \frac{\dot{A}_{t}}{A_{t}} = \alpha \left(\frac{X}{Q}\right)_{t-1} + \beta \ln \left(\frac{A^{\max}}{A}\right)_{t-1} + \gamma \left(\frac{X}{Q}\right)_{t-1} \times \ln \left(\frac{A^{\max}}{A}\right)_{t-1}$$
(g)

where (X/Q) indicates research intensity, *X* is the R&D activities and *Q* is the product variety. The technology gap is lagged by one period to allow for the time it takes for the domestic economy to absorb the technology developed at the frontier country.

4.2. Testable Hypothesis

The following hypotheses will be tested for a panel of 55 sample countries consisting of 23 high income OECD and 32 low and medium income developing countries spanning from the period of 1970 to 2004.

Hypothesis 1: *R&D intensity has significant positive impact on TFP growth.* R&D intensity has a direct effect on a country's ability to knowledge creation or, innovation. Therefore, the higher the domestic R&D based innovation the higher will be the productivity growth.

Hypothesis 2: Distance to technology frontier is significantly positively related to TFP growth. Following convergence literature, the countries those are further behind the technological frontier experience higher TFP growth. It usually captures autonomous technology transfer or, catch-up to the technology frontier.

Hypothesis 3: *R&D based absorptive capacity has positive and significant effect on TFP growth.* The investment in R&D by the non-frontier countries has potential to generate TFP growth through technology transfer.

Hypothesis 4: *Human capital based absorptive capacity has a significant positive relation with TFP growth.* The investment in human capital by the technologically backward countries has potential to generate TFP growth through technology transfer.

V. Research Design

5.1. Data and Measurement Issues

The basic dataset for this study combines variables from six different sources.⁴ The latest 6.2 version of the Penn World Tables (PWT 6.2-Heston, Summers and Aten, 2006) is used to extract the output growth and its decomposition into factor accumulation and TFP for a panel of 55 countries consisting of 23 OECD and 32 developing countries spanning from the period

⁴ A complete definition of the variables and their sources are listed in the Appendix Table A1.

of 1970 to 2004.⁵ This paper defines developed countries as those the World Bank defines as high-income OECD countries and developing countries as all others. According to the 'World Bank Classification' based on 2006 GNI per capita, the range of GNI per capita in developed countries are US\$ 11,116 to more, whereas US\$ 11,115 to less in the developing nations. The UNESCO Statistical Yearbook (various issues) is used to extract R&D input data such as R&D scientists and engineers and R&D expenditures. Patents data are R&D output data collected from the "Industrial Property Statistics" of The World Intellectual Property Organization's (WIPO) website. Data for openness are compiled from the World Development Indicators (WDI) 2006 online database. Foreign Direct Investment (FDI) inflows data are collected from the International Financial Statistics (IFS) 2006 CD-ROM. Average years of schooling in the population aged 25 and over as a proxy for human capital is extracted from Barrow and Lee (2001) schooling dataset. As an alternative measure for human capital secondary school enrolment ratio (gross) is extracted from the World Development Indicators (WDI) 2006 online database.

TFP Growth ($\Delta \ln A_{ii}$): In order to calculate the TFP growth rate for the sample countries, this study follows growth accounting⁶ decomposition procedure by considering the benchmark Hall and Jones'(1999) aggregate production function, where a country's real gross domestic product (GDP), *Y*, is stated as :

$$Y = AK^{\alpha}L^{1-\alpha}$$
(i)

where, K is the aggregate capital stock and L is the aggregate workforce or labor. α is the share of income goes to capital stock and it is assumed to be constant.

Now dividing equation (i) by the number of workers L:

$$y = Ak^{\alpha}$$
 (ii)

where, y is the output-worker ratio (y = Y/L), k is the capital-worker ratio (k = K/L). Both k and y are in real terms. The objective of this decomposition is to examine how much

⁵23 high income OECD countries are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States.

³² low and middle income developing countries are: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, Egypt, Guatemala, India, Indonesia, Iran, Malaysia, Mauritius, Mexico, Niger, Pakistan, Panama, Paraguay, Peru, Philippines, Rwanda, Senegal, South Africa, Sri Lanka, Sudan, Thailand, Tunisia, Turkey, Uruguay, Venezuela, Zambia

⁶ Growth accounting offers a means of allocating observed output growth between the contributions of changes in factor inputs and a 'residual', total factor productivity (TFP), which measures a combination of changes in efficiency in the use of those inputs and changes in technology. Growth regression allows researchers to regress various indicators of output growth on a vast array of potential determinants (Bosworth and Collins, 2003).

of the variation in y is explained by the observed factor accumulation, k and how much is unobserved 'residual' variation which, in other words, is termed as variations in TFP. We can estimate TFP from the equation (ii) as follows,

$$A = TFP = v/k^{\alpha}$$
(iii)

The share of α is assumed equal to 0.30, meaning that the physical capital's share is 30% and the worker's share is 70% for the entire sample. In order to estimate the TFP equation (iii), this study needs capital stocks data which are not available at PWT 6.2 and thus it has constructed the capital stocks by following perpetual inventory method as used in Caselli (2005).⁷ Therefore, the capital accumulation equation becomes,

$$K_{it} = I_{it} + (1 - \delta) K_{i,t-1}$$
 (iv)

where, K is the amount of capital, δ is the depreciation rate, assumes 5% as used in Bosworth and Collins (2003), I is the amount of investment, subscript 'i' denotes a particular country and subscript 't' indicates a specific time period. In order to construct capital stock data series according to equation (iv), initial capital stock (at time t = 0) can be estimated as follows:

$$K_{i0} = \frac{I_{i0}}{g_{ss} + \delta} \tag{v}$$

Where, g_{ss} indicates the steady state rate of economic growth, measured by the simple average of the real GDP growth rate over the period of 1970 to 2004.

Finally, TFP growth rate can be calculated from the first difference of the log of TFP: \dot{A} .

$$g_{A_{it}} = \frac{A_{it}}{A_{it}} = \Delta \ln A_{it} = \ln A_{it} - \ln A_{i,t-1}$$
(vi)

R&D Intensity (X/Q): The ratio of X to Q is termed as R&D intensity where X and Q measure R&D activity and product variety respectively. There are four alternative measures for R&D intensity used in this study. The indicators are: (i) the ratio of R&D scientists and engineers to total labor force, (N/L);⁸ (ii) the ratio of total R&D expenditures to GDP, (R/Y); (iii) the ratio of patent application by the residents to total labor force, (PA/L); and (iv) the ratio of patent granted to the residents to total labor force, (PG/L). An increase in labor force,

⁷ 'y' is measured as the real GDP per worker in international dollar (PPP) originally called 'rgdpwok' at PWT 6.2. Number of workers, 'L' is computed as '(rgdpch*pop)/rgdpwok', where 'rgdpch' is the real GDP per capital obtained with the chain method and 'pop' is the number of population. Investment, 'I' is calculated as 'rgdpl*pop*ki', where 'rgdpl' is the real income per capita obtained with the Laspeyers method, and 'ki' is the investment share in the total income. All the figures are in million units. All the relevant notations are in the original form as mentioned at Penn World Table (PWT 6.2).

⁸ PWT 6.2 database does not have labor data. Therefore, number of labor (L) is obtained as '(real GDP per capita * number of population)/ real GDP per worker'. The same process is followed by Caselli (2005).

population or, income leads to an expansion in the variety of inputs or, product variety in Schumpeterian models (Krugman, 1989; Aghion and Howitt, 1998; Ha and Howitt, 2007). Therefore, this study uses GDP and employment as measures for product variety. R&D scientists and engineers as well as R&D expenditures are also adjusted by productivity (TFP) to allow increasing complexity of innovative activity resulting from the advancement of economies (Madsen, 2008a).

R&D personnel especially scientists and engineers involved in R&D activities are directly engaged to create new products and processes and thus they are widely accepted critical factor contributing innovation (Griliches, 1984). R&D expenditures are often interpreted as a significant determinant of innovation. R&D expenditures are usually deflated by weighted average of hourly labor costs and the GDP deflator (Coe and Helpman, 1995). Although long time series labor wage data are not consistent and available for most of the developing countries, this study tries to collect available labor wages data from ILO and International Historical Statistics 1750-2005(Mitchell, 2007) and constructs a deflator by averaging of the total labor cost deflator (50%) and the GDP (50%) deflator, where the number in the parentheses specifies respective weight. The weighted index does not improve the estimated results rather shows abnormal fluctuations in labor wages in most of the Latin American as well as a few African countries. Therefore, this study uses GDP deflator for both the OECD and developing countries to deflate R&D expenditures.

Patent applications by the residents are more appropriate than patent granted to the residents because the frequency of patent granting activities varies significantly across countries (Griliches, 1990; Jaffe and Palmer, 1997). Patent flows are better than the patent stock to measure innovation (Kortum, 1993) and therefore, the former is used in this study. These measures of R&D based innovation are not beyond criticism. R&D expenditure is a flow variable and thus it may not accurately represent the R&D intensity across countries. Again, appropriate deflators of R&D expenditures for developing countries are hardly available. Patent is an R&D output and thus using patent as a proxy for R&D intensity may not be adequate measure for product proliferation. Since R&D scientists and engineers directly involve in R&D activities and are stock variable as well as R&D input, they might be the most representative measures for R&D intensity. Although this study estimates all of the four alternative R&D indicators, it emphasizes on R&D scientists and engineers to measure innovation while reporting its empirical findings.

Distance to Technological Frontier $[(A^{max}-A)/A^{max}]$: The potential for distance to technological frontier, or autonomous technology transfer, is measured by the relative TFP gap between the US (A^{max}) and the sample countries, denoted by DTF. Being the technology leader as well as the major trading partner of most of the developing countries, the US technology is assumed here as the technology frontier of the world. Therefore, autonomous technology transfer implies that, other things remain unchanged, countries which are further behind from the technology frontier will have faster rates of TFP growth. Although those countries that are behind the technological frontier may have potentiality to increase productivity growth through technology transfer but the output depends on appropriate institutional development and governmental policy, which may have significant impact on the autonomous technology transfer (Griffith *et al.*, 2003, 2004).

R&D based Absorptive Capacity $[(X/Q) \times (A^{max}-A)/A^{max}]$: It is measured by the interaction between R&D intensity (X/Q) and the distance to frontier $[(A^{max}-A)/A^{max}]$. The rationale behind this concept is that the further a country lies behind the technological frontier, the greater is the potential for its R&D to increase TFP growth through technology transfer from the more advanced countries (Howitt, 2000).

Human Capital based Absorptive Capacity $[SCH \times (A^{max}-A)/A^{max}]$: It is measured by the interaction between human capital (*SCH*) and the distance to frontier $[(A^{max}-A)/A^{max}]$. The rationale behind this concept is that the further a country lies behind the technological frontier, the greater is the potential for its human capital to increase TFP growth through the speed of adoption of technology from industrially developed countries (Nelson and Phelps, 1966).

Control Variables: In a classic study on the effectiveness of macroeconomic control variables, Levine and Renelt (1992) identify that initial real GDP per capita , initial secondary school enrolment ratio, and the ratio of domestic investment to GDP are robust control variables across different specifications. Later Sala-i-Martin (1997) departs from Levine and Renelt's (1992) "extreme bound test" and uses the normality of distribution of the coefficients of the control variables and finally argues that substantial number of control variables can be found to be strongly related to growth. Using initial GDP per capita for convergence effect is not a usual practice in productivity studies. Instead distance to technological frontier deals with the convergence issue in our study. In estimating production function, this study has already included physical capital as production inputs and thus it will be redundant to use investment

as a control variable. Since this study has only 55 countries in the entire sample, it has incorporated three important control variables, such as human capital proxied by average years of schooling in the population aged 25 and over (*SCH*), trade openness measured by the ratio of the sum of exports and imports to GDP (*OP*) and the ratio of FDI inflow to GDP (*FDI*). As an alternative measure to human capital, it uses secondary school enrolment ratio from WDI 2007 online database.

Human capital or the educational attainment of the labor force helps to speed up the technological catch-up and diffusion by the technologically follower countries. The level of human capital not only enhances the ability of a country to develop its own technological innovation, but also increases its ability to adopt the already existed knowledge (Nelson and Phelps, 1966; Kneller, 2005). Openness is found to be one of the important control variables widely used in growth regression. Countries that are more open to the rest of the world have greater ability to absorb foreign technology (Grossman and Helpman, 1991b; Barro and Sala-i-Martin, 1995). Foreign Direct Investment (FDI) may be another important channel for the international transmission of technology (Savvides and Zachariadis, 2005).

5.2. Model Specification

To test the underlying hypotheses, this study follows the similar empirical methodology used by Griffith *et al.* (2003, 2004). They use their model for micro level analysis, whereas this study applies their methodology in its macro level study. As an alternative estimation of absorptive capacity, it follows Howitt (2000) and Nelson and Phelps (1966) models, where the former looks at innovation and the latter focuses on human capital based absorptive capacity. In order to test the hypothesis that R&D intensity as well as absorptive capacity has significant positive significant effect on TFP growth, it uses panel estimators to estimate a cross-country TFP growth regression. The basic panel regression takes the following form:

$$\Delta \ln A_{it} = \beta_{0i} + \beta_1 (X / Q)_{it} + \beta_2 \left(\frac{A^{\max} - A_i}{A^{\max}} \right)_{t-1} + \beta_3 (X / Q)_{it} \times \left(\frac{A^{\max} - A_i}{A^{\max}} \right)_{t-1} + \lambda' C_{it} + \varepsilon_{it} (1)$$

where, $\Delta \ln A$ is total factor productivity growth, (*X/Q*) indicates R&D intensity measured by four different indicators, such as : (i) the ratio of R&D scientists and engineers to total labor force, (*N/L*); (ii) the ratio of total R&D expenditures to GDP, (*R/Y*); (iii) the ratio of patent application by the residents to total labor force, (*PA/L*) ; and (iv) the ratio of patent granted to the residents to total labor force, (*PG/L*). Labor and GDP are used as measures for

product variety. R&D scientists and engineers as well as R&D expenditures are also adjusted by productivity (N/LA & R/LA respectively) to allow increasing complexity of innovative activity resulting from economic progress. Distance to technological frontier captures autonomous technology transfer and hence it is measured by the relative TFP gap between the US and the sample countries $[(A^{max}-A)/A^{max}]$. Being the technological leader as well as the major trading partner of most of the countries in the world, the US technology is considered as the frontier's technology (A^{max}) of the world. The interaction term between R&D intensity (X/Q) and distance to frontier $[(A^{max}-A)/A^{max}]$ measures R&D based absorptive capacity as used by Griffith et al. (2003, 2004) (Eq. g). C indicates the vector of control variables, where this study incorporates three of them based on their relative importance; they are average years of schooling in the population aged 25 and over (SCH), trade openness (OP) and the ratio of the inflow of foreign direct investment to GDP (FDI). The subscript 'i'denotes a particular country, whereas, subscript 't' indicates a particular time period. In order to reduce business cycle effects TFP growth $(\Delta \ln A)$ is calculated in 5-year differences whereas, research intensity (N/L or, R/Y or, PA/L or, PG/L) is measured in 5-year averages. Distance to technology frontier $[(A^{max}-A)/A^{max}]$ is measured in 5-year lags, and finally all of the control variables are measured in 5-year averages in the interval over which the 5-year differences have been considered to estimate productivity growth.

In order to support Schumpeterian second generation or, fully endogenous growth model, β_1 is expected to be positive and significant. For evidence of conditional convergence of TFP growth or, for autonomous technology transfer, β_2 is needed to be positive and significant and finally R&D based absorptive capacity might be supported by obtaining positive and significant value for β_3 . As an alternative to Griffiths' model for R&D based absorptive capacity, this study uses only the interaction term between (X/Q) and $[(A^{max}-A)/A^{max}]$ dropping their individual effects as prescribed by Howitt (2000) (Eq. e):

$$\Delta \ln A_{it} = \beta_{0i} + \beta_1 (X/Q)_{it} \times \left(\frac{A^{\max} - A_i}{A^{\max}}\right)_{t-1} + \lambda' C_{it} + \varepsilon_{it}$$
(1a)

Similarly, in order to incorporate human capital based absorptive capacity, this study also uses only the interaction term between human capital (*SCH*) and distance to technological frontier $[(A^{max}-A)/A^{max}]$ dropping their individual effects as suggested by Nelson and Phelps (1966) (Eq. f) :

$$\Delta \ln A_{it} = \beta_{0i} + \beta_1 (SCH_{it}) \times \left(\frac{A^{\max} - A_i}{A^{\max}}\right)_{t-1} + \lambda' C_{it} + \varepsilon_{it}$$
(1b)

5.3 Estimation Techniques

Generally, panel data analysis allows one to exploit both the time-series variation and crosssectional heterogeneity of the concerned variables. This study uses 5-year differences unbalanced panel data consisting of 55 countries' (23 OECD and 32 developing countries) observation spanning from the period of 1970 to 2004. The data are averaged over 5-year period (except 4-year average for 2000-2004) so that there could be 7 observations per country from 1970 to 2004, which is commonly used in macro-level panel study in order to avoid transitional dynamics and business cycle effects.⁹ The nature of this panel is unbalanced since data are not available for all the sample countries for all the seven time periods. Such panel data incorporates time series as well as cross sectional deviations. This study estimates its empirical model for the entire sample at first and then divide the sample into developed and developing countries to examine the effect of R&D intensity as well as absorptive capacity on TFP growth.

The basic panel model in equation (1) shows pooled ordinary least squares (OLS) relationship between the TFP growth and its potential determinants and thus one can argue that there could be unobserved country specific characteristics, such as institutional quality, investment climate etc. which might affect the TFP growth rate and are not captured by the pooled OLS model. These unobserved country specific effects may be correlated to the regressors and thus one needs to control those unobserved time invariant country specific effects by allowing the error term (ε_{ii}) to include a country-specific fixed effects (θ_i). Again by allowing the error term (ε_{ii}) to include time dummies (ρ_i), one can easily capture common macroeconomic shocks that might have significant impact on TFP growth in the sample. Therefore, by incorporating fixed effects and time dummies into the basic model (equation 1), this study can construct its empirical panel model as follows:

⁹This study has also conducted 10-year differences estimation (not reported) and estimated results are not significantly different from that of 5 -year differences. Since it has only 35 year sample period (1970-2004), 5-year differences may help it to apply different estimators for robustness check without losing much degree of freedom which may not be possible in 10-year differences estimation for its small number of sample.

$$\Delta \ln A_{it} = \beta_{0i} + \beta_1 (X / Q)_{it} + \beta_2 \left(\frac{A^{\max} - A_i}{A^{\max}}\right)_{t-1} + \beta_3 (X / Q)_{it} \times \left(\frac{A^{\max} - A_i}{A^{\max}}\right)_{t-1} + \lambda' C_{it} + \theta_i + \rho_t + e_{it}$$
(2)

where, $\varepsilon_{it} = \theta_i + \rho_t + e_{it}$, and e_{it} is serially uncorrelated error.

If two and more variables are jointly determined in the empirical model is stated as endogeneity problem. Fixed effects model may suffer from biases due to possible endogeneity of the regressors (Nickell, 1981). In order to reduce such endogeneity problem, instrumental variable method such as, generalized method of moments (GMM) is widely used where the endogenous explanatory variables are instrumentalized with their suitable lags so that the instruments are not correlated to the error term. Anderson and Hsiao (1982) suggested a first-differenced transformation to eliminate fixed effect as well as constant. However, the correlation still remains between the differenced error term and the differenced endogenous regressors and thus one can intrumentalize the differenced endogenous variables with their further lags.

Arellano and Bond (1991) argue that the Anderson-Hsiao estimator fails to take all orthogonality conditions and thus it is not an efficient estimator. Therefore, they propose difference GMM estimator as a system of equations allowing lagged values of the endogenous regressors as instruments. Arellano and Bover (1995) and Blundell and Bond (1998) demonstrate that the lagged level of the endogenous variables may be poor instruments for the first differenced variables and thus they suggest lagged differences as instruments which is popularly known as system GMM. The main difference between the difference and system GMM is that the difference GMM estimates first difference equation using the lagged levels of instruments series, whereas system GMM estimates system of the level and first difference equations using the lagged differences instruments for the level series, and the lagged levels of instruments for the differenced series. Both difference and system GMM estimators are designed for few time periods (small T) and large cross-sections (large N). If T is large, dynamic panel biases become insignificant and a more straightforward fixed effects estimator works. If N is small, the Arellano and Bond autocorrelation tests become unreliable (Roodman, 2006). In this study number of cross-sections (N) is larger than number of time periods (T) and thus it can use system GMM estimator.¹⁰

¹⁰ There is huge literature on the description of how GMM estimator works. For detailed description please see Green (2000), Wooldridge (2002), Roodman (2006) etc. Bond, Hoeffler and Temple (2001) give an excellent explanation on GMM estimation of the macro level empirical growth models.

Hayashi (2000) points out that GMM estimator may require large sample sizes and hence it may have small sample biases. Since the sample size used in this study is small, it applies 2SLS (two stage least squares) method for robustness check which implements instrumental variable (IV) estimation of the fixed effects panel data models with possibly endogenous regressors. The advantage of GMM over IV (2SLS) is that the GMM estimator is more efficient than the simple IV in the presence of heteroskedasticity, whereas if there is no heteroskedasticity, the GMM estimator is no worse asymptotically than the IV estimator (Baum, Schaffer and Stillman, 2003). Although estimated results using IV are consistent to that of GMM, this study conducts Pagan and Hall (1983) test of heteroskedasticity for IV and finds the evidence of heteroskedasticity in the error term. Hence GMM estimator is preferable to IV (2SLS) here. While using GMM, this study also compares results between difference and system GMM estimators. Although estimated results obtained from difference GMM are quite similar to that of the system GMM, the former does not satisfy second order serial correlation tests in most of the specifications and therefore, empirical results from system GMM is preferable to difference GMM in this study.¹¹ In Monte Carlo simulations Blundell and Bond (1998) observe that system GMM estimator produces efficiency gain when the number of time series observation is relatively small. Furthermore, Beck, Levine, and Loayza (2000) argue that system GMM estimator is efficient in exploiting time series variations of data, accounting for unobserved country specific effects, allowing for the inclusion of the lagged dependent variables as regressors and thereby providing better control for endogeneity of the entire explanatory variables. Using too many instruments relative to number of crosssection may overfit endogenous variables in GMM estimation and hence this study has handled this important issue applying 'collapse' option available in STATA (version 10) while estimating system GMM using 'xtabond2' program.¹²

Arellano and Bover (1995) and Blundell and Bond (1998) prescribe several specification tests that are needed to satisfy while using system GMM estimators. Therefore, the validity of the instruments used can be tested by reporting both a Hansen test of the over-identifying

¹¹ A number of authors such as, Baum, Schaffer and Stillman (2003), Baum (2006) and Roodman (2006) have clearly explained how to conduct GMM estimation in STATA. System GMM estimator is available in STATA's xtabond2 module (Version 10). The program is available for the registered STATA users. All the relevant codes for GMM estimation have been extracted from Roodman (2006).

¹² Two moments conditions, e.g. $E(X_{i,t-1}\Delta\varepsilon_{i,t}) = 0$ and $E(X_{i,t-2}\Delta\varepsilon_{i,t}) = 0$ can be collapsed into $E(X_{i,t-1}\Delta\varepsilon_{i,t} + X_{i,t-2}\Delta\varepsilon_{i,t}) = 0$. The rationale behind this strategy is to reduce potential biases resulting from too many instruments or, overidentifying restrictions.

restrictions, and direct tests of serial correlation in the residuals or error terms. The key identifying assumption in Hansen test is that the instruments used in the model are not correlated with the residuals. The AR(1) test checks the first order serial correlation between error and level equation. The AR(2) test examines the second order serial correlation between error and first differenced equation. The null hypotheses in serial correlation tests are that the level regression shows no first order serial correlation as well as the first differenced regression exhibit no second order serial correlation.

The use of cross-country growth regressions in empirical analysis is not beyond criticism (Brock and Durlauf, 2001; Aghion and Durlauf, 2007). First, the regressors of the growth models may be endogenous and hence results from OLS may not reflect clearly whether the estimated coefficients reflect causality or correlation. Using instrumental variable method such as GMM may be potential solution of this problem. Second, although linear specifications treat each growth determinant acts separately from others, new growth theories consider interactions between different determinants of growth. Using products of different determinants as additional regressors may solve this problem. Third, innovation models under new growth theories focus on interactions that are defined with respect to firms and industries. Therefore, identification the interaction effects exclusively in aggregate data may be problematic. Finally, growth regressions may encounter the problem of residual heterogeneity. Growth is in general country specific and thus allowing country specific fixed effects could solve the problem. Limitations imposed by the incorporation of fixed effects in panel analysis are well known and hence differencing of panel data may remove the fixed effects though makes inference difficult if the control variables move slowly over time.

5.4. Data Analysis

Table 1 presents descriptive statistics for the variables used in the empirical study for the entire sample of 55 countries consisting of 23 OECD and 32 developing countries over the period of 1970 to 2004. The mean values of all the R&D intensity proxies are far larger in OECD countries as compared to those of their developing counterparts. In other words, the degree of R&D intensity is extremely thin in developing countries. Since, R&D scientists and engineers, R&D expenditures and patents data are not available in several years especially for some developing countries, this study has considered countries with at least 9 data points from 1970 to 2004 and then interpolate them using a geometric growth trend. To examine robustness, it tried to restrict its sample developing countries with at least 14 data points that

reduced the sample to 25 countries but did not obtain significant change in the estimated results. In the case of R&D expenditures data, it finds sudden drop of the monetary unit for some of the developing countries, such as Argentina, Brazil etc. due to possible change in their currency denomination and thus it did not include those observations in our study. R&D expenditures are deflated by the GDP deflator. Griliches (1984) suggests that R&D expenditures should be deflated by an weighted average of hourly labor wages and the GDP deflator. Since labor wages data are not consistent for most of the developing countries, it had to rely only on the GDP deflator. During the extraction of R&D data, this study also observes substantial inconsistency in data arrangements for transitional economies like Romania, Poland etc. and therefore, it excludes those countries.

Although Penn World Table (PWT 6.2) has available data from 1950 to 2004, cross-country R&D intensity measures are mostly available from 1970 and thus this study has selected its time period from 1970 to 2004. As a measure for human capital stock, Barro and Lee's (2001) average years of schooling data are available in 5 year intervals till 2000 and thus this study extrapolates them using geometric growth trend for further four years so that they can match with the overall ending period 2004. As an alternative human capital measure, this study also considers secondary school enrolment ratio (gross) available at World Development Indicator 2006 online database.

	$\Delta ln A_{it}$	DTF i,t-1	$(N/L)_{it}$	$(R/Y)_{\rm it}$	(PA/L) _{it}	$(PG/L)_{it}$	DTF $_{i,t-1} \times (N/L)_{it}$	$\frac{\text{DTF}_{i,t-1} \times}{(R/Y)_{it}}$	$\frac{\text{DTF}_{i,t-1} \times}{(PA/L)_{it}}$	$\frac{\text{DTF}_{i,t-1} \times}{(PG/L)_{it}}$	$\frac{\text{DTF}_{i,t-1} \times}{(SCH_{it})}$	SCH it	OP_{it}	FDI_{it}
Total Sample	(55 Cour	ntries)												
Mean	0.045	0.465	2.251	0.105	0.254	0.109	0.633	0.035	0.066	0.027	0.664	1.650	0.577	0.016
Std. Dev.	0.098	0.230	2.616	0.292	0.304	0.137	0.701	0.107	0.086	0.038	0.370	0.653	0.314	0.018
Minimum	-0.352	0.000	0.010	0.00002	0.004	0.001	0.000	0.000	0.000	0.000	-0.995	-1.266	0.096	-0.004
Maximum	0.371	0.926	15.203	1.787	0.828	0.373	4.957	0.803	0.409	0.179	1.576	2.508	2.116	0.130
Observation	384	385	370	311	326	306	370	311	326	306	384	384	380	351
OECD Count	ries (23)													
Mean	0.062	0.259	4.531	0.197	0.539	0.232	1.094	0.063	0.136	0.057	0.538	2.120	0.616	0.016
Std. Dev.	0.062	0.123	2.540	0.386	0.329	0.173	0.839	0.144	0.116	0.056	0.236	0.266	0.280	0.019
Minimum	-0.086	0.000	0.479	0.009	0.120	0.018	0.000	0.000	0.000	0.000	0.000	0.973	0.140	0.000
Maximum	0.292	0.678	15.203	1.787	1.145	0.557	4.957	0.803	0.566	0.267	1.275	2.508	1.617	0.130
Observation	160	161	160	159	159	156	160	159	159	156	160	160	160	139
Developing Co	ountries (32)												
Mean	0.033	0.613	0.515	0.009	0.023	0.008	0.282	0.005	0.010	0.004	0.754	1.314	0.548	0.015
Std. Dev.	0.116	0.168	0.411	0.024	0.036	0.015	0.213	0.012	0.013	0.005	0.419	0.640	0.333	0.017
Minimum	-0.352	0.210	0.010	0.00002	0.002	0.001	0.007	0.000	0.001	0.000	-0.995	-1.266	0.096	-0.004
Maximum	0.371	0.926	2.572	0.243	0.168	0.112	1.452	0.104	0.068	0.037	1.576	2.161	2.116	0.111
Observation	224	224	210	152	167	150	210	152	167	150	224	224	220	212

Table 1. Descriptive Statistics: 1970-2004

Notes: (i) Variable Specifications: $\Delta ln A = Total Factor Productivity Growth, DTF = Distance to Frontier measured by the relative TFP gap between the US (A^{max}) and the sample countries (A_i) [i.e. {(A^{max}-A_i)/A^{max}}_{t-1}], N/L = R&D Scientists and Engineers/Labor (in thousands), R/Y = R&D Expenditures/GDP (in percentage), PA/L= Patent Applications by Residents/Labor (in thousands), PG/L= Patent Granted to Residents/Labor (in thousands), SCH = (log) Average Years of Schooling in the Population Aged 25 years and over, OP = Trade Openness = (Export+Import)/GDP and FDI = Foreign Direct Investment Inflows/GDP ; (ii) Estimation period is 1970-2004; (iii) The period 2000-2004 is used for the last observation; (iv) TFP growth (<math>\Delta lnA$) is calculated in 5-year differences; (v) Research intensity (N/L or, R/Y or, PA/L or, PG/L) is measured in 5-year averages; (vi) Distance to technology frontier (DTF) is measured in 5-year lags; and (vii) Control variables such as SCH, OP and FDI are measured in 5-year averages in the interval over which the 5-year differences have been considered to estimate productivity growth.

To ensure that the empirical results are not driven by outliers, this study winsorizes all the four different measures for R&D intensity at the top and bottom 5 percent of their distributions. Winsor takes the non-missing values of a variable L and generates a new variable M identical to L except that the highest and lowest values are replaced by the next value counting inwards from the extremes. Therefore, winsorizing at 5% level might shrink extreme values to the 5% and 95% percentiles over the years. Omitting outliers may result significant information loss and thereby winsorizing has become popular technique to handle outliers and extensively used in Finance & Accounting literature (Loughran, 1997; Fama and French, 2006; Billet and Xue, 2007). The estimated results after winsorizing do not show significant differences except the case of patent application by residents (PA/L) and patent granted to residents (PG/L). Therefore, this study keeps other two alternative R&D intensity measures (R&D Scientists and Engineers, N/L and R&D expenditures, R/Y) at their original form and consider patent application (PA/L) and granted (PG/L) to residents at its winsorized form during the empirical estimation.

[Insert Table A2]

Table A2 presents correlation matrix for the entire as well as splitted samples. There is no evidence of high pairwise correlations between the variables except the interaction terms. In order to examine R&D based absorptive capacity, this study takes interaction between R&D intensity and distance to technological frontier and therefore pairwise correlation matrix shows high collinerarity (more than 0.80) between different measures of R&D intensity and their interaction with distance to frontier. The interaction term may likely to result in some multicollinearity problems in the estimation. While this does not necessarily bias the estimates, it does increase the size of the estimated variance, and given the relatively small sample sizes, it may cause instability in the parameter estimates. Examination of Variance Inflation Factor (VIF)¹³ (not reported) justifies the prediction and thus as an alternative to reduce muticollinearity resulting from interaction term (product of two independent variables) this study follows the process of "centering" the variables by computing the mean. This is known as 'deviation score' and widely used to reduce multicollinearity while using interaction terms. Both the centered (deviation score) and non-centered (simple product of two independent variables) approaches yield very similar results in this study.

¹³ The Variance Inflation Factor (VIF_i) for a variable X_i from a vector of regressor X is computed as $1/(1-R_i^2)$, where R_i^2 is the multiple correlation coefficients from a regression of X_i on all other elements of X. The larger the value of VIF_i , the more collinear the variable X_i . As a common rule of thumb, if the VIF of a variable exceeds 10, which will happen if R_i^2 exceeds 0.90, the variable is said to be highly collinear, in other word the existence of severe multicollinearity (Gujarati, 2003).

VI. Empirical Results

In order to test the underlying hypothesis, this study at first estimates its empirical model for the entire sample (N=55 countries) and then divide them into high income OECD (N =23) and low and middle income developing countries (N=32) based on 2006 GNI per capita (World Bank 2006 classification) to examine the effect of R&D intensity as well as absorptive capacity on TFP growth in aggregate as well as individual group of countries over the period of 1970 to 2004 (T=35).

6.1. Graphical Representation

Prior to running the formal TFP growth regression (equation 2), this study can observe the following scatter diagram in Figure-1, which is a graphical representation of the relationship between initial (1970) distance to frontier or, autonomous technology transfer and average TFP growth over the period of 1970 to 2004 for the entire sample countries (55 countries).

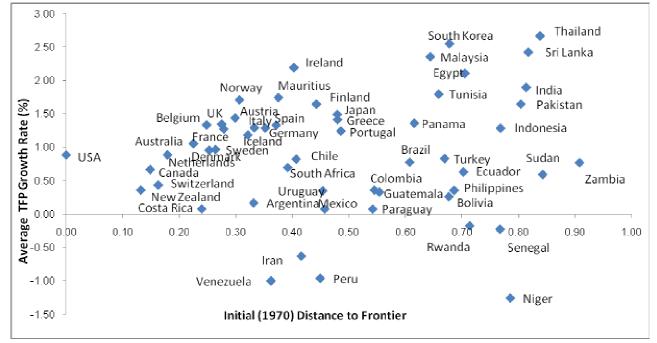


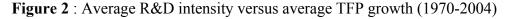
Figure 1: Initial distance to the frontier versus average TFP growth (1970-2004)

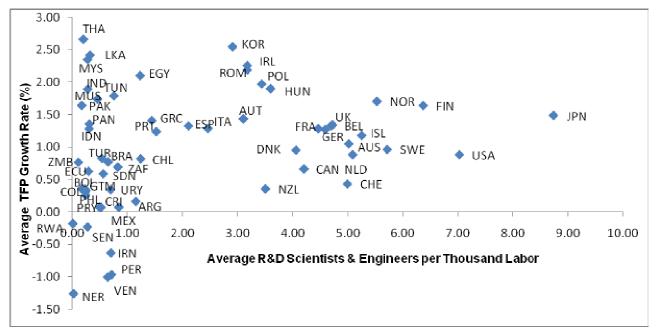
Notes: Initial distance to frontier is measured as the relative TFP gap between the US and sample countries in 1970.

Figure 1 clearly demonstrates a positive relation between initial distance to frontier and average TFP growth over the sample period and hence the empirical estimation is likely to support the evidence of technology convergence among sample countries. In other word, countries which are further behind from the technology frontier will have faster productivity growth. The above scatter plot gives some interesting observation about the possible variety of productivity growth experiences in the sample countries. Despite technologically backward initially (1970), Latin American countries like Venezuela and Peru, Sub-Saharan African countries such as, Niger,

Rwanda and Senegal, and Asian country like Iran appear to be 'growth disasters' with no sign of taking off. Whereas East Asian countries like Thailand, Malaysia and South Korea appear to be 'growth miracles' with strong growth records over the last few decades. Growth improvements have also been observed in South Asian countries like India, Pakistan and Sri Lanka. Therefore, there is some evidence of productivity convergence and divergence among our sample countries.

Since technology transfer is complex and skill incentive process, the receiving country cannot adopt foreign technology costlessly, rather they should maintain domestic R&D investment to understand the foreign technology and adapt them in local condition (Griffith *et al.*, 2004 ; Howitt and Mayer-Foulkes, 2005).





Notes: R&D intensity in the figure is measured as the average share of scientists and engineers in the total labor force. Figure 2 plots the average R&D intensity, measured by the ratio of R&D scientists and engineers to labor, over the period of 1970-2004 against the average TFP growth over the same period. Such long averages may filter out transitional dynamics as well as cyclical fluctuations (Madsen, 2008a). The scatter diagram shows that more than 90% of total R&D intensity has been concentrated in high income OECD (especially in G-7) countries. Most of the developing countries have little investment in domestic R&D. The scatter plot demonstrates that apparently there is no clear relationship between R&D intensity and TFP growth in the OECD as well as developing countries.

Technology transfer may act as a force of convergence through absorptive capacity to the technologically laggard countries. By investing in domestic R&D, countries may increase their ability to absorb and understand the foreign technology and thereby raising the speed of technology transfer (Griffith *et al.*, 2003; Howitt, 2000).

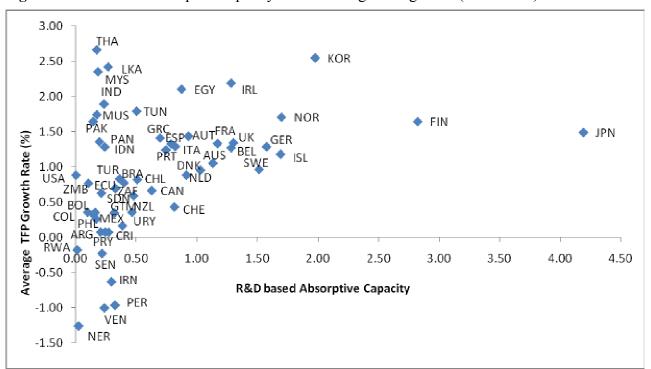
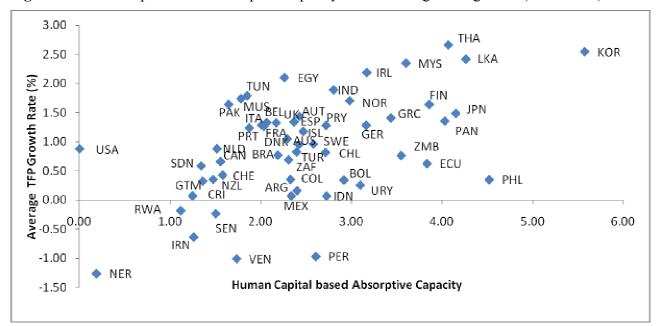


Figure 3: R&D-based absorptive capacity versus average TFP growth (1970-2004)

Notes: R&D intensity in the figure is measured as the average share of scientists and engineers in the total labor force. Figure 3 plots scatter diagram of the interaction between R&D based innovation and initial distance to frontier against average TFP Growth over the period of 1970 to 2004 for our entire sample. The scatter plot shows that the standard specification is unlikely to yield any systematic relationship between TFP growth and R&D-based absorptive capacity for very low values of the interaction between R&D intensity and the distance to the frontier. There is, however, some positive correlation for higher values of the interaction between R&D intensity and the distance to the frontier. Since the countries with low levels of interaction between R&D intensity and the distance to the frontier are also far from the frontier, the former result suggests that R&D has not played an important role for low income countries.

The level of human capital in a country may increase its ability to adopt the already existed knowledge more appropriately (Nelson and Phelps, 1966). Therefore, absorptive capacity in Nelson and Phelps' model is assumed to be a function of human capital. Human capital is measured by the average years of schooling in the population aged 25 and over. Figure 4 plots the interaction between human capital, measured by average years of schooling and initial distance to frontier, against the average TFP growth over 1970-2004. Both the developing and OECD countries are likely to exhibit positive relation between productivity growth and human capital based absorption. The high-growth Asian countries have experienced high growth rates in conjunction with initially large distances to the frontier and a reasonably highly educated labor force. The opposite holds true

for many African and Latin American countries. A complete scatter plot matrix for our alternative measures of R&D intensity as well as absorptive capacity is shown in Figure A1 in the appendix. There is no evidence of significant outliers that may distort the empirical results in this study. **Figure 4**: Human capital-based absorptive capacity versus average TFP growth (1970-2004)



Notes: Human capital is measured as the average years of schooling in the total population aged 25 and over.

In the empirical estimation, this study estimates TFP growth using unbalanced panel regression models for the entire (55 countries) as well as splitted (23 OECD & 32 developing countries) samples. It uses different panel estimators such as pooled OLS, fixed effects, and system GMM for robustness check. GMM results may suffer from small sample biases and thus it uses two stages least squares (2SLS) instrumental variable (IV) method for robustness check and found consistent result (not reported) though did not pass the heteroskedasticity tests. It also obtains similar results in both the difference and system GMM though the former did not satisfy second order serial correlation tests [AR(2)] in most of the specifications. Therefore, it concentrates on system GMM to reduce endogeneity problem. Both the fixed effects and system GMM estimators provide similar results with a very few exceptions and thus it has only reported the important results to save space. Empirical results which are mentioned in the paper but not reported will be provided on request. Although there are four alternative measures for innovation used in this study, scientists and engineers engaged in R&D are assumed to be the most representative one that directly relates to the innovative activities. Therefore, this study only reports empirical results based on R&D scientists and engineers while discussing the important findings. Results from the rest of the R&D indicators are shown in the appendix.

6.2. Panel Estimates

6.2.1. Pooled OLS estimates of TFP growth

Dependent Var.:	Total Factor	Productivity G	rowth $(\Delta \ln A_{it})$)						
Method/Period:	Pooled OLS	/1970-2004								
R&D Proxy:	Domestic Scientists & Engineers engaged in R&D (N)									
Sample:	Total (55 C	ountries)	OECD Cou	untries (23)	Developing Countries (32)					
R&D Intensity:	N/L	N/LA	N/L	N/LA	N/L	N/LA				
(X/Q) _{it}	0.01***	0.06***	0.05**	0.030**	0.03*	0.16				
	(4.52)	(4.50)	(2.22)	(2.06)	(1.67)	(1.51)				
DTF i,t-1	0.17***	0.17***	0.18***	0.18***	0.24***	0.23***				
y.	(4.01)	(3.98)	(3.49)	(3.35)	(3.58)	(3.55)				
SCH _{it}	0.04***	0.04***	-0.01	-0.01	0.040***	0.04***				
	(3.00)	(2.97)	(-0.43)	(-0.37)	(2.70)	(2.72)				
OP _{it}	0.05***	0.04***	0.03*	0.03	0.05**	0.05**				
	(3.24)	(3.24)	(1.66)	(1.62)	(2.55)	(2.52)				
FDI _{it}	0.74**	0.75**	0.53	0.53	0.99**	0.98**				
	(2.09)	(2.12)	(1.21)	(1.21)	(2.01)	(1.99)				
Constant	-0.23***	-0.23***	-0.01	-0.01	-0.30***	-0.29***				
	(-5.89)	(-5.84)	(-0.16)	(-0.17)	(-4.77)	(-4.74)				
R-Squared	0.23	0.23	0.17	0.17	0.26	0.27				
F-test [p-value]	0.00	0.00	0.00	0.00	0.00	0.00				
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes				
Observations	335	335	139	139	196	196				

TABLE 2. R&D Intensity, Distance to Frontier and TFP Growth (Pooled OLS): 1970-2004

Notes: (i) Variable specification is the same as illustrated in Table 1; (ii) X/Q represents R&D intensity measured by the ratio of domestic Scientists & Engineers engaged in R&D (N) to product varieties proxied by labor (L) or, productivity adjusted labor (LA) ; (iii) Figures in parentheses () are t-values significant at 1% level (***) or, 5% level (**) or, 10% level (*); (iv) F-test indicates joint significance test of the estimated coefficients; (v) Heteroscedasticity and Autocorrelation consistent (HAC) robust standard errors are obtained using the Newey-West procedure assuming a lag length of one; (vi) Time dummies are not reported for brevity.

Table 2 summarizes estimated results of TFP growth using pooled OLS for the entire as well as splitted samples. There are four different measures for innovations - R&D Scientists & Engineers, R&D expenditures, patents applications by residents and patents granted to residents-used in the estimation though results from only R&D Scientists & Engineers are reported here and the rests are shown in appendix (Table A3). GDP and employment are used to measure for product variety. Also productivity adjusted R&D Scientists & Engineers and R&D expenditures are used to allow for the increasing complexity with the economic advancement (Madsen 2008a). The estimated coefficient of domestic R&D intensity measured by R&D Scientists & Engineers is positive and statistically significant at the 1% level in the full sample, providing empirical support for the hypothesis of the Schumpeterian fully endogenous growth theories where R&D based innovation has significant positive effect on productivity growth. The estimated coefficients of R&D intensity are also significant in both the OECD and developing countries at the 5% and 10% levels respectively. Productivity adjusted R&D intensity is found significant in overall as well as OECD countries but

insignificant in developing countries. The estimated coefficients of distance to frontier are positive and statistically significant at the 1% level regardless of the country groups, implying the evidence of technology convergence among the sample countries. In other word, the further a country lies behind the technology frontier, the greater will be its potential to accelerate productivity growth. These results are consistent with the results of Griffith *et al.* (2003,2004) who provided microeconomic foundations for reduced –form equations for TFP growth using industry-level data and found R&D induced innovation and technology transfer are key sources of productivity growth.

There are three fundamental control variables used in this study, they are human capital, openness and inflow of FDI. Human capital shows positive and significant effect on TFP growth at the 1% level in the full as well as developing countries. The significance of human capital disappears in OECD countries, which is consistent with the argument of Krueger and Lindahl (2001) that there is no significant relation between initial schooling and subsequent growth in developed countries. The estimated results remain very similar while considering secondary school enrolment ratio as an alternative indicator for human capital. The rest of the two control variables-openness and FDI inflow- show consistent and significant positive effect on productivity growth at the conventional level in the full and developing countries. Openness is found weakly significant at the 10% level, whereas FDI inflow produces insignificant effect on TFP growth in OECD countries. The rest of the measures for innovation (R&D expenditures, patents applications and patents granted) exhibit similar findings as stated in Table 2 except the effects of R&D intensity becomes insignificant in both the OECD and developing countries (see appendix Table A3).

6.2.2. Fixed Effects Estimates of TFP growth

Pooled OLS estimator assumes that the omitted variables are independent of the regressors and are independently, identically distributed. Such estimation, however, can create problems of interpretation if country-specific characteristics, such as political regimes, policy changes, and so on that affect productivity, are not considered. If those omitted country-specific variables correlate with the explanatory variables, then pooled OLS may produce biased and inconsistent coefficient estimates (Hsiao, 1986). Therefore, this study allows for the presence of such time invariant omitted variables by including country specific fixed effects in the resgression model. Incorporating such fixed effects within the regression model, panel study may remove potential heteroskedasticity problems resulting from possible differences across countries (Green, 2000). It also uses robust standard errors to control for possible heteroskedasticity and autocorrelation. Finally, it includes time dummies in order to increase the reliability of the fixed effects estimation and control time specific fixed effects.

Dependent Var.:	Total Factor Productivity Growth ($\Delta \ln A_{it}$)								
Method/Period:	Fixed Effects	s/1970-2004							
R&D Proxy:		Domestic	Scientists & E	ngineers engag	ed in R&D (N)				
Sample:	Total (55 C	ountries)	OECD Cour	ntries (23)	Developing (Countries (32)			
R&D Intensity:	N/L	N/LA	N/L	N/LA	N/L	N/LA			
(X/Q) _{it}	0.01***	0.08***	0.0095***	0.053***	0.012	0.024			
	(3.61)	(3.53)	(4.05)	(3.85)	(0.42)	(0.16)			
DTF i,t-1	0.68***	0.67***	0.661***	0.654***	0.720***	0.717***			
-,	(6.03)	(5.95)	(5.81)	(5.83)	(4.71)	(4.64)			
SCH _{it}	0.06	0.06	0.108	0.103	0.125**	0.128**			
	(1.31)	(1.23)	(1.21)	(1.17)	(2.08)	(2.13)			
OP _{it}	0.11***	0.10***	0.133	0.132	0.098**	0.099**			
	(2.84)	(2.81)	(1.13)	(1.11)	(2.23)	(2.25)			
FDI _{it}	1.38***	1.39***	0.794**	0.806**	1.711***	1.688^{***}			
	(4.50)	(4.52)	(2.33)	(2.36)	(3.70)	(3.69)			
	-0.41***	-0.40***	-0.453**	-0.442**	-0.542***	-0.541***			
Constant	(-4.92)	(-4.87)	(-2.29)	(-2.26)	(-4.68)	(-4.65)			
R-Squared	0.33	0.33	0.55	0.55	0.35	0.35			
F-test [p-value]	0.00	0.00	0.000	0.000	0.000	0.000			
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes			
Country Dum.	Yes	Yes	Yes	Yes	Yes	Yes			
Observations	335	335	139	139	196	196			

TABLE 3. R&D Intensity, Distance to Frontier and TFP Growth (Fixed Effects): 1970-2004

Notes: : (i) Variable specification is the same as illustrated in Table 1; (ii) X/Q represents R&D intensity measured by the ratio of domestic Scientists & Engineers engaged in R&D (N) to product varieties proxied by labor (L) or, productivity adjusted labor (LA) ; (iii) Figures in parentheses () are t-values significant at 1% level (***) or, 5% level (**) or, 10% level (*); (iv) F-test indicates joint significance test of the estimated coefficients; (v) robust standard errors are used; (vi) Time and country dummies are not reported for brevity.

Table 3 illustrates estimated results of TFP growth for the entire as well as splitted samples using fixed effects estimator. The estimated coefficient of domestic R&D intensity is positive and statistically significant at the 1% level in full and OECD countries where research intensity is measured by Scientists & Engineers involved in R&D. This result supports to the Schumpeterian theories where it is assumed that the productivity growth is positively and significantly related to domestic research intensity (Aghion and Howitt, 1998 ; Madsen 2008a). None of the coefficients of local innovating activities are significant in developing countries. The estimated coefficients of the distance to frontier are positive and highly significant in all of the estimations. This is consistent with the argument of Griffith *et al.* (2003, 2004) and Aghion and Howitt (2006) that the countries those are further behind the technological frontier experience higher TFP growth provided that their local institutions are sufficiently developed and they have undertaken necessary R&D activities domestically. The estimated coefficients of human capital, openness and FDI inflow are found to be positive and statistically significant at the conventional level in developing countries, whereas only FDI inflow shows significant positive effect on productivity growth in OECD countries. The estimated results are quite similar to the rest of the measures for R&D intensity except R&D based

innovations become insignificant while measuring domestic innovation by number of patents granted to residents (see appendix Table A4).

6.2.3. System GMM Estimates of TFP growth

The possible endogeneity of the explanatory variables could create problem in estimating the fixed effects model. To account for this endogeneity problem this study estimates its panel model using Arellano and Bover (1995) and Blundell and Bond's (1998) system GMM that estimates a system of equations in both first-differences and levels, where the instruments used in the levels equations are lagged first-differences of the series. System GMM is widely used to deal with unobserved heterogeneity and endogeneity biases in the estimation (Beck *et al.*, 2000).

TABLE 4. R&D Intensity, Distance to Frontier and TFP Growth (System GMM): 1970-2004

Dependent Var.:	Total Factor	Productivity G	rowth ($\Delta \ln A_{it}$)				
Method/Period	System GMN	И/1970-2004					
R&D Proxy:		Domestic S	scientists & Er	igineers engag	ed in R&D (N)		
Sample:	Total (55 C	ountries)	OECD Cou	ntries (23)	Developing Countries (32)		
R&D Intensity:	N/L N/LA		N/L	N/LA	N/L	N/LA	
(X/Q) _{it}	0.019***	0.114***	0.017**	0.094**	0.081**	0.408**	
	(3.04)	(3.08)	(2.18)	(2.13)	(2.61)	(2.48)	
DTF i,t-1	0.342*	0.334*	0.807***	0.794***	0.657***	0.654***	
y.	(1.91)	(1.91)	(5.45)	(5.41)	(3.00)	(2.91)	
SCH _{it}	0.059	0.057	0.085	0.068	0.086*	0.090*	
	(1.20)	(1.16)	(0.64)	(0.52)	(1.82)	(1.87)	
OP _{it}	0.116***	0.116***	0.251*	0.253*	0.094**	0.094**	
	(2.76)	(2.78)	(1.71)	(1.70)	(2.55)	(2.49)	
FDI _{it}	0.384	0.413	0.757**	0.760*	0.199	0.192	
	(0.54)	(0.57)	(2.04)	(2.03)	(0.19)	(0.18)	
Constant	-0.426**	-0.419**	-0.681**	-0.634*	-0.685***	-0.688***	
	(-2.18)	(-2.18)	(-2.06)	(-1.96)	(-2.96)	(-2.92)	
F-test [p-value]	0.000	0.000	0.000	0.000	0.000	0.000	
Hansen [p-value]	0.310	0.321	0.999	0.998	0.754	0.968	
AR(1) [p-value]	0.000	0.000	0.000	0.000	0.000	0.000	
AR(2) [p-value]	0.342	0.339	0.678	0.764	0.139	0.135	
Observations	299	299	130	130	169	169	

Notes: (i) Variable specification is the same as illustrated in Table 1; ii) X/Q represents R&D intensity measured by the ratio of domestic Scientists & Engineers engaged in R&D (N) to product varieties proxied by labor (L) or, productivity adjusted labor (LA); (iii) Figures in parentheses () are t-values significant at 1% Level (***) or, 5% Level (**) or, 10% Level (*); (iv) F-test is the joint Significance tests of the estimated coefficients; (v) Hansen test measures the validity of the instruments where the null hypothesis is that the instruments are not correlated with the residuals; (vi) The null hypotheses in AR(1) and AR(2) tests are that the error terms in the first difference regression exhibit no 1st order and 2nd order serial correlation respectively; (vii) 2nd and 3rd lags of the explanatory variables are taken as instruments for the differenced equation, whereas 1st difference of the explanatory variables are taken as instruments for the level equation in the System GMM; (viii) Robust Standard Errors are used; (ix) Time dummies and country dummies are included but not reported.

Table 4 summarizes estimated results of TFP growth for the entire as well as splitted samples using system GMM estimator, where it satisfies all the standard tests such as, F-test for joint significance, Hansen's test for instrument validity, and AR(1) and AR(2) test for 1st order and 2nd order serial correlation test respectively. The estimated results obtained from the system GMM are similar to

those of the fixed effects. There are few exceptions. First, estimated coefficient of domestic R&D intensity measured by R&D Scientists & Engineers is positive and statistically significant at the 5% level in both the OECD and developing countries. This significance disappears when domestic research intensity is measured by R&D expenditure and patents granted to residents (Table A5). This result is consistent with the results of Madsen (2008a) who did not find any clear relationship between TFP growth and research intensity measured by R&D expenditure in OECD countries. Second, the degree of significance of estimated coefficients for human capital reduces from conventional level to 10% in developing countries. Third, both openness and FDI inflow show significant positive impact on productivity growth at the 10% level in OECD countries. Finally, FDI inflow is no more significant in developing countries. The estimated results using the rest of the R&D intensity measures are reported in the appendix (Table A5).

6.2.4. System GMM Estimates of TFP growth with Absorptive capacity

Countries may differ in their effort and ability to understand and adopt new technologies compatible to their local condition which is popularly known as 'absorptive capacity' (Arrow, 1969). Abromovitz (1986) and Nelson and Phelps (1966) assume that absorptive capacity depends on the level of human capital, whereas Fagerberg (1994) and Griffith *et al.* (2003, 2004) assume that the absorptive capacity is a function of domestic innovation activities.

Dependent Var.:	Total Factor Productivity Growth ($\Delta \ln A_{it}$)								
Method/Period	System GMN								
Proxies		Scientists & Engineers engaged in R&D (N) ; Average years of schooling for human capital (SCH)							
Sample:	Total (55 Co	/	OECD Cour	ntries (23)	Developing C	ountries (32)			
Absorp. Channel	R&D Human cap.		1		R&D	Human cap.			
	(N/L)	(SCH)	(N/L)	(SCH)	(N/L)	(SCH)			
$(X/Q)_{it}$	0.024*	0.013**	0.014	0.014**	0.072	0.085**			
	(1.88)	(2.60)	(0.91)	(2.17)	(-0.49)	(2.68)			
DTF _{i,t-1}	0.276	0.581*	0.789***	0.423	0.416*	0.409			
	(1.43)	(1.69)	(4.56)	(0.39)	(1.68)	(1.05)			
(X/Q) _{it} ×DTF _{i,t-1}	-0.019		0.013		0.270				
	(-0.58)		(0.30)		(1.10)				
SCH _{it}	0.035	0.151	0.118	0.378	0.074*	0.026			
	(0.68)	(1.27)	(0.94)	(0.22)	(1.85)	(0.16)			
SCH _{it} ×DTF _{i,t-1}		-0.175		0.236		0.057			
		(-1.02)		(0.44)		(0.29)			
Constant	-0.343	-0.557**	-0.751**	-0.615	-0.516**	-0.487			
	(-1.62)	(-2.03)	(-2.40)	(-1.58)	(-2.25)	(-1.38)			
F-test [p-value]	0.000	0.000	0.000	0.000	0.000	0.000			
Hansen [p-value]	[0.260]	[0.968]	[0.999]	[0.968]	[0.950]	[0.968]			
AR(1) [p-value]	0.000	0.000	0.000	0.000	0.000	0.000			
AR(2) [p-value]	[0.315]	[0.135]	[0.281]	[0.135]	[0.132]	[0.135]			
Observations	299	299	130	130	169	169			

TABLE 5. Absorptive Capacity and TFP Growth (System GMM): 1970-2004

Note: Same as stated in Table 4

Table 5 summarizes estimated results of TFP growth with absorptive capacity for the entire as well as splitted samples using system GMM estimators. The fixed effects results are very similar to those of GMM and hence reported in the appendix (Table A6). The estimated coefficients of both the R&D and human capital based absorptive capacity exhibit insignificant relation with productivity growth in all of the specifications suggesting that productivity growth is not clearly driven by the interaction between absorptive capacity and unconditional distance to frontier. This result is contradictory to the results of Griffith et al. (2003, 2004) who found positive and statistically significant relationship between R&D based absorptive capacity and TFP growth in their industrylevel analysis. Similar findings are also obtained for the rest of the measures for research intensities (see appendix Table A7). Interestingly, while incorporating interaction term between R&D intensity and distance to frontier in the regression, the independent R&D intensity indicator loses its significance. Since the correlation coefficient between the interaction term and the independent R&D intensity variable is very high (more than 80%), there is a possible multicollinearity problem in the estimated model. The similar incidence also found in the human capital channel. Therefore, it is necessary to examine the sensitivity of the estimated results of the absorptive capacity to the allowance of the distance to frontier as well as research intensity measures.

6.2.5. Sensitivity Analysis for Estimates of TFP growth with Absorptive capacity

Howitt (2000) argues that all countries engage in R&D will grow at the same rate in the long run. In Howitt's model TFP growth is positively related to R&D based absorptive capacity (i.e. the interaction between R&D intensity and distance to frontier), whereas both distance to frontier and R&D based absorptive capacity are positively related to productivity growth in Griffith *et al.*'s (2003, 2004) model that exclusively deal with disaggregated data. Since innovation models in new growth theories focus on interactions that are originally defined with respect to firms and industries, identification of such interaction effects may be problematic when the exclusive focus is on aggregate data (Aghion and Durlauf, 2007). Therefore, this study conducts sensitivity analysis of the estimates of TFP growth with absorptive capacity for the entire as well as splitted sample countries.

Table 6 summarizes results of the sensitivity analysis of growth regression with absorptive capacity for the entire sample using system GMM estimator. The fixed effects results are very similar to those of GMM and hence reported in the appendix (Table A8). The measure of R&D intensity has been limited to R&D Scientists & Engineers for brevity. This study follows iterative process including the potential regressors one by one into the regression model to examine the sensitivity of the estimated results while using interaction term.

Estimation Method:	System G	MM Intensity Cha	annal (Dama	atia DeDSa	iontists P- T	nginoona/La	har). N/I	Human Ca	nital Channal	(Awaraga Va	and of Sahaaling
Regression	(1) KaD	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(Average rea (10)	ars of Schooling (11)
Total Sample (55 Co		(-)	(0)	(-)	(0)	(0)	(')		(*)	(10)	(11)
(X/Q) _{it}	0.010** (2.54)			0.019*** (3.04)	0.005 (0.74)		0.024* (1.88)	0.033** (2.46)	0.018*** (2.95)	0.017*** (3.69)	0.013** (2.60)
DTF _{i,t-1}		0.723*** (3.56)		0.342* (1.91)		0.280* (1.80)	0.276 (1.43)		0.173** (2.37)		0.581* (1.69)
$(X/Q)_{it} \times DTF_{i,t-1}$			0.032** (2.41)		0.020 (0.82)	0.047** (2.58)	-0.019 (-0.58)				
SCH _{it}	-0.024 (-0.84)	0.064 (1.14)	-0.014 (-0.61)	0.059 (1.20)	-0.017 (-0.59)	0.076 (1.57)	0.035 (0.68)			-0.040** (-2.19)	0.151 (1.27)
$SCH_{it} \times DTF_{i,t-1}$								0.354*** (2.84)	0.031 (0.38)	0.109*** (2.75)	-0.175 (-1.02)
OECD Countries (23											
(X/Q) _{it}	0.019** (2.21)			0.017** (2.18)	-0.013 (-1.03)		0.014 (0.91)	0.016** (2.07)	0.017** (2.62)	0.016** (2.24)	0.014** (2.17)
DTF _{i,t-1}		0.769*** (4.18)		0.807*** (5.45)		0.773*** (4.96)	0.789*** (4.56)		0.495 (0.83)		0.423 (0.39)
$(X/Q)_{it} \times DTF_{i,t-1}$			0.080*** (3.33)		0.081** (2.21)	0.044** (2.28)	0.013 (0.30)				
SCH _{it}	-0.168 (-1.38)	0.104 (0.70)	-0.180 (-1.65)	0.085 (0.64)	-0.31*** (-4.11)	0.036 (0.30)	0.118 (0.94)			-0.103 (-0.89)	0.378 (0.22)
$SCH_{it} \times DTF_{i,t-1}$								0.411*** (4.37)	0.146 (0.47)	0.357*** (4.45)	0.236 (0.44)
Developing Countrie	s (32)							•			
(X/Q) _{it}	0.039* (1.74)			0.081** (2.61)	-0.227** (-2.64)		0.072 (-0.49)	0.080 (1.19)	0.088** (2.62)	0.094*** (2.78)	0.085** (2.68)
DTF i,t-1		0.811*** (3.31)		0.657*** (3.00)		0632** (2.74)	0.416* (1.68)		0.445*** (3.00)		0.409 (1.05)
$(X/Q)_{it} \times DTF_{i,t-1}$			0.115** (2.26)		0.488*** (2.99)	0.149*** (2.77)	0.270 (1.10)				
SCH _{it}	-0.003 (-0.16)	0.103* (1.94)	-0.015 (-0.41)	0.086* (1.82)	0.028 (1.08)	0.096* (1.92)	0.074* (1.85)			-0.160** (-2.27)	0.026 (0.16)
$SCH_{it} \times DTF_{i,t-1}$. ,	0.335*** (2.75)	0.153* (1.89)	0.295** (2.17)	0.057 (0.29)

TABLE 6. R&D Intensity, Distance, Absorptive Capacity and TFP Growth (System GMM): 1970-2004

Note: (i) Variable specification is the same as illustrated in Table 1; (ii) X/Q represents R&D intensity measured by the ratio of domestic R&D scientists and engineers (N) to labor (L); (iii) Figures in parentheses () are t-values significant at 1% Level (***) or, 5% Level (**) or, 10% Level (*); (iv)Human capital is measured by the average years of schooling in the Population Aged 25 years and over (*SCH*); (v) Constants and other control variables such as, OP and FDI are not reported due to space conservation; (vi) Time and country dummies are included but not reported for brevity; (vii) Robust standard errors are used (viii) Estimated results from system GMM satisfy all of the relevant diagnostic tests such as F-test, Hansen test, AR(1) and AR(2) tests. The p-values of those tests are not reported for brevity.

R&D based innovation appears to be significant in full, OECD and developing countries but it becomes insignificant when absorptive capacity or, the interaction between R&D intensity and distance to frontier is included in the regression. The estimated coefficients of distance to frontier are strongly significant independently as well as with the interaction terms. Also distance to frontier is found to have smaller correlation (less than 0.40) with interaction terms (see appendix Table A1). Therefore, there is less likely to have multicollinireaty problem between the interaction term and the distance to frontier. Since coefficient of research intensity loses its significance after including the interaction term and both of them show high pair-wise correlation (more than 0.80), the estimated results are more likely to be affected by multicollinearity.

Finally, when productivity growth is regressed only on R&D based absorptive capacity (i.e. interaction between R&D Scientists & Engineers and distance to frontier) as prescribed by Howitt (2000), the estimated coefficients of the interaction term become positive and significant at the 5% level in full, OECD and developing countries. This is consistent with the argument of Howitt (2000) that all countries engage in R&D will grow at the same rate in the long run. The similar results also found for human capital based absorptive capacity though the direct effect of human capital is found insignificant in OECD countries. This is consistent with the argument of Nelson and Phelps (1966) that the rate at which technological latecomers realize technology improvements made in technologically developed countries is a positive function of their human capital and proportional to the gap between the technology frontier and their own.

Considering Howitt (2000) model for R&D based absorptive capacity and Nelson and Phelps (1966) model for human capital based absorptive capacity, this study also compares results between fixed effects and system GMM in estimating TFP growth with absorptive capacity using the rest three measures for research intensities (R&D expenditure, patents application by residents and patents granted to residents) and the estimated results are reported in the appendix Table A9. The fixed effects results are found different from system GMM while considering absorption through R&D intensity channel. Since system GMM estimator can successfully handle unobserved country specific effects and endogeneity problem, it is wise to concentrate on results estimated from system GMM. After dropping their individual effects, the interaction between research intensity and distance to frontier does not show any significant effect on productivity growth in the rest three R&D intensity proxies, implying that R&D based absorptive capacity channel is not robust in developing countries though it

shows significant support while research intensity is measured by R&D scientists and engineers. The channel is found robust in OECD countries. While using the rest three indicators for research intensity as control variables, the interaction between human capital and distance to frontier is found to have positive and consistently significant effect on TFP growth at the 1% level in both the OECD and developing countries, indicating that human capital channel for absorption is robust in those economies. The results are consistent with the argument of Benhabib and Spiegel (1994, 2005) that human capital affects TFP growth through influence on the rate of technological catch up. The direct effect of human capital on productivity growth is less robust.

In sum, the R&D based absorptive capacity is significant in developing countries only when research intensity is measured by R&D scientists and engineers and therefore, the effectiveness of R&D based absorptive capacity is not robust for the developing countries. While running the growth regression only on human capital based absorptive capacity (i.e. interaction between human capital and distance to frontier), the estimated coefficients of the interaction terms become significant in most specifications with their expected positive sign in both the OECD and developing countries. Results from this sensitivity analysis suggest that multicollinearity may play an important role in the earlier estimation of growth regression with absorptive capacity (see Table 6 & A8). This is consistent with the argument of Madsen (2008a) that the empirical results for absorptive capacity are sensitive to model specification and the measurement of innovative activity and measurement of product variety where multicollinearity has played an important role in the empirical estimations.

VII. Concluding Remarks

The role of R&D based innovation in promoting total factor productivity (TFP) growth has recently become a major subject for empirical research in the line of Schumpeterian version of the second generation endogenous growth theory (Griffith *et al.*, 2003, 2004; Ha and Howitt, 2007; Ulku, 2007a; Madsen, 2008a). The empirical findings as well as theoretical developments in endogenous growth models have not gone unanimously. Almost all of the empirical studies till today focus on industrially developed OECD countries where substantial level of R&D investment has already been well documented. Since developing countries are latecomers, they may have potential to catch up the technology leader through R&D based innovation, technology transfer and diffusion of existing technology. Therefore, this study

aims to examine the empirical relationship between R&D intensity and TFP growth in the line of the Schumpeterian fully endogenous growth theory for a panel of 55 countries consisting of 23 high income OECD and 32 low and middle income developing countries over the period of 1970 to 2004. Furthermore, it tries to investigate the role of autonomous technology transfer as well as R&D based technology transfer to accelerate TFP growth. Finally, it examines the effects of human capital based absorptive capacity on productivity growth. It uses four alternative measures for R&D intensity and applies three different estimators, such as pooled OLS, fixed effects and system GMM based on their relevant justifications. It produces consistent results in different panel estimators and therefore its estimated results are robust and not likely to be induced by unobserved country specific effects, endogeneity, simultaneity, and omitted variables biases.

The empirical results in this study find the evidence that Schumpeterian fully endogenous growth theory can account for TFP growth for both the OECD and developing countries. Domestic research intensity as well as R&D based absorptive capacity, to a large extent, shows significant positive effect on productivity growth over time across those economies. Distance to frontier has positive and significant relation with productivity growth which is also consistent with the prediction of Schumpeterian theory. Autonomous technology transfer is found to have significant positive effect on TFP growth regardless of applying different estimators and specifications, implying that the countries that are far behind the technological frontier experience higher TFP growth. In estimating absorptive capacity, this study follows two alternative models proposed by Griffith et al. (2003, 2004) and Howitt (2000). The former model is based exclusively on disaggregated data, whereas our estimations consider macro-level aggregated data.¹⁴ It does not find any significant effect of absorptive capacity on productivity growth in any of the specifications while using Griffith's model. High degree of correlation between research intensity and its interaction with distance to frontier may be responsible for these insignificant results. R&D based absorptive capacity seems to enhance productivity growth in both the OECD and developing countries though not robust in the later group, while using Howitt's model to estimate the effects of absorptive capacity.¹⁵

¹⁴Innovation models in new growth theories focus on interactions that are originally defined with respect to firms and industries and therefore, identification of such interaction effects may be problematic when the exclusive focus is on aggregate data (Aghion and Durlauf, 2007).

¹⁵ If the growth in TFP is regressed on R&D based absorptive capacity as the only regressor together with country dummies, the estimated coefficients of R&D based absorptive capacity becomes highly significant, suggesting that multicollinearity has played an important role in the estimates where productivity growth is

Similarly, human capital based technology transfer is found significant and robust in both the OECD and developing countries while using Nelson and Phelps (1966) model to estimate human capital based absorptive capacity.

However, human capital accumulation itself is found to have significant positive impact on TFP growth in developing countries, justifying the influential role of human capital to accelerate productivity growth in those economies. The significance of human capital disappears when considering OECD countries and this result is consistent with the argument of Krueger and Lindhal (2001) that education is statistically significant and positively associated with growth only for the countries with low level of human capital. Trade openness shows significant positive effect on TFP growth in developing countries, whereas both trade openness and FDI inflow seem to enhance productivity growth in OECD countries.

While the findings of this study are more or less encouraging, some caveats are in order. An inherent problem with panel data is that there is potential heterogeneity while one is observing a relationship across countries. Although this study tries to control for many of these variables, it cannot rule out the possibility of country specific effects due to omitted variables. Another limitation is the narrow database for R&D intensity indicators particularly for developing countries, where missing observation is a common phenomenon. Therefore, interpolating missing data may not represent the true variation of the research intensity over time across those developing countries. One must be careful while drawing policy implications on the basis of such cross-country empirical analysis. General findings from this study may not be effective for each and every member countries in the group. Therefore, any policy lesson should be supported by more detailed investigations and case studies of the individual countries.

To conclude, empirical results of this study demonstrate that Schumpeterian fully endogenous growth theory can adequately account for the TFP growth for both the OECD and developing countries over time and across countries. Its findings are, to a large extent, consistent to Schumpeterian growth theory: (i) differences in domestic research intensity can account for the differences in TFP growth and (ii) distance to technology frontier is positively related to

regressed on R&D intensity, distance to frontier and absorptive capacity (interaction between R&D intensity and distance to frontier) and produce less significant estimated coefficients for absorptive capacity. The results may be sensitive to the model specification and measurement of innovative activity as well as product variety (Madsen, 2008a)

TFP growth. Furthermore, research intensity and human capital are found important for technology transfer through the channel of absorptive capacity across those economies. Absorptive capacity may be sensitive to the model specification and measurement of innovation. However, recent versions of Schumpeterian theory also assume that the rate of technological progress in one country depends not only on domestic innovations but also on international technology spillovers resulting from innovation in other countries (Howitt, 2005). Technology is embodied in capital and intermediate goods and therefore the direct import of these goods is one of the important channels for international technology spillovers (Grossman and Helpman, 1991b; Coe and Helpman, 1995). Therefore, investigating cross-country technology spillovers could be a scope for further research.

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Appendix

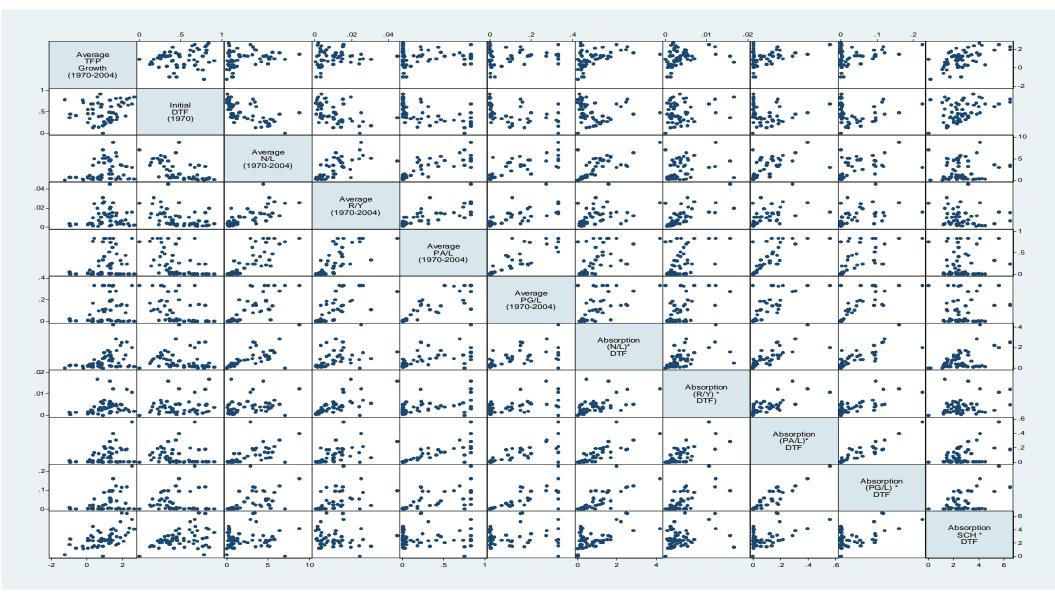
Table A1. Variable Sources and Definitions
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Variable	Source and Definition
ΔlnA	Total Factor Productivity Growth is calculated from the 6.2 version of the Penn World Table (PWT6.2-
	Heston, Summers and Aten ,2006) available at, <u>http://pwt.econ.upenn.edu/php_site/pwt_index.php</u>
	R&D scientists and engineers based innovation measured by the ratio of R&D scientists and
N/L	engineers(N) to total labor force (L), taken from the UNESCO Statistical Yearbook (various issues) and
	also from the concerned website at, $\underline{http://stats.uis.unesco.org/unesco/ReportFolders/ReportFolders.aspx}$
	R&D expenditure based innovation measured by the ratio of R&D expenditure (R) to GDP (Y), taken
R/Y	from the UNESCO Statistical Yearbook (various issues) and also from the concerned website at,
	http://stats.uis.unesco.org/unesco/ReportFolders/ReportFolders.aspx
	Patent (application) based innovation measured by the ratio of patent applications by the residents (PA)
PA/L	to total labor force (L), taken from the "Industrial Property Statistics" of The World Intellectual Property
	Organization's (WIPO) website at, http://www.wipo.int/ipstats/en/statistics/patents/
	Patent (granted) based innovation measured by the ratio of patent granted to the residents (PG) to total
PG/L	labor force (L), taken from the "Industrial Property Statistics" of The World Intellectual Property
	Organization's (WIPO) website at, http://www.wipo.int/ipstats/en/statistics/patents/
	Autonomous Technology Transfer measured by the ratio of the distance from the technology frontier to
	the frontier's technology $[(A^{max}-A)/A^{max}]$, taken from productivity growth (ΔlnA) calculation as stated
DTF	above. Being the technology leader as well as the major trading partner of most of the countries, the US
	technology is assumed here as the world technological frontier (A ^{max}).
SCH	Average years of schooling in the population aged 25 years and over , collected from Barro and Lee
	(2001) schooling database.
	R&D scientists and engineers based absorptive capacity measured by the interaction between R& D
(N/L) ×DTF	scientists and engineers based innovation (N/L) and the distance to technological frontier (DTF).
(R/Y)×DTF	R&D expenditure based absorptive capacity measured by the interaction between R/Y and DTF
(PA/L)×DTF	Patent (application) based absorptive capacity measured by the interaction between PA/L and DTF
(PG/L)×DTF	Patent (granted) based absorptive capacity measured by the interaction between PG/L and DTF
SCH×DTF	Human capital based absorptive capacity measured by the interaction between SCH and DTF
SEC	Secondary school enrolment ratio (as an alternative schooling data), taken from the World Development
	Indicators (WDI) 2006 online database.
	Trade Openness measured by the ratio of the sum of total exports and imports to GDP, taken from the
OP	World Development Indicators (WDI) 2006 online database.
	Inflow of Foreign Direct Investment (FDI) measured by the ratio of foreign direct investment (FDI)
FDI	inflow to GDP, taken from the International Financial Statistics (IFS) 2006 CD-ROM.

]	Table A2.	Correlatio	on Matrix: 1	970-2004					
	ΔlnA	DTF	N/L	R/Y	PA/L	PG/L	(N/L) ×DTF	(R/Y) ×DTF	(PA/L) ×DTF	(PG/L) ×DTF	SCH×DTF	SCH	ОР	FDI
Total Sample (55		DIF	IN/L	N / I	TA/L	FG/L	^DIF	^DIF	^DIF	^D1F	SCH^DIF	scn	Or	гл
ΔlnA	1.000													
DTF	0.024	1.000												
			1 000											
N/L	0.097	-0.672*	1.000											
R/Y	0.055	-0.159*	0.051	1.000										
PA/L	0.080	-0.650*	0.758*	-0.100	1.000									
PG/L	0.074	-0.623*	0.729*	0.006	0.871*	1.000								
(N/L) ×DTF	0.153*	-0.358*	0.824*	0.059	0.605*	0.548*	1.000							
$(R/Y) \times DTF$	0.072	-0.073	-0.011	0.954*	-0.115	-0.034	0.054	1.000						
(PA/L) ×DTF	0.141*	-0.391*	0.619*	-0.061	0.860*	0.730*	0.751*	-0.050	1.000					
(PG/L) ×DTF	0.128*	-0.356*	0.589*	0.050	0.758*	0.843*	0.708*	0.049	0.896*	1.000				
SCH×DTF	0.164*	0.370*	-0.240*	-0.098	-0.377*	-0.391*	0.031	-0.026	-0.087	-0.091	1.000			
SCH	0.117*	-0.702*	0.595*	0.061	0.674*	0.588*	0.446*	0.014	0.529*	0.450*	0.351*	1.000		
OP	0.132*	-0.167*	0.096	0.037	-0.025	-0.032	0.050	-0.043	-0.027	-0.043	0.116*	0.258*	1.000	
FDI	0.163*	-0.058	0.113*	0.005	0.040	0.024	0.103	-0.013	0.013	0.015	0.2022*	0.243*	0.431*	1.000
OECD Countries	(23)													
ΔlnA	1.000	0.365*	-0.043	0.046	-0.040	-0.098	0.163*	0.087	0.164*	0.080	0.343*	-0.155*	0.101	0.249*
DTF		1.000	-0.286*	0.254*	-0.116	-0.184*	0.350*	0.363*	0.422*	0.329*	0.929*	-0.474*	-0.096	-0.089
N/L			1.000	-0.293*	0.457*	0.489*	0.722*	-0.324*	0.295*	0.344*	-0.089	0.611*	0.048	0.251*
R/Y				1.000	-0.486*	-0.296*	-0.143	0.952*	-0.298*	-0.173*	0.121	-0.430*	0.037	0.026
PA/L					1.000	0.768*	0.410*	-0.434*	0.769*	0.657*	0.062	0.500*	-0.301*	-0.033
Developing Count	tries (32)													
ΔlnA	1.000	0.158*	-0.041	-0.017	-0.086	-0.058	0.058	0.022	-0.027	-0.014	0.188*	0.071	0.127	0.138*
DTF		1.000	-0.444*	-0.081	-0.518*	-0.421*	-0.152*	0.028	-0.446*	-0.359*	0.044	-0.476*	-0.151*	-0.040
N/L			1.000	0.033	0.365*	0.342*	0.927*	-0.002	0.398*	0.378*	0.090	0.345*	-0.067	0.017
R/Y				1.000	0.128	0.230*	0.008	0.968*	0.133	0.211*	-0.101	-0.011	-0.095	-0.056
PA/L					1.000	0.892*	0.152	0.076	0.972*	0.869*	-0.237*	0.231*	-0.195*	-0.136

Notes: (i) Variable Specifications: $\Delta ln A =$ Total Factor Productivity Growth, DTF = Distance to Frontier measured by the relative TFP gap between the US (A^{max}) and the sample countries (A_i) [i.e. { $(A^{max}-A_i)/A^{max}$ }_{t-1}], N/L = R&D Scientists and Engineers/Labor (in thousands), R/Y = R&D Expenditures/GDP (in percentage), PA/L= Patent Applications by Residents/Labor (in thousands), PG/L= Patent Granted to Residents/Labor (in thousands), SCH = (log) Average Years of Schooling in the Population Aged 25 years and over, OP = Trade Openness = (Export+Import)/GDP and FDI = Foreign Direct Investment Inflows/GDP ; (ii) Estimation period is 1970-2004; (iii) The period 2000-2004 is used for the last observation; (iv) TFP growth (ΔlnA) is calculated in 5-year differences; (v) Research intensity (N/L or, R/Y or, PA/L or, PG/L) is measured in 5-year averages; (vi) Distance to technology frontier (DTF) is measured in 5-year lags; and (vii) Control variables such as OP and FDI are measured in 5-year averages in the interval over which the 5-year differences have been considered to estimate productivity growth; and (viii) One asterisk (*) indicates 5% level of significance.

Figure A1. Scatterplot Matrix for Total Sample (55 Countries): 1970-2004



Note: Variable specification is the same as mentioned in Table A2

Dependent Variable:		Productivity Grov	wth $(\Delta \ln A_{it})$					
Estimation Method/Sample Period:	Pooled OLS		F P	D				
R&D Indicators:		Domestic R&D		Patents Applications (PA)		Patents Granted (PG)		
R&D Intensity Measures:	R/Y	(t-value)	R/LA	(t-value)	PA/L	(t-value)	PG/L	(t-value)
Total Sample (55 Countries)								
$(X/Q)_{it}$	0.024*	(1.81)	0.04*	(1.83)	0.08***	(3.69)	0.16***	(3.45)
DTF _{i,t-1}	0.10**	(2.35)	0.11**	(2.37)	0.12***	(2.71)	0.12**	(2.37)
SCH _{it}	0.04*	(2.03)	0.04**	(2.06)	-0.01	(-0.01)	0.011	(0.50)
OP _{it}	0.03**	(2.44)	0.04**	(2.40)	0.07***	(3.66)	0.06***	(3.55)
FDI _{it}	0.37	(0.94)	0.38	(0.94)	0.45*	(1.26)	0.43	(1.06)
R-Squared	0.17		0.17		0.20		0.19	
Observations	283		282		298		279	
OECD Countries (23)								
(X/Q) _{it}	-0.018	(-0.20)	-0.095	(-1.21)	0.010	(0.52)	0.022	(0.67)
DTF _{i.t-1}	0.18***	(3.21)	0.181***	(3.02)	0.173***	(2.88)	0.184***	(3.26)
SCH _{it}	0.001	(0.05)	-0.001	(-0.06)	0.004	(0.15)	-0.001	(-0.01)
OP _{it}	0.025	(1.36)	0.036*	(1.66)	0.031	(1.46)	0.028	(1.42)
FDI _{it}	0.554	(1.24)	0.556	(1.26)	0.494	(1.10)	0.585	(1.31)
R-Squared	0.20		0.23		0.17		0.19	
Observations	137		128		138		136	
Developing Countries (32)								
(X/Q) _{it}	0.064	(0.16)	-0.226	(-1.31)	0.265	(1.05)	0.485	(0.56)
DTF _{i,t-1}	0.18**	(2.42)	0.181**	(2.43)	0.208**	(2.53)	0.193**	(2.18)
SCH _{it}	0.033	(1.26)	0.031	(1.12)	-0.012	(-0.47)	-0.010	(-0.37)
OP _{it}	0.046*	(1.96)	0.045*	(1.89)	0.071**	(2.40)	0.067**	(2.15)
FDI _{it}	0.187	(0.38)	0.188	(0.33)	0.595	(0.87)	0.510	(0.67)
R-Squared	0.21		0.22		0.25		0.25	
Observations	146		142		160		143	

Notes: (i) Variable specification is the same as illustrated in Table A2; (ii) Figures in parentheses () are t-values significant at 1% Level (***) or, 5% Level (**) or, 10% Level (*); (iii) X/Q represents R&D intensity measured by the ratio of innovative activities (R for domestic R&D expenditure or, PA for patents applications or, PG for patents granted) to product varieties proxied by GDP (Y) or, labor (L) or, productivity adjusted labor (LA); (iv) Constants are not reported due to space conservation; (v) Time dummies are included but not reported for brevity; (vi) Heteroscedasticity and Autocorrelation consistent (HAC) robust standard errors are obtained using the Newey-West procedure assuming a lag length of one.

Dependent Variable:		Productivity Grow	wth ($\Delta ln A_{it}$)					
Estimation Method/Sample Period:	Fixed Effect							
R&D Indicators:		Domestic R&D	Expenditures (Patents Ap	plications (PA)	Patents Granted (PG)	
R&D Intensity Measures:	R/Y	(t-value)	R/LA	(t-value)	PA/L	(t-value)	PG/L	(t-value)
Total Sample (55 Countries)								
(X/Q) _{it}	0.032**	(2.10)	-0.418	(-0.69)	0.103**	(2.37)	0.065	(0.99)
DTF _{i,t-1}	0.603***	(3.93)	0.644***	(3.92)	0.669***	(5.02)	0.653***	(4.70)
SCH _{it}	0.052	(0.85)	0.088	(1.02)	-0.004	(-0.07)	-0.011	(-0.13)
OP _{it}	0.038	(0.71)	0.074	(1.33)	0.118**	(2.06)	0.137**	(2.34)
FDI _{it}	1.16***	(3.22)	1.22***	(3.18)	1.265***	(3.82)	1.181***	(3.35)
R-Squared	0.30		0.32		0.33		0.33	
Observations	283		269		298		279	
OECD Countries (23)								
$(X/Q)_{it}$	0.228*	(1.93)	-0.109	(-0.23)	0.069**	(2.52)	0.073	(1.50)
DTF _{i.t-1}	0.67***	(6.09)	0.632***	(5.00)	0.764***	(5.87)	0.761***	(6.06)
SCH _{it}	0.152	(1.56)	0.175	(1.41)	0.124	(1.47)	0.180*	(2.00)
OP _{it}	0.112	(0.94)	0.138	(1.18)	0.132	(1.11)	0.112	(0.97)
FDI _{it}	0.930**	(2.48)	1.1273***	(2.86)	0.986***	(2.84)	0.977**	(2.58)
R-Squared	0.53		0.55		0.54		0.53	
Observations	137		128		138		136	
Developing Countries (32)								
(X/Q) _{it}	-0.047	(-0.18)	-0.343	(-0.58)	0.761	(0.91)	0.933	(0.66)
DTF _{i,t-1}	0.67***	(3.34)	0.735***	(3.64)	0.77***	(5.02)	0.79***	(4.48)
SCH _{it}	0.182**	(2.28)	0.203**	(2.38)	0.082	(0.85)	0.110	(0.91)
OP _{it}	0.004	(0.08)	0.038	(0.62)	0.085**	(1.29)	0.121*	(1.77)
FDI _{it}	0.675	(1.44)	0.670	(1.26)	1.523**	(2.23)	1.511*	(1.75)
R-Squared	0.33	·	0.35		0.36		0.38	
Observations	146		142		160		143	

TABLE A4. R&D Intensity.	Distance to Frontier and TFP	Growth (Fixed Effects):	1970-2004

Notes: (i) Variable specification is the same as illustrated in Table A2; (ii) Figures in parentheses () are t-values significant at 1% Level (***) or, 5% Level (**) or, 10% Level (*); (iii) X/Q represents R&D intensity measured by the ratio of innovative activities (R for domestic R&D expenditure or, PA for patents applications or, PG for patents granted) to product varieties proxied by GDP (Y) or, labor (L) or, productivity adjusted labor (LA); (iv) Constants are not reported due to space conservation; (v) Time and country dummies are included but not reported for brevity; (vi) Robust standard errors are used.

Dependent Variable: Estimation Method/Sample Period:	Total Factor Productivity Growth (ΔlnA _{it}) System GMM/1970-2004								
R&D Indicators:	System GMI	Domestic R&D	Expenditures	(R)	Patents Ap	plications (PA)	Patents (Patents Granted (PG)	
R&D Intensity Measures:	R/Y	(t-value)	R/LA	(t-value)	PA/L	(t-value)	PG/L	(t-value)	
Total Sample (55 Countries)									
$(X/Q)_{it}$	0.031**	(2.11)	-0.060	(-0.42)	0.190**	(2.02)	0.136	(1.11)	
DTF _{i,t-1}	0.120*	(1.62)	0.077	(0.89)	0.321**	(2.41)	0.100	(0.79)	
SCH _{it}	0.055	(1.37)	0.038	(0.84	0.034	(0.51)	0.012	(0.20)	
OP _{it}	0.045*	(1.84)	0.053**	(2.01)	0.141**	(2.11)	0.130**	(2.10)	
FDI _{it}	0.210	(0.45)	0.184	(0.36)	1.513**	(2.18)	1.403*	(1.85)	
Hansen Test [p-value]	0.999		1.000		0.400		0.414		
AR(2) Test [p-value]	0.224		0.152		0.171		0.565		
OECD Countries (23)									
$(X/Q)_{it}$	0.921	(1.47)	-0.065	(-1.05)	0.088**	(2.74)	0.124**	(2.19)	
DTF _{i.t-1}	0.885***	(4.39)	0.191***	(3.15)	0.991***	(3.85)	0.905***	(4.24)	
SCH _{it}	0.202	(1.26)	0.006	(0.21)	0.115	(0.75)	0.176	(1.01)	
OP _{it}	0.280*	(1.84)	0.021	(0.72)	0.283*	(1.95)	0.197	(1.37)	
FDI _{it}	0.937**	(2.15)	0.697	(1.64)	0.749**	(2.30)	1.029**	(2.60)	
Hansen Test [p-value]	0.999		1.000		0.999		1.000		
AR(2) Test [p-value]	0.967		0.182		0.952		0.804		
Developing Countries (32)									
$(X/Q)_{it}$	-0.124	(-0.13)	-0.222	(-0.58)	0.470**	(2.20)	0.335	(0.89)	
DTF _{i,t-1}	0.698***	(3.24)	0.365**	(2.53)	1.140***	(3.24)	0.721***	(2.73)	
SCH _{it}	0.143	(1.53)	0.042	(0.79)	0.044	(0.38)	0.111	(0.92)	
OP _{it}	0.067	(1.12)	0.059	(1.36)	0.125	(1.54)	0.067	(1.00)	
FDI _{it}	0.320	(0.23)	0.131	(0.10)	0.306	(0.23)	1.643	(1.32)	
Hansen Test [p-value]	0.970		0.999		0.899		0.987		
AR(2) Test [p-value]	0.090		0.084		0.304		0.518		

TABLE A5. R&D Intensity, Distance to Frontier and TFP Growth (System GMM): 1970-2004

Notes: (i) Variable specification is the same as illustrated in Table A2; (ii) Figures in parentheses () are t-values significant at 1% Level (***) or, 5% Level (**) or, 10% Level (*); (iii) X/Q represents R&D intensity measured by the ratio of innovative activities (R for domestic R&D expenditure or, PA for patents applications or, PG for patents granted) to product varieties proxied by GDP (Y) or, labor (L) or, productivity adjusted labor (LA); (iv) Hansen test measures the validity of the instruments where the null hypothesis is that the instruments are not correlated with the residuals ; (v) The null hypotheses in AR(2) tests are that the error terms in the first difference regression exhibit no 2^{nd} order serial correlation ; (vi) 2^{nd} and 3^{rd} lags of the explanatory variables are taken as instruments for the differenced equation, whereas 1^{st} difference of the explanatory variables are taken as instruments for the level equation in the System GMM ; (vii) Constants are not reported due to space conservation; (viii) Time and country dummies are included but not reported for brevity; (ix) Robust standard errors are used .

Dependent Variable: Estimation Method:	Total Factor Productivity Growth (ΔlnA _{it}) Fixed Effects/1970-2004											
R&D Indicators:				neers (N)	Domestic R&D Expenditures (R)				Patent Applications by Residents (PA)			
Absorptive Capacity	DomesticR&DScientists & Engineers (N)R&D(t-value)Human(t-value)						(t-value)	R&D	(t-value)	Human	(t-value)	
Channels:	Intensity (N/L)	(() () () () () () () () () (Capital (SCH)	(t fuint)	Intensity (R/Y)	(t varac)	Capital (SCH)	(((und))	Intensity (PA/L)	(t varac)	Capital (SCH)	(t fuide)
Total Sample (55 Countries)												
$(X/Q)_{it}$	0.015	(1.61)	0.016***	(3.65)	-0.011	(-0.14)	0.024	(0.89)	0.105	(1.38)	0.11**	(2.41)
DTF _{i,t-1}	0.682***	(5.29)	0.521**	(2.35)	0.605***	(3.91)	0.635*	(1.78)	0.670***	(4.74)	0.58**	(2.05)
$(X/Q)_{it} \times DTF_{i,t-1}$	-0.001	(-0.05)			0.156	(0.69)			-0.007	(-0.04)		
SCH _{it}	0.063	(1.30)	-0.003	(-0.05)	0.058	(0.95)	0.068	(0.50)	-0.004	(-0.07)	-0.037	(-0.43)
SCH _{it} ×DTF _{it-1}			0.101	(1.08)			-0.012	(-0.08)			0.048	(0.36)
R-Squared	0.33		0.33		0.31		0.30		0.33		0.33	
Observations	335		335		281		285		298		298	
OECD Countries (23)												
(X/Q) _{it}	0.005	(0.53)	0.009**	(4.02)	0.023	(0.26)	0.222*	(1.82)	0.076*	(1.88)	0.071**	(2.43)
DTF _{i,t-1}	0.602***	(3.74)	0.613	(0.75)	0.67***	(5.20)	0.526	(0.69)	0.774***	(5.56)	0.974	(1.35)
(X/Q) _{it} ×DTF _{i,t-1}	0.014	(0.51)			-0.007	(-0.04)			-0.021	(-0.27)		
SCH _{it}	0.084	(0.89)	0.099	(0.73)	0.142	(1.08)	0.126	(0.88)	0.127	(1.41)	0.161	(1.14)
SCH _{it} ×DTF _{i,t-1}			0.022	(0.06)			0.071	(0.20)			-0.097	(-0.29)
R-Squared	0.55		0.55		0.53		0.53		0.54		0.54	
Observations	139		139		136		138		138		138	
Developing Countries	<u>`</u>	(1.05)	0.007	(0.00)	0.417	(0.05)	0.100	(1.40)	1 770	(0.74)	0 501	(0.70)
(X/Q) _{it}	-0.229 0.470**	(-1.65)	0.027 0.336	(0.88) (1.27)	-0.417 0.674***	(-0.85) (3.31)	0.130 0.379	(1.43) (0.92)	-1.776 0.655	(-0.74) (3.90)	0.591 0.317	(0.73) (0.89)
DTF _{i,t-1} (X/Q) _{it} ×DTF _{i,t-1}	0.470**	(2.56) (1.87)	0.330	(1.27)	1.88	(0.94)	0.379	(0.92)	0.855 5.87	(3.90) (1.22)	0.317	(0.89)
SCH_{it}	0.114*	(1.07) (1.72)	-0.093	(-0.91)	0.183**	(0.34)	0.009	(0.05)	0.068	(0.74)	-0.132	(-1.00)
SCH _{it} ×DTF _{i.t-1}		(1.1.2)	0.325**	(2.45)	0.100	(2.20)	0.249	(1.01)	0.000	(3.1.1)	0.345*	(1.67)
R-Squared	0.36		0.36	< - /	0.34		0.34		0.37		0.38	· · · · /
Observations	196		196		145		147		160		160	

TABLE A6. Absorptive Capacity and TFP Growth (Fixed Effects): 1970-2004

Notes: (i) Variable specification is the same as illustrated in Table A2; (ii) Figures in parentheses () are t-values significant at 1% Level (***) or, 5% Level (**) or, 10% Level (*); (iii) X/Q represents R&D intensity measured by the ratio of innovative activities to product varieties proxied by labor (L) for domestic R&D scientists& engineers (N) and patent applications(PA) or, GDP (Y) for domestic R&D expenditures (R); (iv) Human capital is measured by the average years of schooling in the Population Aged 25 years and over (SCH); (v) Constants and other control variables such as, OP and FDI are not reported due to space conservation; (vi) Time and country dummies are included but not reported for brevity; (vii) Robust standard errors are used .

Dependent Variable:	Total Factor Productivity Growth (ΔlnA_{it})									
Estimation Method/Sample Period: R&D Indicators:	System GMM/1970-2004 Domestic R&D Expenditures (R) Patents Applications by Residents (PA									
Absorptive Capacity Channels:	R&D Intensity (R/Y)	(t-value)	Human Capital (SCH)	(t-value)	R&D Intensity (PA/L)	(t-value)	<u>s by Residents</u> Human Capital (SCH)	(t-value)		
Total Sample (55 Countries)	~ /									
$(X/Q)_{it}$	-0.008	(-0.16)	0.040**	(2.44)	0.401**	(2.02)	0.120*	(1.86)		
DTF i.t-1	0.115*	(1.67)	0.443**	(2.16)	0.377**	(2.54)	0.654	(1.54)		
$(X/Q)_{it} \times DTF_{i.t-1}$	0.089	(0.57)			-0.583	(-1.31)				
SCH _{it}	0.057	(1.57)	0.146**	(2.04)	0.010	(0.15)	0.34	(0.92)		
SCH _{it} ×DTF _{1t-1}			-0.183**	(-2.05)			-0.257	(-1.24)		
Hansen Test [p-value]	0.999		1.000		0.711		0.512			
AR(2) Test [p-value]	0.229		0.245		0.196		0.174			
OECD Countries (23)										
(X/Q) _{it}	0.825	(1.52)	0.829	(1.40)	0.036	(0.45)	0.088**	(2.52)		
DTF _{i.t-1}	0.843***	(4.42)	0.407	(0.42)	1.074***	(3.52)	1.070	(1.20)		
$(X/Q)_{it} \times DTF_{i,t-1}$	-0.133	(-1.28)			0.183	(1.17)				
SCH _{it}	0.253	(1.44)	0.106	(0.61)	0.164	(1.01)	0.129	(0.74)		
SCH _{it} ×DTF _{i,t-1}			0.250	(0.52)			-0.042	(-0.10)		
Hansen Test [p-value]	0.999		1.000		0.999		0.999			
AR(2) Test [p-value]	0.779		0.878		0.907		0.884			
Developing Countries (32)	-0.026	(111)	-0.366	(0.41)	0.101	(0.67)	0.983	(0.5.4)		
(X/Q) _{it} DTF _{i,t-1}	-0.026 0.524***	(-1.11) (2.94)	-0.366 0.411	(-0.41) (0.82)	1.048**	(0.67) (2.84)	0.983 1.018**	(0.54) (2.36)		
$(X/Q)_{it} \times DTF_{i,t-1}$	0.334	(2.54) (0.68)	0.411	(0.02)	0.963*	(1.94)	1.010	(2.00)		
SCH _{it}	0.146	(1.36)	0.121	(0.53)	0.027	(0.27)	0.267	(1.61)		
SCH _{it} ×DTF _{1t-1}		()	-0.055	(-0.22)		()	-0.452*	(-2.01)		
Hansen Test [p-value]	0.999		0.998		0.977		0.996	· · · · · · · · · · · · · · · · · · ·		
AR(2) Test [p-value]	0.084		0.047		0.441		0.136			

TABLE A7. Absorptive Capacity and TFP Growth (System GMM): 1970-2004

Notes: (i) Variable specification is the same as illustrated in Table A2; (ii) Figures in parentheses () are t-values significant at 1% Level (***) or, 5% Level (**) or, 10% Level (*); (iii) X/Q represents R&D intensity measured by the ratio of innovative activities (R for domestic R&D expenditure or, PA for patents applications) to product varieties proxied by GDP (Y) or, labor (L); (iv) Hansen test measures the validity of the instruments where the null hypothesis is that the instruments are not correlated with the residuals ; (v) The null hypotheses in AR(2) tests are that the error terms in the first difference regression exhibit no 2^{nd} order serial correlation ; (vi) 2^{nd} and 3^{rd} lags of the explanatory variables are taken as instruments for the differenced equation, whereas 1^{st} difference of the explanatory variables are taken as instruments for the differenced equation and other control variables such as, OP and FDI are not reported due to space conservation; (vi) Time and country dummies are included but not reported for brevity; (vii) Robust standard errors are used .

Dependent Variable:	Total Facto	or Productivity	r Growth (Δln	A _{it})									
Estimation Method:	Fixed Effects/1970-2004												
Regression		•	· ·		R&D Scientists & Engineers/Labor): N/L				Human Capital Channel (Years of Schooling): SCH				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)		
Total Sample (55 Co													
	0.0063**			0.014***	-0.018*		0.015	0.017***	0.016***	0.017***	0.016***		
(X/Q) _{it}	(2.21)			(3.61)	(-1.96)		(1.61)	(4.19)	(3.63)	(3.92)	(3.65)		
		0.641***		0.680***		0.610***	0.682***		0.527***		0.521**		
DTF _{i,t-1}		(4.93)		(6.03)		(5.21)	(5.29)		(3.00)		(2.35)		
			0.038***		0.086***	0.038***	-0.001						
(X/Q) _{it} ×DTF _{i,t-1}			(3.61)		(3.18)	(3.62)	(-0.05)						
	0.048	0.048	0.047	0.063	0.020	0.041	0.063			-0.172***	-0.003		
SCH _{it}	(1.23)	(1.05)	(1.22)	(1.31)	(0.46)	(0.87)	(1.30)			(-3.15)	(-0.05)		
								0.241***	0.097	0.353***	0.101		
SCH _{it} ×DTF _{i,t-1}								(5.95)	(1.54)	(6.88)	(1.08)		
OECD Countries (23)													
	0.010***			0.009***	-0.0136		0.005	0.009***	0.009***	0.009***	0.009***		
(X/Q) _{it}	(5.29)			(4.05)	(-1.58)		(0.53)	(3.85)	(4.03)	(4.20)	(4.02)		
5 7 7		0.668***		0.661***		0.553***	0.602***		0.297		0.613		
DTF _{i,t-1}		(6.37)		(5.81)		(5.26)	(3.74)		(0.60)		(0.75)		
			0.049***		0.077***	0.027***	0.014						
(X/Q) _{it} ×DTF _{i,t-1}	0.007	0.400	(4.19)	0.400	(3.05)	(2.98)	(0.51)			0.014	0.000		
COL	-0.087	0.129	-0.119	0.108	-0.122	0.067	0.084			-0.014	0.099		
SCH _{it}	(-1.03)	(1.38)	(-1.47)	(1.21)	(-1.34)	(0.80)	(0.89)	0.000***	0.100	(-0.18)	(0.73)		
SCH _{it} ×DTF _{i,t-1}								0.299*** (5.89)	0.160 (0.65)	0.298***	0.022 (0.06)		
Developing Countries	a (32)							(5.69)	(0.05)	(5.72)	(0.00)		
Developing Countries	-0.003			0.011	-0.45***		-0.229	0.005	0.019	0.034	0.027		
(X/Q) _{it}	-0.003 (-0.01)			(0.42)	-0.45		-0.229 (-1.65)	(0.18)	(0.70)	(1.16)	(0.88)		
$(\Lambda/Q)_{\rm lt}$	(-0.01)	0.738***		(0.42) 0.720***	(-4.00)	0.699***	(-1.03) 0.470**	(0.10)	0.472**	(1.10)	0.336		
DTF i,t-1		(4.30)		(4.71)		(4.41)	(2.56)		(2.41)		(1.27)		
		(4.50)	0.094	(4.71)	0.904***	0.047	(2.30) 0.472*		(2.71)		(1.67)		
(X/Q) _{it} ×DTF _{i,t-1}			(1.38)		(4.60)	(1.01)	(1.87)						
(())) 1,1-1	0.097**	0.134**	0.072	0.125**	0.095	0.117*	0.114*			-0.230***	-0.093		
SCH _{it}	(2.13)	(2.20)	(1.47)	(2.08)	(1.47)	(1.86)	(1.72)			(-2.81)	(-0.91)		
~	(2.10)	(2:20)	()	(2.00)	()	(1.00)	(1.1.2)	0.330***	0.213***	0.522***	0.325**		
SCH _{it} ×DTF _{i.t-1}								(5.51)	(3.02)	(6.03)	(2.45)		

TABLE A8. R&D Intensity, Distance, Absorptive Capacity and TFP Growth (Fixed Effects): 1970-2004

Notes: (i) Variable specification is the same as illustrated in Table A2; (ii) X/Q represents R&D intensity measured by the ratio of domestic R&D scientists and engineers (N) to labor (L); (iii) Figures in parentheses () are t-values significant at 1% Level (***) or, 5% Level (**) or, 10% Level (*); (iv) Human capital is measured by the average years of schooling in the Population Aged 25 years and over (SCH); (v) Constants and other control variables such as, OP and FDI are not reported due to space conservation; (vi) Time and country dummies are included but not reported for brevity; (vii) Robust standard errors are used.

Dependent Variable:		Productivity Gro	(,							,
Estimation Method:		& System GMN								
R&D Intensity /	R&D Expenditures/GDP		Patents		Patents Granted /Labor		Human Capital (SCH)		Human Capital(SCH)	
Human cap. Measures			Applications/Labor (PA/L)		(PG/L)		R&D Intensity (R/Y)		R&D Intensity (PA/L)	
Estimation Technique	Fixed Eff.	Sys. GMM	Fixed Eff.	Sys. GMM	Fixed Eff.	Sys. GMM	Fixed Eff.	Sys. GMM	Fixed Eff.	Sys. GMM
Total Sample (55 Cou									-	
	0.134***	0.063**	0.171	0.291**	0.027	0.708**				
$(X/Q)_{it} \times DTF_{i,t-1}$	(3.38)	(2.20)	(0.85)	(2.50)	(0.10)	(2.66)				
	0.059	0.004	-0.003	-0.034	-0.002	-0.023				
SCH _{it}	(0.91)	(0.22)	(-0.06)	(-0.98)	(-0.04)	(-0.70)				
							0.183***	0.314**	0.189***	0.088*
SCH _{it} ×DTF _{i,t-1}							(3.62)	(2.65)	(3.46)	(1.92)
							0.034**	-0.047	0.036	0.131**
(X/Q) _{it}							(2.15)	(-0.67)	(0.91)	(2.32)
OECD Countries (23)										
	0.210***	0.053	0.130	0.126***	-0.018	0.782**				
(X/Q) _{it} ×DTF _{i.t-1}	(4.69)	(0.43)	(0.83)	(2.83)	(-0.03)	(2.45)				
	-0.128	-0.158	-0.090	-0.042	-0.030	-0.245				
SCH _{it}	(-1.24)	(-1.22)	(-0.98)	(-1.60)	(-0.32)	(-1.41)				
2 n	()	()	()	()	()	()	0.303***	0.106***	0.332***	0.099**
SCH _{it} ×DTF _{i.t-1}							(6.33)	(3.93)	(5.80)	(2.21)
							0.004	-0.004	0.054*	0.001
(X/Q) _{it}							(0.21)	(-0.42)	(1.98)	(0.03)
Developing Countries	(32)						(0121)	(0.12)	(1100)	(0.00)
	0.385	-0.379	0.995	0.748	0.999	0.230				
$(X/Q)_{it} \times DTF_{i,t-1}$	(0.51)	(-0.23)	(1.12)	(0.69)	(0.87)	(0.08)				
	0.166**	0.007	0.049	-0.042	0.088	-0.025				
SCH _{it}	(2.27)	(0.30)	(0.75)	(-0.72)	(0.93)	(-0.52)				
ocr _{lt}	(~~~)	(0.00)	(0.70)	(0.1 %)	(0.00)	(0.0%)	0.345***	0.179*	0.345***	0.526***
SCH _{it} ×DTF _{i.t-1}							(3.66)	(1.79)	(4.34)	(3.21)
SCH _{lt} ~DTT _{1,t-1}							-0.051	-0.991	-0.513	-0.912
(X/Q) _{it}							(-0.17)	(-1.34)	(-0.68)	(-0.46)

TABLE A9. Absorptive Capacity and TFP Growth (Using Only Interaction Terms): 1970-2004

Notes: (i) Variable specification is the same as illustrated in Table A2; (ii) X/Q represents R&D intensity measured by (a) the ratio of domestic R&D expenditures (R) to GDP (Y), (b) the ratio of patents applications by residents (PA) to labor (L) and (c) the ratio of patents granted to residents (PG) to labor (L); (iii) Figures in parentheses () are t-values significant at 1% Level (***) or, 5% Level (**) or, 10% Level (*); (iv) Human capital is measured by the average years of schooling in the Population Aged 25 years and over (SCH); (v) Constants and other control variables such as, OP and FDI are not reported due to space conservation; (vi) Time and country dummies are included but not reported for brevity; (vii) Robust standard errors are used ; (viii) Estimated results from system GMM satisfy all of the relevant diagnostic tests such as F-test, Hansen test, AR(1) and AR(2) tests. The p-values of those tests are not reported for brevity.