ÇOK FAKTÖRLÜ VERİMLİLİK BELİRLEMESİ: ÜNİVERSİTELERCE ÜRETİLEN BİLGİ VE VERİMLİLİĞİN REKABETÇİ TEORİLER ARASINDAKİ İLİŞKİSİ NE KADAR GÜÇLÜDÜR

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ÖZET

Bilginin kaynakları ve çok faktörlü verimlilik (MFP) üzerindeki etkileri Ar-Ge çalışmalarının ana hedefi olmuştur. Ancak, ülkelerin MFP seviyeleri bilgi stokları dışındaki faktörlere duyarlı oldukları görülmektedir ki bu dahil edilmeyen değişkenler ülkeler arasindaki MFP'nin farklılıklarının esaslarını, büyüme oranlarını açıklamada önemli olabilirler. Ar-Ge teorilerine rakip olan teoriler, verimliliği etkileyen diğer fakörler teklif etmişlerdir; beşeri sermaye, kamu altyapı yatırımları, ihracat pazarlarına erişim (yaparak öğrenme), ithalat, doğrudan yabancı yatırımlar bunlaran bazılarıdır. Bu teoriler MFP'nin bu değişkenler tarafından nasıl etkilendiğini analiz etmişlerdir. Ancak, bunların hiçbiri hem bilimsel bilgi üreten hem de iktisat teorilerinde belirtilen verimliliği belirleyen kaynakların sağlamlığını birarada incelememişlerdir. Yerek MFP belirleyicileri, üniversite Ar-Ge stoğu ve rekabetçi verimlilik teorilerinde belirtilen değişkenler kullanılarak, 13 OECD ülkesi ve 1985-2005 yılları için tahmin edilmiştir. Sonuçlar göstermektedir ki, OECD ülkelerri genelinde homojen verimlilik ilişkisi olduğu varsayımı oldukça güçlü görünmektedir, çünkü tahmin edilen katsayılar çalışmadaki bütün ülkeler için farklı tahmin edilmiştir. Her ülkeye özgü parametreler görünürde ilişkisiz regresyon tekniği kullanılarak tahmin edilmiştir ve sadece üniversite Ar-Ge stoğu ve konjonktürel dalgalanmalar MFP'nin önemli belirleyicileri olarak genelleştirilebilir.

Anahtar Kelimeler: *Üniversite Ar-Ge stoku, çok faktörlü verimlilik, amortisman oranı tahmini, görünürde ilişkisiz regresyon, katsayılarının heterojenliği*

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DETERMINING MULTIFACTOR PRODUCTIVITY: HOW ROBUST THE RELATIONSHIP BETWEEN KNOWLEDGE GENERATED THROUGH UNIVERSITIES AND COMPETING THEORIES OF PRODUCTIVITY

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ABSTRACT

The sources and effects of knowledge on multifactor productivity (MFP) have been the main object of the R&D studies. However, if MFP levels of countries seem to be sensitive to the factors other than knowledge stocks; these omitted variables could be significant in explaining cross-country MFP differences, their growth rates and the fundamentals that drive them. Competing theories to R&D propose a range of other factors that may affect productivity, such as, human capital, public infrastructure, access to export markets (learning-by-doing), imports, foreign direct investments (FDI). These theories hypothesized how these variables influenced the MFP; however, none of them has analyzed the robustness of the sources that generate scientific knowledge and other determinants of productivity that emerge from economic theory. The determinants of domestic MFP are estimated using the university R&D stock and competing theories of productivity for 13 OECD countries for the period 1985-2005. Results shows that the assumption of homogenous productivity relationship across OECD nations appears quite strong and it is unlikely to hold and estimated coefficients are significantly differ for all countries. Country specific parameters were estimated by Seemingly Unrelated Regression estimator and we can only generalize the results for countries that university R&D stock and business cycles are important determinants of MFP.

Keywords: *University R&D stock, multifactor productivity, depreciation rate estimation, seemingly unrelated regression, heterogeneity of coefficients*

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INTRODUCTION

The economies of western world have grown at a pace that greatly exceeds anything previously known in the long sweep of human history for more than two centuries now. In the last few decades, we have experienced what have come to be called the "information age" and the "knowledge economy". These labels, in fact, do reflect a very real transformation that it is now "knowledge"—not labor, machines, land or natural resources—that is the key economic asset that drives long-run economic performance.

Recent changes in the global environment and the new generation of "information age" force economists to generate new theories that try to figure out what happens to our understanding of economics if the large numbers of economy's labor force are employed to create ideas, solve problems, and sell services rather than to produce any tangible goods. Furthermore, traditional production factors land, labor, and capital are loosing their significance in a boundless global environment because in such global environment where land in the form of office space or manufacturing infrastructure is no longer important. Labor can also be employed wherever it is most cost-effective worldwide. Another production factor capital is equally available to finance a project in Washington D.C. or in İstanbul.

At the heart of this phenomenon lies a complex, multifaceted process of continuous, widespread and far-reaching innovation and technical change. Yet, "knowledge", "innovation", and "technical change" are elusive notions, difficult to conceptualize and even harder to measure in a consistent, systematic way. Therefore, while economists from Adam Smith on have recognized their crucial role in shaping the process of economic growth, until the last several decades have seen a number of pioneering efforts to overcome these measurement problems and gather data that can be used for the systematic empirical analysis of technological knowledge.

Neoclassical growth models assume that innovation is an exogenous process, with the implication that investments in research and development (R&D) have no systematic and predictable effect on output growth. But, can it really be true that the huge amount of R&D investments made in recent years was undertaken without any expectations of gain? A more plausible approach is to abandon the assumption that the innovation is exogenous to the economic system, and recognize that some part of innovation is, in fact, a form of capital accumulation. This is precisely the view incorporated in the "endogenous" growth theory of Romer (1986, 1990) and Lucas (1988). The concept of capital expanded to include knowledge and human capital, and added to conventional fixed capital, thus arriving at total capital. Increments to knowledge are put on an equal footing with all other forms of investment, and therefore the rate of innovation is endogenous to the model.

Following the implications of endogenous growth theories economist start showing more interest in the underlying determinants of the multifactor productivity (MFP) growth[1].

Most empirical studies that investigate the role of knowledge on multifactor productivity concentrate on various measures of R&D such as business, public, and foreign, as the sources of productivity. In contrast to these studies, another measure of R&D that is performed at the universities is used as only source of knowledge, since previous studies did not make this distinction. They are either multi-country cross-sectional or panel studies (Lichtenberg, 1992; Coe and Helpman, 1995; Park, 1995; Keller, 1998). Time series studies are limited (Luintel and Khan, 2004). These studies also report: *i)* a significant positive effect of domestic R&D on domestic productivity and *ii)* positive and significant international knowledge spillovers. These studies rarely allow for other determinants of productivity that emerges from theoretical models. There might be some omitted variables and these variables could be important if domestic multifactor productivity of countries seems to be sensitive to factors other than stock of knowledge. In addition to omitted variables issues, the existing literature mostly estimates the fixed effect models with the implication of parameters of multifactor productivity relationships are homogenous across the sample countries. On the other hand, countries may exhibit great difference in their productivity level, stock of R&D capital, etc. In such situation, the assumption of homogeneous productivity relationships across countries might be quite strong and it is unlikely to hold.

The purpose of this paper is to analyze both issues; search for an omitted variables and dropping the assumption of parameters of multifactor productivity relationship is homogenous across the countries and estimate the country specific parameters using the seemingly unrelated regression (SUR) technique that also corrects for the contemporaneous correlation of the error terms across countries.

This study is also argue that to measure the social returns to R&D it is better to use stock of R&D capital instead of intensity ratio which is share of R&D expenditures in gross domestic product (GDP) of the economy, because stock variables captures cross country differences better that intensity ratios. However, the problem with the calculating the R&D stock capital from flow of R&D expenditures is problematic because one has to make an assumption about the unknown depreciation rates of R&D capital. Generally, empirical studies construct to R&D capital stock using the perpetual inventory method with the assumption of depreciation rates ranges from 5% to 15%. In this study we propose to construct R&D capital and estimates returns to R&D simultaneously with grid search methodology that given depreciation rates ranges from –20% to 20%. By doing that our aim is to show that knowledge stock generated through R&D expenditures

[1] Multifactor productivity measures reflect output per unit of some combine inputs. A change in multifactor productivity reflects the change in output that cannot be accounted for by the change in combined inputs. As a result, multifactor productivity measures reflect of joint effects of many factors including new technologies, economies of scale, managerial skills, and changes in the organization of skills. Rest of the study multifactor productivity, total factor productivity, and productivity is used interchangeably.

through spillovers and externalities it generates will be effective in the future innovations. In addition, we will also argue that the difference between the depreciation ratio that provides the maximum value of log of the likelihood function and that of conventional theories assume (*e.g.* 10%) will be significant.

To determine the effect of both knowledge stocks generated through universities and other competing theories that might influence multifactor productivity, in the first section we will discuss the changing role of universities that make one to measure university R&D stock and analyze its impact on MFP.

1. Universities and Multifactor Productivity

Changes in the economic, social and knowledge environment provide opportunities to new or improved products. Research knowledge of university is increasingly considered as providing a significant number of opportunities to develop new or improved product. There are growing number of studies on the opportunities of knowledge transfer undertaken by universities and university researchers (see among others, Jensen and Thursby 2001; Dietz and Bozeman, 2005; Adams, Black, Clemmons, and Stephan 2005; Sampat, 2006; and Adams and Clemons 2008). In recognition of this fact, governments throughout the industrialized world have launched numerous initiatives since the 1970s to link universities to industrial innovation more closely.

The three major forms of mechanism through which universities and university researchers transfer knowledge are the diffusion of research knowledge through conferences and scientific publications, the training of a skilled labor force, and the commercialization of knowledge. The first two-knowledge transfer mechanism related the Mertonian open science argument has been the main objective of the United State universities for centuries. On the other hand, the third source of diffusion of research knowledge through commercialization of knowledge has become very significant over the past quarter-century. The commercialization of knowledge can itself be considered under many alternative mechanisms, notably through consulting activities, research contracts with industry, patenting and spin-off formation.

We witnessed a dramatic increase in patenting and licensing activities of publicly funded research by American universities. The main reason for change in the context of university research has been the evolution of legislation that has enabled the capitalization of knowledge, by which Etzkowitz, Webster and Healey signify “the translation of knowledge into commercial property in the literal sense of capitalizing on one’s intellectual (scientific) assets”, as well as “the way in which society at large draws on, uses, and exploits its universities, government funded research labs, so on to build the innovative capacity of the future” (1998, p.9). Slaughter and Leslie (1997) review some of the most relevant federal legislation in the United States, of which the Bayh-Dole Act of 1980 is arguably one of the most significant (see also Etzkowitz and Stevens, 1998). This act allowed universities to patent the results of research that the federal government had funded, thereby earning royalties by licensing innovations to private corporations. Thus even as the federal government was reducing direct support for academic research, it was removing obstacles to universities’ ability to profit from research. Such a development was not without controversy: "Some in Congress argued that granting private companies the rights to publicly funded research amounted to an enormous giveaway to corporations: others pronounced the act a visionary example of industrial policy that would help America compete in the fast moving information age" (Press and Washburn, 2000, p. 41). Bowie claims that the second argument won out because of "the growing threat of international economic competition and … the perceived decline in research and development capabilities of American Industry" (1994, p. 14). The Bayh-Dole Act's effect has been significant. Before its passage, universities were producing approximately 250 patents per year (Press and Washburn, 2000), and as 1978, the government owned title to over 28,000 patents, of which fewer than 4% had been licensed (Etzkowitz and Stevens, 1998). On the other hand, in 1998 alone, universities produced over 4,800 patent applications (Press and Washburn, 2000).

In addition to changing property rights, Slaughter and Leslie (1997) argue that globalization changed the nature of corporate competition, putting a premium on products and processes derived from scientific innovation: "As the economy globalizes, the business or corporate sector in industrialized countries pushed the state to devote more resources to the enhancement and management of innovation so that corporations and nations in which they were headquartered could compete more successfully in world markets" (p.7). Increased demand on industry's side, together with the decreases in the supply of federal funding, thus put marketlike pressures on faculty members and their institutions to shift focus in their pursuit of support for research. Not surprisingly, then, the market-oriented behaviors of faculty and universities have become the key components of what Slaughter and Leslie describe as "academic capitalism".

Unique characteristics of U.S. academic environment are emphasized by Pianos (2002). Especially, the "flexibility" of the U.S. academic system and other make it relatively straightforward for leading academic scientists to become deeply involve with commercial firms, thus facilitating the formation of successful start-up companies. The willingness to exploit the results of academic research commercially distinguishes the United States environment that of either Japan or Europe. Mobility of academic scientists into commercial venture is difficult in the later regions where academic scientists are essentially civil servants operating on a rigid and hierarchical system. While Pisano's comments are directed at the biotechnology sector, they would seem to be generalized to other areas of technology.

Since empirical studies considers university R&D as a part of public R&D, returns to R&D that performed in the universities are measured by publications' received patents, and citations. Compare to European counterparts U.S. universities generate significant scientific knowledge. For instance, Nickell and Van Reenen (2001) reports that even though the United Kingdom has a relatively strong science base build around an ensemble of university-related research institutes; nation has been having difficulties translating the science base into innovation and industrial performance. The authors argue that due to constraints researchers faces while they are doing consulting work, their commercial payoffs from their research efforts are limited.

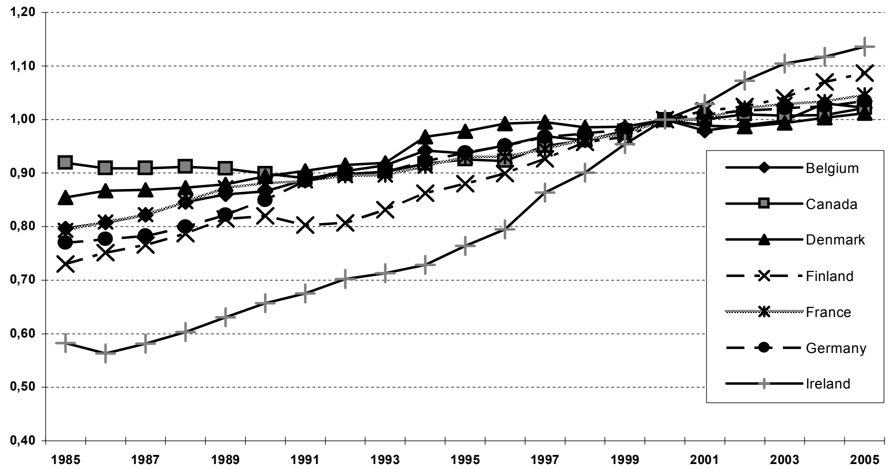
As a result of these changes with the improvement of property rights towards universities that can utilize the patent rights received from an innovation if the funds of R&D performed at the universities received from government made universities act in "market-like" behavior instead of basic knowledge generator. This change made us to analyze the contribution of university R&D stock to domestic productivity increases should be examined separately.

2. Countries differ in their economic conditions (dropping the homogeneity assumption)

Figure 1 plots the log of MFP for the countries and shows that they exhibit substantial fluctuations between countries. US multifactor productivity shows a modest upward trend throughout the sample period. UK multifactor productivity slows first 5 years of the period, and then improves somewhat since 1992. German total factor productivity shows noticeable increase during the later part of the 80s, but it stagnates from the early 1990s. Plots for Canada, Denmark, and Netherlands appear flat throughout. French and Spanish total factor productivity also appears to be flat during the sample period. Spanish productivity seems to be recovering from its decline starting at 1997. Ireland's multifactor productiviy shows a rapid rate of growth from its low base. The Finnish total factor productivity trend appears similar to the Irish but the Finland's total factor productivity growth rate is smaller. Belgian and Italian multifactor productivity exhibit similar patterns of slow growth. Japanese multifactor productivity increased quite rapidly during the first five years of the sample period then appears quite similar to the other major developed nations.

In addition, Table 1 presents some summary statistics of data set we applied in this study. Descriptive statistics show heterogeneity in the growth rates of multifactor productivity and their determinants across the sample OECD nations. The average annual growth rate of MFP ranges between a minimum 0.4% (Spain) to a maximum of 3.2% (Ireland); the sample mean is 1.3%. The multifactor productivity of the United States and the United Kingdom increased by around 1.1% during the period 1985-2005. On the other hand,

Figure 1. Multifactor productivity (logarithms): period 1985-2005



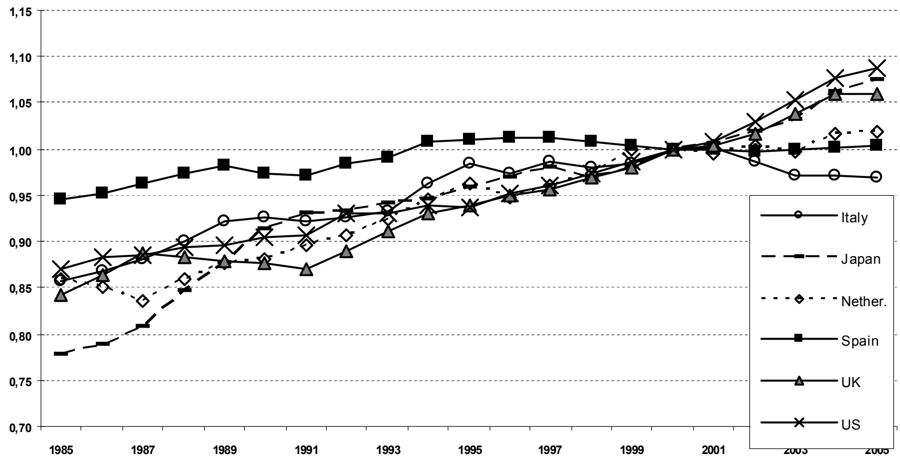


Table 1: Descriptive Statistics (1985-2005 mean value)											
	MFP[1]	University R&D[2,5]		Human Capital[6]	Public Infrastructure[2,7]		High-technology[2,8]		Outward FDI[2,9]	Inward FDI[2,10]	Life Expectancy
	Growth rate	Expenditure	Intensity	Stocks	Intensity	Stock	Exports [Intensity}	Imports [Intensity]	Stocks	Stocks	AGE1[11]
Belgium	1.2	0.9	0.4	10.4	1.9	59.8	18.7 [9.5]	20.2 [10.8]	117.1	148.8	76.4
Canada	0.5	3.8	0.5	12.8	2.6	157.5	20.8 [7.5]	35.8 [14.2]	184.5	181.4	77.7
Denmark	0.9	0.6	0.4	11.3	1.8	22.8	5.8 [10.3]	5.6 [11.3]	31.7	31	75.4
Finland	2	0.6	0.5	11	3	37.1	5.9 [12.7]	5.1 [14.61]	26.7	15	75.8
France	1.4	5.2	0.4	10.5	3.2	393.5	50.9 [14.4]	48.4 [14.3]	294.7	217.9	77.4
Germany	1.6	7.3	0.4	12.6	2.1	414.3	77.9 [13.4]	75.7 [14.7]	341.4	182.7	76.1
Ireland	3.2	0.2	0.2	9.9	2.8	26.8	21.9 [32.3]	11.7 [21.1]	29.9	81.4	75.5
Italy	0.6	3.9	0.3	8.8	2.6	379.1	24.5 [8.0]	34.8 [12.1]	139.7	100.6	77.6
Japan	1.7	11.9	0.4	11.8	5.1	1561.3	86.3 [26.6]	39.6 [13.5]	182.5	27.2	79.3
Nether.	0.8	2	0.5	11.4	3.2	109.2	36.2 [14.0]	37.0 [15.9]	233.7	170.7	77.1
Spain	0.4	1.8	0.2	7.9	3.8	223.4	9.9 [5.5]	22.6 [12.3]	117.6	161.2	77.6
UK	1.1	5	0.4	11.4	1.8	238.3	61.9 [17.6]	61.8 [16.5]	509.5	317.2	76.3
US	1.1	26.1	0.3	12.7	3.4	2402.8	178.5 [21.1]	191.1 [17.7]	937.3	763.1	75.7
Mean	1.3	5.3	0.4	11	2.9	463.5	46.1 [14.8]	45.4 [14.5]	242	184.5	76.8

1. Multifactor Productivity. 2. Billions of constant 2000 PPP US dollars. 3. Intensity (R&D expenditures performed at higher education institutions as a % of GDP). 4. Stock of human capital is proxied by the average number of years of schooling of the population from 25 to 64 years of age. 5. Public infrastructure is proxied by the stock of public physical capital stock. 6. Intensity (high-technology imports (exports) as a % of total imports (exports)). 7. Stock (Outflow of foreign direct investment). 8. Stock (Inflow of foreign direct investment). 9. Life expectancy at age 1.

Japan, Germany and France experienced higher growth rates of 1.4% or above (1.7%, 1.6%, and 1.4% respectively).

As we discussed in the second section, universities share of receiving funds from government past 20 years and “market-like” behaviors of universities made us to not to consider university performed R&Ds as a part of public R&D. University R&D intensities of the sample OECD countries varies from 0.2% to 0.5% with a sample mean of 0.4 percent. Canada, Finland, and Netherlands have the same university R&D intensity of 0.5%. On the other hand, Spain and Ireland represents the lowest intensity of university R&D (0.2%). Comparison of R&D intensities of domestic R&D performed sectors and institutions represent that R&D intensities differ respectively by a factor of 21 and 1 across the sample nations.

The stock of human capital appears to be the lowest in Spain (7.9 average years of schooling of the population from 25 to 64), while Canada has the highest (12.8) years of schooling; sample mean is 11 years. The United States and Germany follows the Canada with 12.7, 12.6 years of schooling, respectively. Public infrastructure intensity (government’s infrastructure related gross fixed capital formation to GDP ratio) varies between a minimum of 1.8% (the United Kingdom) and a maximum of 5.1& in Japan. The cross country-intensity of high-tech exports differs by a factor of nearly 6 [from Spain (5.5%) to Ireland (32.3%)]. On the other hand, Belgium’s intensity of high-tech imports (10.8%) is smaller by a factor of 2 than Ireland (21.1%).

A corollary to comparison of intensity measures is that; although number of nations in the sample has comparable (in some cases almost same) intensity measures, the differences in their R&D expenditures that generate stocks of knowledge are quite large. The reason for that is the significant dissimilar size of OECD economies. For instance; universities of the United Kingdom spent on average 2.3 billions of constant 2000 PPP US dollars less than those German universities. If the relationship is linear between knowledge stocks generated through R&D performance of domestic economies and their positive and significant contribution to multifactor productivity, then Germany should have higher multifactor productivity growth for the sample period considered. Table 1 is also shows that Germany has experienced higher multifactor productivity growth (1.6%) then the United Kingdom (1.1%) and supports the idea that using the R&D intensities to explain cross-country differences in multifactor productivity could be misleading.

The analysis of descriptive statistics for the sample of OECD countries considered above suggest that domestic multifactor productivity levels may be affected by the factors other than knowledge. Competing theoretical models of productivity argues that there are significant productivity differences across the countries and R&D may not be the only source that affects the productivity.

3. Depreciation Rate Estimation

A corollary that using R&D intensities (R&D expenditures as a % of GDP) as a proxy for domestic technological knowledge to explain the cross-country differences in the multifactor productivity appear rather problematic, because it does not capture the substantial differences in their stock of knowledge. Therefore, it is better to calculate the stock of R&D then estimate private or social returns to R&D[2]. However, computing net rate of return or interpreting shadow value of the R&D stock required an assumption about the private depreciation or obsolescence of the assets generated by the R&D investment. But, determining the suitable depreciation rate is difficult for two reasons. According to Hall (2007) appropriate depreciation rate will change slowly over time. Acceptable depreciation rate is determined by a firm's and its competitor's behavior. Progress of public research and science is also an important factor determining appropriate depreciation rate. As a result of not having enough natural experiments determining the lag structure of R&D in generating will be very difficult. Since such lag structure is required to identify an appropriate depreciation rate Hall argues that it is really difficult to measure appropriate depreciation rate.

Hall (2007) clearly illustrates the some of the issues associated with the estimating R&D depreciation rates using a production function by discussing the types of identifying assumptions that are often needed to separately identify R&D depreciation rates. The first of these models assume that firms exist in a perfectly competitive market place that Hall mentions is inconsistent with the notion of R&D is often conducted to generate monopolistic returns. The second assumes that the output elasticities of ordinary capital and R&D capital are proportional to their input shares, which Hall characterizes as a "heroic" assumption that also may introduce a notable amount of specification error into estimation results. Hall (2007) by using Compustat data for a large panel of the United States manufacturing firms between 1974 and 2003 period estimates an "implied depreciation rate" of -6% in a production function approach to measure the returns to R&D capital stock. She also reports that dividing the entire period into 6 different 5-year periods shows "implied depreciation rates" are different for each 5-year period. For instance, "implied depreciation rate" is -17.8% for the 1979-1983 period, and -4.7% for the 1999-2003 period. In the same study Hall also estimates R&D depreciation rates from a model related to the market value of the firm. Her estimates in this model is different than what she found using the production function approach. She estimates that R&D depreciation ratios ranging from 20 to 40 percent depending on the period.

4. Methodology and Data

We estimated the impact of creation of scientific knowledge through university R&D expenditures on productivity growth. The following system of equation is generally referred in order to evaluate the contribution of R&D to output growth:

$$Y = MFP \cdot F(H, K) \tag{5.1}$$

$$MFP = G(S, O) \tag{5.2}$$

[2] The term "social" used because the analysis we performed at the aggregate level. It implicitly measures the direct impact of R&D (i.e. the internal return at the firm level) and the externalities (i.e. the inter firm R&D spillovers) generated by innovative activities.

$$S_t = \sum w_l I_{t-l}^{RD} \tag{5.3}$$

where Y is the output, H is the stock of private labor measured in hours worked, K is the stock of private capital, MFP states the current state of technological or scientific knowledge (multi-factor productivity), S stands for the measure of accumulated R&D capital (as a proxy for the knowledge *stocks* generated by domestic firms, public research institutions and foreign institutions), O is the other factors affecting multi-factor productivity. I^{RD} represents the gross R&D expenditures in period t, and w_l connects the level of past research to the current state of knowledge. For estimation purposes, a production function of a country i's explicit structure is generally of the Cobb-Douglas type, which has a log-additive form, and an exponential trend (t) approximates O[3].

$$Y_i = \exp[\phi_i t + u_i] H_i^{\alpha_1} K_i^{\alpha_2} S_i^{\beta} \qquad i = 1,2,\ldots,N \tag{5.4}$$

where u is random term, ϕ is the rate of disembodied technical change and α_1, α_2, and β are the output elasticities of labor, capital and R&D capital stock, respectively. The estimation of these parameters may be calculated by taking the natural logarithm of equation (5.4), as follows:

$$\ln Y_i = \phi_i t + \alpha_1 \ln H_i + \alpha_2 \ln K_i + \beta \ln S_i + u_i \tag{5.5}$$

It is common to drive an index of multi-factor productivity $\ln MFP$ from equation (5.5):

$$\ln MFP_i = \ln Y_i - \hat{\alpha}_1 \ln H_i - (1-\hat{\alpha}_1) \ln K_i = \phi_i t + \beta \ln S_i + u_i \tag{5.6}$$

the assumption of constant returns to scale with respect to labor and capital and payments of these traditional inputs are required for this analysis. In other words, the output elasticities with respect to labor (capital) are assumed to be equal to the labor (capital) cost share in total output and α_2 is equal to $(1-\alpha_1)$.

Given the theoretical and empirical discussions of previous chapter we eventually estimated the following equation:

$$\ln MFP_{it} = \phi_i + \beta_1 \ln S_{it}^{u} + \beta_2 \ln G + \beta_3 \ln H_{it}^{h} + \beta_4 \ln L_{it}^{1} + \beta_5 \ln M_{it}^{h} + \beta_6 \ln X_{it}^{h} + \beta_7 \ln F_{it}^{I} + \beta_8 \ln F_{it}^{O} + \beta_9 \Delta U_{it} + \varepsilon_{it} \tag{5.7}$$

The variables (for country i and time t) are defined as follows[4]:

MFP is an index of multi-factor productivity of total economy. *MFP* is computed as the ratio of the domestic product of industry to the weighted sum of the

[3] In this study, we introduce the omitted relevant variables that will be discussed.

[4] For simplicity we will drop the country i and time t subscripts for the rest of the chapter.

quantity of labor and fixed capital stock, the weights being the annual labor cost share and the capital cost share, respectively as given in equation (5.6). 13 OECD countries were selected according to availability of multifactor productivity data and resources devoted to research and development between the periods 1985 and 2005. These countries are Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Spain, the United Kingdom and the United States. Data for *MFP* is obtained from the OECD productivity database.

S^u denotes the source of knowledge, R&D capital stock performed at university institutions. Data on S^u for each sample country is constructed from the real R&D expenditures performed by the universities. The stock measures are constructed the way we discussed in the previous section. Interpretation of point elasticity should take into account the fact that the explained variable is not output (or GDP of industry) but MFP. That means we capture the social excess returns to university R&D, and not the total effects on output growth (which includes the direct effect or private return also). The source for R&D performed in universities is OECD's R&D Database with the exception of the U.S. that is taken from the National Science Foundation. Finally, it is expected that $\beta_1 > 0$

A measure of public infrastructure related physical capital is denoted by G. Theories of public infrastructure argues that the "quality" and the "size" of the public infrastructure affect productivity and growth through cost reduction and/or improved specialization. We proxy the stock of public infrastructure by the stock of public physical capital stock constructed from government's gross fixed capital formation following the perpetual inventory method. Government's gross fixed investment data exclude expenditures on public R&D and military[5]. Data is taken from the OECD Economic Outlook Database (No. 82, 2007). Even though empirical studies are mixed we expect a positive impact of infrastructure on multifactor productivity on theoretical grounds; thus $\beta_2 > 0$.

H represents the stock of human capital, which is proxied by the average years of education for the age group 25 to 64. According to Bassanini and Scarpetta (2002) there are practically and theoretically better reasons to use a stock variable (average years of education) instead of a flow variable (e.g., school enrolment rate) to measure the impact of human capital on productivity and growth. First of all, quality of data on enrollment rates are generally lower than years of education, and to see the impact of changes in enrollment on growth one needs long lags, which are difficult to accommodate in our framework since we work on relative to shorter time span. Second, the alternative to using changes in years of education as a proxy for the accumulation of human capital is not suitable, as it refers to a net investment in

[5] We acknowledge that this is crude way of measuring public infrastructure. No data exits on governments' aggregate stock of physical infrastructure. Studies use measures such as road mileage, phone lines, supply of electricity, number of airport terminals, etc. However, such indicators of public infrastructure appear more suitable for developing countries. Since our sample of OECD countries may not show any important changes in these measures of infrastructure during the late 20th and early 21st century, which covers our sample period, physical capital stock of governments' is used to proxy public infrastructure.

human capital rather than the required measure of gross investment. Finally, reverse causality problems are less severe when a stock measure is considered. Data for average years of education of the population aged from 25 to 64 is obtained from Arnold, Bassanini and Scarpetta (2007), and it is expected that $\beta_3 > 0$.

L^1 is the life expectancy at age one. In general, life expectancy is a proxy for good health and desirable performance of nations. Barro and Sala Sala-i-Martin (1995) state that "higher life expectancy may go along with better work habits and a higher levels of skills" (p. 432). In this study we used life expectancy at age one, instead of life expectancy at birth, because differences in reporting the infant mortality across the countries. According to Healy (2006), in the United States, prematurity or size is not considered when counting the births. In other words, all births are considered as alive if they show any sign of life. On the other hand, European countries have different constraints to count a birth as alive, otherwise they don't report newborn babies, and thus they will have lower mortality rates compared to the United States. For instance, in Germany, fetal weight must be at least 1 pound to count as a live birth; in other parts of Europe, such as Switzerland, the fetus must be at least 12 inches long, in Belgium and France, births at less than 26 weeks of pregnancy are registered as lifeless. Moreover, in some countries babies who die within the first 24 hours of birth are not reliably registered. Since probability of dying in every age group is a part of life expectancy calculations for those ages and the discrepancies in registering live births across countries, using life expectancy at birth may not be good indicator for cross-country comparisons. Thus, life expectancy at age one is used in this study. However, we don't have available data for all the sample countries in this study. Thus, we used a formula that with data available for life expectancy at birth and for infant mortality, it is possible to calculate life expectancy at age one[6] (Morris, 1979). A comparison of life expectancy at age one same data we were able to find from National Vital Statistics Reports for the United States and from EUROSTAT database for European Countries shows that formula is calculating life expectancy at age one values with close proximity. For instance, correlation coefficient of 0.998852 is calculated between the estimated life expectancy at age one data from sung formula and those received from National Vital Statistics Reports for the United States. Data for life expectancy at birth and infant

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[6] The formula used to approximate the life table values at age one was:

$$LE_1 = \frac{LE_0 - 1 + q(1-k)}{1-q}$$

where LE_1 is the infant mortality rate per thousand live births;

k is the average survival period (0.2 years) during the first year;

LE_o is life expectancy at birth; and

q is the infant mortality rate per thousand live births.

mortality rates are taken from OECD Health Database (2007). Eventually, we use calculated life expectancy at age one data for all countries and expect β_4>0.

Grossman and Helpman (1991); Coe and Helpman (1995); van Pottelsberghe and Lichtenberg (2001); Keller (2004) are all argue that imports are also another way of technology diffusion, and are denoted by M^h. Countries engage in imports benefit from international knowledge spillovers. Since, recent literature on this issue emphasize the significance of trade in differentiated capital goods, we use a ratio of high tech imports of goods to total imports of goods to capture this effect and expect β_5>0.

X^h stands for the ratio of high tech exports to total export of goods. The theory of "learning by exporting" argues that domestic companies increase their specialization and multi factor productivity in the process of meeting the high product quality imposed by the foreign customers. Therefore, we expect β_6>0[7]. Relevant series to compute the ratios is obtained from OECD's STAN Indicators database[8].

Another variable discussed in the literature among the competing theories of multifactor productivity is foreign direct investment (FDI)[9]. Since FDI has two different angles, F^I stands for foreign companies invest in domestic country (inward FDI), and F^O is domestic companies invest abroad (outward FDI), both type of FDI is included the model. Despite mixed empirical results we expect β_7 and β_8 to be positive. The data for both FDI stock variables are obtained from the United Nations Conference on Trade and Development (UNCTAD) database.

Finally, a control variable that is added to model is the annual growth of the rate of unemployment, ΔU. It is a stylized fact that productivity is pro-cyclical, and such periods of economies must be captured; therefore it is expected that β_9<0. Data for the unemployment rates of nations are obtained from OECD Economic Outlook Database (No. 82, 2007).

4.1 Formula Used in Calculation of R&D Stocks

Going back to equation (5.3), and assumption that there exist a relationship between the current level of technological knowledge stock, S_t, and an index of

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7 We use the ratio of high tech exports to total exports assuming that it captures the quality aspects of exports better—for instance, improving quality (productivity) through exporting. In order to export high tech goods the exporting country needs to be technologically efficient and hence more productive. Similarly, a ratio of high tech imports to total imports is used to capture the productivity effect emanating from imports.

8 OECD's definition of high tech industries includes the following International Standard Industrial Classification, Revision 3 (ISIC): Aircraft and spacecraft; Pharmaceuticals; Office, accounting, and computing machinery; Radio, TV and communication equipment; Medical, precision and optical instruments (OECD, 2005).

9 See among others, Lipsey (2002)

current and past levels of research and development expenditures, $w_l I^{RD}$, where w_l is a lag polynomial, describing the relative contribution of past and current research development levels to S_t, and l is lag (backward shift) operator, equation (5.3) can be rewritten as:

$$S_t = \left(w_0 + w_1 l + w_2 l^2 + \cdots\right) I_t^{RD} = w_0 I_t^{RD} + w_1 I_{t-1}^{RD} + w_2 I_3^{RD} + \cdots \tag{5.8}$$

Since we have available data on the flow of business performed R&D and it's known that some rate of depreciation of knowledge links flow of R&D to the stock of R&D, equation (5.8) can be re written as the stock of R&D at time t, S_t, and the flow of R&D at time t, I_t over time are related by the rate of depreciation of knowledge (δ) in the following equation:

$$S_t = I_t^{RD} + \frac{I_{t-1}^{RD}}{1+\delta} + \frac{I_{t-2}^{RD}}{(1+\delta)^2} + \frac{I_{t-3}^{RD}}{(1+\delta)^3} + \cdots + \frac{I_{t-l}^{RD}}{(1+\delta)^l} \tag{5.9}$$

Measuring R&D capital stock S_t requires both knowledge of its private depreciation or obsolescence rate, and time lag of l, again where l is the number of years it takes for a flow of R&D spending to become useful in private production (or to go through the phase of generating marketable products or process).

Hall (2007) also argues that as long as both growth rate and depreciation rate of R&D capital stocks do not change very much within firm over time, the estimated elasticity of output with respect to either R&D capital stock or R&D capital flow will be the same. On the other hand, even thought the choice of depreciation rate may not influence the elasticity of output with respect to R&D, the same is not correct of the rate of return derived from the elasticity. To see this, note that the gross, κ^G, and net, κ, rates of returns to R&D stock, S, are:

$$\kappa^G \equiv \frac{\partial Y}{\partial S} = \beta \frac{Y}{S} \text{ and } \kappa = \beta \frac{Y}{S} - \delta \tag{5.10}$$

therefore, to measure the returns to R&D one needs to know depreciation rate both to compute the correct level of R&D capital stock and also to convert gross returns to net returns.

In case of deciding the depreciation rate to construct R&D capital stock, previous studies used the perpetual inventory method, which requires calculation of benchmark R&D capital stock, which calculated as dividing the first year R&D expenditure of the sample period by sum of average growth rate of R&D expenditures during the period, and assumed depreciation ratio $\left(I_t^{RD} \big/ (g+\delta) \right)$. Assumed depreciation ratio used in cross-country studies ranges from 5% to %15. After calculating the benchmark year R&D stock, the rest of the sample period's R&D

stock is calculated by sum of previous year R&D stock after discounting foe depreciation plus the current year's R&D expenditures in the economy.

$$S_t = (1-\delta)S_{t-1} + I_t^{RD} \tag{5.11}$$

However, perpetual inventory methodology does not consider the idea of *negative* depreciation ratio or another words *appreciation*. In other words knowledge generated through R&D expenditures become obsolete, and will not contribute the societies general stock of knowledge in a relatively short period of time. Moreover, the calculation of benchmark R&D capital stock calculation requires $(g+\delta)$ to be greater than zero, otherwise we might run into negative stock of R&D capital values. Finally, perpetual inventory method does not consider the fact that the research and development process takes time and that current research and development may not have an impact on measured productivity. Griliches (1998) argue that completion of an R&D project, then turning into a product of this initial R&D project, and then seeing the revenue generated from this R&D project for the companies may take longer lags. Thus, we constructed the R&D capital stock using the formula (5.9) with the depreciation rates ranges between –20% and 20% with 28-year embodiment lag from R&D expenditures.

Bayoumi, Coe, and Helpman (1996) argue that it takes 80 years to see the full effect of initial R&D investment. In other words, if we increase the current R&D expenditures by 10 percent, in about 80 years the R&D capital stock will reach the full amount of its steady-state increase of about 10 percent. In their version of augmented International Monetary Fund's MULTIMOD simulation model, multi-factor productivity is endogenized by relating multi-factor productivity to the stock of R&D capital, international R&D spillovers, and trade. However the fact of the matter is that the impact is large early on and very small in the last phases of the growth process. In particular, about half of the steady-state value of the R&D capital stock is obtained after 15 years. Thus, our approximation of taking 28 years of lags might be apposite. Thus, we started R&D stock calculations from 1953, because the availability of R&D expenditure data for the United States. Rest of the OECD countries' data start at 1981. Since previous studies show that the United States is the major generator of R&D spillovers all over the world, and other countries uses the knowledge generated through R&D expenditures in the United States, R&D performed in the United States will influence the multifactor productivity of the other OECD countries considered here, and it will not effect our econometric estimates. Thus, we calculated R&D capital stock for each country starting at 1953, and used zeros for the rest of the OECD countries.

Finally, given the various estimated depreciation rates at the firm level and industry level from a few studies, an estimation of depreciation rate at the aggregate (total economy) level may be helpful to understand spillovers and externalities generated through R&D expenditures are significant for productive knowledge of the society.

5. Empirical Results

Mosteller and Tukey (1977) argue that an econometric strategy would be to consider reasonable alternatives to see whether the results are sensitive to technique or specification. However, during the process of reporting the results we only consider different specifications of the equation (5.7). We systematically exclude variables from the specification (5.7) to check if estimated coefficients are statistically different[10]. We estimated the model using the Seemingly Unrelated Regression (SUR) estimator that corrects for the contemporaneous correlations of the error term across the nations. In addition, SUR allows us to estimate country specific parameters for the countries considered in this study. We have argued that assuming homogenous parameters and adjustment dynamics across all the sample countries in the panel would not be suitable because of the heterogeneity in multifactor productivity levels (or growth rates) and its determinants among the sample nations. In this context, the best empirical strategy would be to conduct country-by-country econometric analyses of equation (5.7). However, we only have 21 observations for each country and twelve theoretical determinants of multifactor productivity. Unfortunately, not having enough observation coupled with the number of the explanatory variables, degrees of freedom problems wouldn't let us conduct country-by-country time series analysis.

Another reason to use Seemingly Unrelated Regression is that the disturbances in equations for each country at a given time are likely to reflect some common unmeasurable or omitted factors, and therefore, could be correlated. When such correlations exist, it may be more efficient to estimate all equations jointly. Plus, Breusch-Pagan LM test shows that errors are contemporaneously correlated, hence we used the SUR rather than ordinary least square (OLS).

Finally, since we construct the R&D stock and estimate the returns to R&D simultaneously, our results will depend on the, using Hall's notation, "implied depreciation rate" (2007, p. 36). The estimated parameters would be the ones where estimated log of the likelihood function of SUR reaches maximum or minimum point for given depreciation ratios during the grid search process. In the calculations of R&D capital stocks we assumed depreciation rate is constant across countries and during the sample period of this study

The distribution of log of the likelihood function can be seen in figure 2, and it is shown that log of the likelihood function reaches maximum value (1211.453) where depreciation rate is **–2%**. A depreciation (rather appreciation) rate of **–2%** for university R&D implies that spillovers, and externalities generated through R&D reflected in social returns to R&D is significant and previously generated knowledge may represent itself in the new innovations.

[10] Only the final specification that includes all explanatory variables of MFP reported.

Figure 2: Pattern of log of the likelihood function estimates: SUR

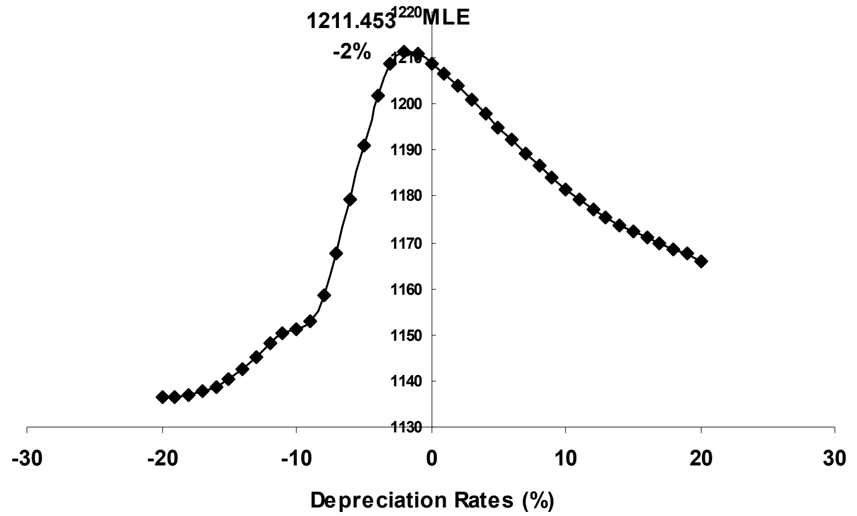

Table 2 reports the country-specific multifactor productivity estimation results (in log levels) obtained from our estimated model in which impact of university R&D stock on multifactor productivity is taken into consideration with the competing theories of productivity.

Changes in the country-specific point estimates of multifactor productivity with respect to university R&D stock, $\partial MFP / \partial S^u$, with the introduction of the competing productivity determining factors one can argue that considerable cross-country heterogeneity is shown across the sample nations. While the estimated coefficients of stock of university R&D is statistically significant for the seven countries (France, Germany, Italy, Japan, the Netherlands, Spain, and the United States) at least 10% or better significance level, for five countries (Belgium, Denmark, Finland, Ireland, and the United Kingdom) the estimated coefficients are *not* significant, implying impact of its university R&D stock upon domestic multifactor productivity is not important.

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Table 2: Country-Specific Parameter Estimates, in log levels;

University R&D stock with competing theories of productivity - t-values

	S^u	G	H	L^l	M^h	X^h	F^I	F^O	□U
BEL	0.075	-0.190	-0.324	1.788	-0.092	0.083	0.113	-0.098	-0.070
	1.376	-1.021	-1.338	1.750	-2.030	1.668	3.795	-2.667	-2.377
CAN	-0.098	0.130	1.324	-0.362	0.014	0.011	0.043	0.054	-0.056
	-2.527	0.844	1.932	-0.400	0.517	0.729	2.023	1.862	-3.764
DEN	0.030	-0.229	2.410	-1.889	-0.085	0.103	-0.042	0.039	-0.071
	0.970	-1.222	2.087	-2.178	-2.056	2.639	-2.361	2.096	-5.854
FIN	-0.013	0.365	0.482	1.709	-0.020	0.011	-0.011	0.044	-0.053
	-0.278	1.533	2.345	1.873	-0.502	0.383	-0.524	2.371	-5.294
FRA	0.220	-0.342	-0.696	0.248	-0.033	-0.063	0.031	0.020	-0.056
	4.871	-2.176	-2.757	0.527	-0.680	-1.478	1.787	1.489	-2.463
GER	0.112	0.365	1.409	-2.297	-0.183	0.213	0.022	0.034	0.033
	3.436	2.265	3.260	-2.242	-2.104	2.113	0.644	1.004	1.463
IRE	-0.015	-0.333	3.410	1.940	-0.245	0.251	0.061	0.015	-0.037
	-0.285	-2.687	5.123	1.372	-3.152	2.526	2.674	0.358	-1.043
ITA	0.155	-0.514	-0.845	0.204	0.054	0.035	-0.017	0.049	0.014
	2.094	-1.488	-2.132	0.187	0.813	0.523	-0.630	1.238	0.174
JAP	0.310	0.173	-1.072	-2.046	-0.184	0.042	0.008	0.038	-0.030
	6.122	1.429	-1.754	-3.115	-2.720	0.568	0.512	2.711	-0.976
NET	0.129	0.219	-0.716	-2.158	0.041	-0.076	-0.080	0.104	-0.042
	1.867	0.716	-0.530	-0.971	0.377	-0.617	-0.942	0.954	-1.136
SPA	0.171	-0.180	-0.469	-0.314	-0.044	0.033	-0.011	-0.014	-0.015
	11.316	-6.433	-4.212	-1.184	-4.244	3.876	-1.623	-2.429	-2.689
UK	0.036	-0.048	0.272	2.563	-0.048	-0.044	-0.041	0.053	-0.056
	1.034	-0.528	1.333	2.793	-1.291	-1.139	-1.722	3.174	-2.933
US	0.347	-0.112	1.060	0.896	-0.118	0.030	-0.009	-0.026	-0.017
	2.363	-0.703	0.902	1.345	-3.665	0.859	-0.436	-0.708	-1.373
Mean est.	0.112	-0.054	0.480	0.022	-0.072	0.048	0.005	0.024	-0.035

significant, implying impact of its university R&D stock upon domestic multifactor productivity is not important.

We also find the influence of the stock of public physical infrastructure on domestic productivity is *not* statistically important for 9 countries. While Germany is the lone country shows positive and significant effect of public physical infrastructure on her multifactor productivity, remaining three countries (France, Ireland and Spain) exhibit negative and statistically significant effect.

Changes in the country-specific point estimates of multifactor productivity with respect to university R&D stock, $\partial MFP \big/ \partial S^u$, with the introduction of the competing productivity determining factors one can argue that considerable cross-country heterogeneity is shown across the sample nations. While the estimated coefficients of stock of university R&D is statistically significant for the seven countries (France, Germany, Italy, Japan, the Netherlands, Spain, and the United

States) at least 10% or better significance level, for five countries (Belgium, Denmark, Finland, Ireland, and the United Kingdom) the estimated coefficients are *not* significant, implying impact of its university R&D stock upon domestic multifactor productivity is not important.

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Results of explanatory power of human capital on multifactor productivity become even more puzzling, since in addition to Italy, three more countries (France, Spain, and Japan (at 10% significance level)) exhibit the domestic productivity reducing impact of human capital. The parameter estimates of multifactor productivity with respect to human capital, $\partial MFP / \partial H$, appear positive and statistically significant for the countries Canada, Denmark, Finland, Germany and Ireland. The rest of the countries do *not* show statistically significant effect on domestic multifactor productivity, even though they have positive signs.

In the case of increases in life expectancy is productivity-enhancing argument, the estimated coefficients of life expectancy at age one, $\partial MFP / L^1$, do *not* show positive and statistically significant estimates for seven countries (Canada, France, Ireland, Italy, Netherlands, Spain, and the United States). Furthermore, the large estimated parameters are puzzling.

The elasticity of high tech imports, $\partial MFP / \partial M^h$, seems negative and statistically significant for seven countries (the United States, Spain, Japan, Ireland, Germany, Denmark, and Belgium); and statistically insignificant for the remaining six countries. On the other hand, exporting high tech products appears productivity-enhancing factor for the countries such as Belgium, Denmark, Ireland, Germany, Ireland, and Spain.

Both inward FDI and outward FDI also appear to have similar parameter estimates compared to previous two sections. In the case of inward FDI, $\partial MFP / \partial F^I$, of the 13 sample countries, four countries (Belgium, Canada, France, and Ireland) exhibit positive and significant impact of inward FDI on domestic multifactor productivity; only the United Kingdom show negative and significant effect; and for the remaining countries the impact is statistically insignificant. Similarly, technological outsourcing (outward FDI) brings productivity improvements to five countries (Canada (at the 10% significance level), Denmark, Finland, Japan, and the United Kingdom); for Belgium, outward FDI reduces her multifactor productivity; and the remaining countries parameter estimates of outward FDI is *not* statistically significant.

Finally, point estimates for growth rate of unemployment rate shows that productivity is procyclical. However, Germany's wrong and statistically insignificant sign exists.

As a robustness check, we also compared our results with the estimates of ordinary least square. OLS estimates also exhibit the similar pattern compared the SUR estimates; however, with OLS we are unable to control the business cycle shocks[11]. Growth of unemployment rate is the only variable that we would be able to generalize according to discussions we have previously. Plus, P-VALUE of 0.009 we received as a result of Breush-Pagan LM test shows that errors are contemporaneously correlated. Thus, the SUR estimates parameters more efficiently.

Finally, we also check the significance of "implied depreciation rates" we estimated where the value of log of the likelihood function reaches maximum with the values of log likelihood function with the conventional 10% depreciation rate used to construct R&D capital stock. While estimated log of the likelihood function value is 1181.431 with the conventional 10%, this value is 1211.453 when the depreciation rate is -2%. Therefore, likelihood ratio test with χ^2 distribution with one degree of freedom shows that the difference between two depreciation rates is highly significant[12]. This also imply that conventional estimated depreciation rates such as 10% or 15% do not reflect the idea of public good characters of intangible capitals, specifically R&D stock we used in this study.

Conclusion

One must be careful when drawing policy conclusions on the basis of an empirical analysis undertaken at an aggregate level and using OECD-wide data over two decades. Any policy lessons should be confirmed by more detailed, country-level investigations and case studies. While it is important to keep in mind the wisdom emphasized in Griliches (1967, p. 17) of "not asking too much from our data", knowledge-multifactor productivity relationship was re-examined in a panel of 13 OECD countries for the period 1985-2005. In this analysis of knowledge-productivity relationship, we specifically focused on the possibility of omitted variables in determining productivity, and the ignorance of the idea that productivity relationship is heterogeneous across countries, since, first, factors other than knowledge stocks might influence the domestic productivity levels; in addition, the cross-country productivity levels show different degrees of sensitivity their determinants.

Compared to exogenous theories of growth, endogenous growth theories, by abandoning the assumption that the scientific knowledge is exogenous to the economic system, have given new life to the investigation of the determinants of long-term growth. The typical arguments over neoclassical growth theory involve issues like how long a burst of investment might spur a higher growth rate of per capita income before reversion to steady state, and whether the marginal product of

[11] Results are not shown here, but it is available on request.

[12] The value of χ^2 distribution with one degree of freedom is 3.84146 at 5 percent significance level.

capital had some minimum bounds. Those questions appear less interesting than articulating a new perspective on the underlying determinants of the rate of the productivity growth with the implications of new growth theories. The case that it is the accumulation of knowledge, rather than the accumulation of physical capital, that is the engine of long-run economic growth relies on the particular properties of knowledge – which it is a public good, that its accumulation is potentially limitless, and that its accumulation does not suffer from diminishing returns. In this paper we followed the implications of new growth theories and analyzed the cross-country differences in multifactor productivity levels.

We argued that other than types of knowledge stock omitted variables proposed by competing theories of multifactor productivity might be significant that omission of these variables might generate difficulties in policy analyses that enhance the multifactor productivity of the domestic economies. Previous empirical studies that analyses the role of knowledge on productivity concentrate on various measures of R&D as the sources of productivity. In addition to knowledge stock - university R&D - we used eight other determinants of multifactor productivity that are proposed by the competing theories. Those are the measures of government infrastructure stock and human capital stock, life expectancy at age one, ratios of high tech imports and exports, inward and outward foreign direct investment, as well as a control variable for the business cycle. We argued that if the omitted variables problem is true, the estimated parameters become biased and their conclusions unreliable. This raises concerns on these results.

Furthermore, autoregressive fixed effects models are used by existing empirical studies. Even though these methods permit for country-specific fixed and country-invariant-time effects, they imply that productivity relationships are homogenous across the sample of countries. In other words, they cannot address the potential cross-country heterogeneity in slope parameters. Hence, we used Seemingly Unrelated Regression (SUR) estimator that differs from the method of pooling time-series or cross sectional data to correct for potential correlations between the error terms associated with the 13 countries. In addition, SUR allows us consider cross-country heterogeneity, because of the assumption that each cross-section unit has a different coefficient vector. Thus, we are able to report country-specific parameters and their significance.

An empirical analysis of this nature has both theoretical and practical applications. At the theoretical level, importance of competing theoretical models can be revealed if they pass the empirical investigation of multifactor productivity determining factor. In practice, policy makers may be better informed by the identification of the key derivers of productivity and their parameters.

The results show that the university R&D stock is statistically significant and have a positive impact on productivity for the countries France, Germany, Italy Japan, the Netherlands, Spain and the United States. On the other hand, remaining countries' university R&D stocks lose their explanatory power on multifactor productivity. In fact, Belgium, Denmark, Finland, Ireland, and the United Kingdom are the countries that represent their university R&D stock are not a factor in determining multifactor productivity. Another country is Canada, which has a negative and statistically significant estimated parameter after introducing the competing theories of productivity. Estimated point elasticities vary across the countries representing that cross-country heterogeneity is important.

Competing theories of productivity also follows the unexpected coefficient estimates as the stocks of R&D capital. The public infrastructure does not seem to enhance multifactor productivity. Its effects are insignificant for nine countries and significantly negative for the remaining four. The stock of human capital has a positive and significant impact on multifactor productivity. However, the estimated coefficients are very large. In addition to having large coefficient estimates, its negative and significant sign for France are also puzzling. Life expectancy at age one represents the similar pattern with the stock of human capital. Estimated coefficients are very large, and whether their statistically positive or negative impact on productivity brings more puzzling results. Furthermore, other determinants – ratios of high tech imports and exports, inward FDI, and outward FDI – of productivity show mixed results. They appear statistically significant in several cases but the signs of their coefficients do not always confirm the theoretical *priors*. Finally, business cycle control variable, growth of unemployment rate, has negative and statistically significant impact on domestic productivity for the majority of the countries in the panel (11 out of 13 countries have the negative sign and 7 of them are statistically significant). In other words, economic shocks have productivity reducing impact on domestic economies.

The problem with the constructing R&D capital stock is that it requires knowledge of unknown depreciation or obsolescence rate, and time lag that represents the number of years for a flow of R&D to become useful in private production (or to go through the phase of generating marketable products or processes). Previous empirical studies assumed depreciation rates ranges between 5% and 15% to construct the R&D capital stock using the perpetual inventory method. On the other hand, results of a few papers that estimate the private depreciation rates at the firm level and industry level showed that "implied depreciation ratio" ranges from **–17.8% to 46.9%** depending on the time, industry and estimation technique. Compared the results of empirical studies that estimate depreciation rates for R&D capital stock shows that "implied depreciation rates" might be negative and positive. However, in construction of R&D capital stock perpetual inventory method does not allow to use *negative* depreciation rates, or rather appreciation.

On the other hand, we estimated depreciation rate through a grid search considering depreciation rates changes between **–20%** and **20%**[13] by constructing the R&D capital stocks with 28-year embodiment lag from R&D expenditures and estimating their social rate of returns simultaneously using Seemingly Unrelated Regression (SUR) estimator. We estimated depreciation rate (rather appreciation) of -2%.Remanding that we estimated social returns to R&D, and the negative "implied depreciation rates" imply that the positive externalities and the intertemporal

[13] Depending on the specification we estimated we had to check the lower depreciation rates, for example the "implied depreciation ratio" (rather appreciation) was –35% in the specification in which multifactor productivity regresses on only university R&D stock and unemployment rate growth.

spillovers generated through new innovations is higher than the negative effect of business-stealing effect in which innovations destroys the social returns from previous innovations. Another implication is that cost of distributing the idea previously innovated is small that Baumol (2002) argues that most innovations are nothing more than slightly improvements in something that already exists. Finally, estimated negative “implied depreciation rates” represents the public good nature of knowledge, which is summarized by Stephan (1996)

“ .. it is not depleted when shared, and once it is made public others cannot easily be excluded from its use. Moreover, the incremental cost of an additional user is virtually zero and, unlike the case with other public goods, not only is the stock of knowledge not diminished by extensive use, it is often enlarged.” (p. 1200)

Finally, the likelihood ratio test shows that the difference between the “implied depreciation rates” we estimated considering the values of maximum log likelihood function for all specifications and those with the traditional 10% depreciation rate is statistically significant at any significance level. This implies that considering the R&D stock capital similar the tangible capital stock could be misleading, especially at the cross-country studies social returns to generated knowledge or new ideas are higher than obsolescence of the benefits we receive from the previously generated ideas.

In general, since the way we estimated the model we only used the university R&D stock. One can argue that colinearity will be problem, but we can add other domestic knowledge generating factors such as business R&D stock, government R&D stock, and foreign R&D stocks. Then, it would be interesting to see the results. Our results generally contradicts with the theory in estimating the impact of domestic sources that effects domestic productivity, such as, stock of human capital and life expectancy. Another way to estimate the model may be by defining the cross-country heterogeneity in productivity parameters. In this type of modeling, country-specific parameters assumed to be linear function of the country specific mean or per worker stocks of types of knowledge stocks. Eventually, the multifactor productivity estimated by cofactor of previous years productivity levels and mean or per worker stocks of university R&D stock[14]. Considering the cross-country heterogeneity in this manner would in our research agenda for the future.

[14] Pesaran *et al.* (2000) find that when cross-country heterogeneity is accounted in this type, the non-linearity in macroeconomic relationship disappears. In other words, the econometric evidence of non-linearity in macroeconomic relationships may be due to neglected heterogeneity.

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