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Institute of Economic Studies

MASTER'S THESIS

The Cross-Country and Cross-Sectoral Study of TFP and its Determinants

Author: **Bc. Michael Bogren**

Supervisor: **Ing. Vilem Semerak M.A., Ph.D.**

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently; using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.

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Prague, June 14, 2017

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Signature

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Abstract

This paper examines the impact of R&D and share of merchandise exports on total factor productivity in the 15 OECD countries through 1996-2009. The paper also discusses the inclusion of the human capital variable in influencing the TFP. The domestic R&D stocks are based on domestic industry-specific R&D. The share of merchandising exports is sector-invariant. We use the random effects to control for unobserved heterogeneity. In this case, the unobserved heterogeneity reflects the differences in trade and R&D policies. The main findings we have obtained are: i) the R&D stocks have a positive impact on TFP based on the random effects model, ii) the exports have a positive and significant impact on TFP, especially in the manufacturing sector.

1. Introduction

Trade has contributed to the economies in many ways. Trade can expand the choices of products and enhance competitiveness. Innovation plays an increasingly important role in facilitating the transfer of know-how technology and has helped to promote investment in research and development on a global level. The terms “trade” and “innovation” are increasingly found to be linked to each other due to globalization and of the increasing interdependence of many economies. Innovation is reflected through total factor productivity. Total factor productivity encompasses long-term technological change. This thesis will focus on trade channels by which innovation can be transferred between different regions and economies. The relationship between trade and innovation seems to be bidirectional and non-linear. The aim of this work is to analyze the effect of technological innovation on trade by considering sector and country heterogeneity. Analyzing heterogeneity of trade and innovation is an interesting yet complex feature of this paper. The unobserved effects are the innovation processes that have an unobserved effect on total factor productivity. The relationship between innovation and performance may positively contribute to learning-by-doing effects and the other way around. The strong positive relationship contributes to the increase of the availability of resources such as skilled labor. The paper identifies strong correlation between such factors that influence efficiency. Therefore, we are looking at strong correlation between efficiency, innovation and trade.

2. Main research hypotheses

2.1 First hypothesis

This analytical work is aimed at validating two important hypotheses. The first hypotheses is that there is a positive link between R&D and TFP. The difference in TFP levels across countries may reflect the differences in R&D policies. Mancur Olson (1996) emphasized that the difference in incomes across countries is related by the difference in their economic policies and institutions. The author has stressed the differences in national policies at the highest aggregate level. The highest aggregate perspective views that the national boundaries mark the borders of public policies and institutions that are not only different, but in some cases better and in other cases worse. These differences are reflected in the R&D policies as well. The problem can be in the motivation to implement the technology through the lens of the quality of institutions, economic policies and capital flight. The increased intensity of trade, which can occur under a favorable business climate can allow for better production processes to appear in the selected countries. Production processes allow for innovation to take place (e.g. “learning by doing”).

2.2 Second hypothesis

Secondly, I hypothesize that there should be a positive relationship between technological innovation and exports. Participation in export markets should enhance the innovation process and boost export productivity. The exporting market is regarded as competitive and should induce small non-exporting firms to enter the export market. Melitz (2003) indicated that more productive economies are much more likely to export. Higher productivity implies better export performance. More productive firms contribute to the increase in efficiency and productivity of the economy. To test this hypothesis, I evaluated efficiency (TFP) on share of merchandise exports. Filipescu, Prashantham, Rialp and J.Rialp (2013) have used a logit regression model to offer a more complete picture of the relationship between exports market and innovation. The innovation should result in firms having a higher probability of exporting. The discrete choices focus on the probabilities of innovative practices and exporting. In this paper, we use the correlation coefficients and the random effects model to provide a link between exporting and innovation. We may also know that exporting may not necessarily require innovation beforehand or post-entry. However, the main idea relies on the fact that the innovation decisions of different firms within different sectors are related directly to their export decisions. The market share increase of the most productive firms both lead to a productivity gain and an increase in welfare. The component of our analysis relies on industry level data rather than firm-level data. Majority of the papers on firm-level data consist of individual country cases and therefore there are challenges when using firm-level data for 15 OECD countries.

2.2.1 Issues related to obtaining firm-level data

The process of partial pooling in random effects can create problems, when firm-level data are obtained. Bartelsman, Haltiwanger and Scarpetta (2005) have stated that pooled firm-level datasets do not reflect the representative sample of firms in each of the countries. The problem with cross-country comparisons of measures of firm dynamics is that measurement errors vary across countries, especially with respect to the coverage of different types of businesses. Through sector-level data we can generally capture the firms' aggregate behavior in the market.

3. Literature Review

3.1 Endogenous growth theory

The paper will focus on testing trade-related aspects of innovations suggested by the endogenous growth models. The endogenous growth theory suggests that countries will achieve a higher growth path if they can acquire foreign knowledge, say through trade liberalization. The endogenous growth model emphasizes the technological progresses resulting from the investments, capital stock and human capital.

Phillip Aghion and Peter Howitt (1997) use the concept of creative destruction, where entrepreneurs constantly seek new ideas to "win" against their competitive rivals. Phillip Aghion and Peter Howitt (1997) provide a comprehensive survey of theoretical and empirical debates raised by modern growth theory. Authors consider many other phenomena that interact with growth, such as inequality, unemployment, capital, education and much more. The research agenda of Phillip Aghion and Peter Howitt shows that competition can have a positive overall effect on the rate of innovation because firms will try to innovate to escape competition. Econometric investigations that were undertaken provide a strong support for a non-linear relationship in which competition has a positive effect but up to a certain point. The intensity of competition decreases the profits for successful innovators, but decrease profits even more for failing innovators. The product market competition does not necessarily contribute to growth as innovation destroys the value of an existing product by replacing it with a different product. The concept of competition and creative destruction are the essential factors that characterize capitalism. The level of competition is determined by the openness of the economy and on the state of the institutions.

3.1.1 Relevance of endogenous growth theory to our research paper.

An endogenous variable or in other words the dependent variable in this case is the total factor productivity. Total factor productivity measures the efficiency of all inputs to a production process. Increases in total factor productivity often reflect technological innovations or improvements. R&D should benefit and contribute to a country's TFP and lower the economic inequality between nations. Trade is an important mechanism by which knowledge and technological progress is exchanged across countries.

3.2 United Nations presentation on the methods of measuring innovation and finding common indicators that enhance the effectivity of measurement

The United Nations have released a presentation based on measuring innovation with regards to training workshop on science, technology and innovation indicators. These indicators are useful when gathering data from OECD database. Certain business indicators are lacking for developing countries in OECD database. OECD provides more detailed indicators for the OECD members and selected other important countries. The sectors that are included are; computing, engineering, construction other science-related research sectors. Comparable information may be incomplete because the resources and process may not be available. The global data lab analyzes and monitors political, cultural and socio-economic changes in the countries. My research paper does not solely depend on OECD database. Capital expenditures for innovations are composed of gross expenditures on land, buildings, equipment and computer software. There are also non-research and development expenditures that are linked to product and process innovation such as the acquisition of machinery, equipment and other capital goods. The international Industrial classification is a statistical unit of innovation survey classification (ISIC Rev 3.1). For my research paper, we are using the ANBERD database to collect information on total R&D expenditures. The R&D expenditures are used for constructing R&D output.

3.3 How important are Capital and Total Factor productivity for Economic Growth?

Baier, Dwyer and Tamura (2002) have elaborated on the relative importance of human capital and the growth of total factor productivity. The authors have used newly organized data on 145 countries that span more than 100 years for 24 of these countries. Each of the 145 countries is included in one of nine regional groups. The changes in technology can be reflected in the growth of human capital. The analysis focuses on the growth rates of output and inputs relative to the labor force. Output per worker means output per member of the labor force. The measurement of human capital per worker in each country both reflects average education and average number of years employed. Similarly, to my research paper, the authors have computed the education by the average number of years schooling for an employed person. These data are used to calculate the fraction of the population that has primary schooling, secondary schooling and college education. The transformation from educational attainment and experience to human capital is based on the estimated parameters of earnings regression. The authors have shown the behavior over time of the growth rates of output per worker for the nine regions. The authors have noted that the TFP has not increased uniformly for any of the regions. It is not necessary that to suppose that deteriorating technology help explain decreases in TFP. Many other factors, including decreases in competition or disruptions in private markets can account for these developments. The TFP for the United States accounted for only 32 percent of output per worker. The author provides changes in TFP growth relative to output growth for more countries. Importantly, the authors have addressed the variability of TFP across countries. The variance of TFP growth explains all the variance of output growth across countries. All changes in the output growth are predictable by TFP growth are due to TFP growth. In other words, the correlation might reflect differences in input growth rates induced by differences in TFP growth. One possible interpretation of the negative correlation between aggregate input growth and TFP growth is that there might be imprecise data in aggregate input growth that induces an opposite movement in TFP growth. The TFP might fall since output does not rise as much as would predicted otherwise. There might be a common factor that affects aggregate input growth and TFP growth in opposite ways. Such factor could include emigration of the least efficient employees. The authors have concluded that in nine of the regions TFP growth accounts for about twenty percent of average output growth in 3 regions and between 10 and 0 percent in the other 3 regions. In three regions, the TFP growth is negative on average. The variance of TFP growth appears to be associated with negative TFP growth

3.3.1 The relevance of the article to the research paper

My research paper focuses on the differences of TFP across 15 OECD countries. The variation of TFP growth across regions and negative growth rates seem to be present in my paper as well. In some instances, I have obtained negative estimates of TFP of some countries, using the country dummies in my random effects model. [1] The TFP consists the ratio of output produced to the amount of all inputs used.

3.4 Exporting and productivity

Bernard and Jensen (2009) reflect on the role exports on productivity levels. The authors have observed that the exports and productivity are positively correlated across manufacturing industries. The article considers looking at exports across one industry. Exporters do grow faster than non-exporters in terms of shipments and employment. The

[1] The estimates obtained from the country coefficients are in Table 9.

overall contribution of exporters to manufacturing productivity growth exceeds their shares of employment and output. The authors have indicated that the industry data show causality from productivity to exporting.

3.4.1 The relevance of the article to the research paper

In this research paper, we are testing the hypothesis regarding the positive relationship between productivity and exports. In our case, our hypothesis does not consider the causality. The random effects model should illustrate a positive and significant role of exports on total factor productivity. In addition, our dataset consists of 8 sectors, rather than only one sector.

3.5 Empirical analysis of the effects of R&D on productivity: Implications for productivity measurement

Parham (2006) argues that R&D is a major source of long-term productivity growth. The article mainly outlines the empirical difficulties in pinning down a magnitude on the effect that R&D has on productivity. Specifically, the paper highlights the conceptual and empirical difficulties in using the constructed R&D capital on quantitative analysis.[2]Growth in the R&D activity in the OECD area accelerated from the mid-1990s. The effects of R&D capitalization vary across countries according to the relative importance of R&D. There is a defensible argument that capitalizing R&D as part of measurement of output and wealth is an improvement over the current practice of using R&D expenditures. The article has indicated that the effect of R&D capital on the level of TFP would be higher than in the level of labor productivity. In addition, the effect of TFP growth would depend on how rapidly R&D activity is growing.

3.6 TFP growth and its determinants: a model averaging approach

Michael Danquah, Enrique Moral-Benito (2014) stressed that TFP growth is hard to measure empirically. The paper combines non-parametric measure of TFP growth. Their empirical findings suggest that the most robust TFP growth determinants are time-invariant unobserved heterogeneity and trade openness.

3.6.1 The relevance of the article to the research paper

The unobserved heterogeneity is present across countries. The heterogeneity across country and time will be reflected and illustrated in the data section. Non-parametric

[2] The issues related to the construction of R&D stocks are reflected in the data section (section 5.2.17)

categorization of data suggests that our data does partly follow a linear trend, partly at least in coefficients. Non-parametric methods can be used for relationships, which may be linear. Not all variables follow a normal distribution.

3.7 Heterogeneity of total factor productivity across Latin American countries: evidence from manufacturing firms

Kapp and Sanchez (2012) have concluded that the main factors explaining the differences in productivity across firms are related to country-level, not firm-level, characteristics. The authors have stressed that there is significant heterogeneity within the Latin American region. The heterogeneity is reflected through income per capita, poverty levels and financial development. The authors focus solely on the manufacturing sector. The paper reports on the differences in the factor elasticities between countries. The authors have found that aspects such as firms' size, export status and access to credit markets matter, the main factor explaining differences in productivity across firms is related to country-level characteristics. Productivity is mainly driven by factors largely out of control for the firm.

3.7.1 Relevance of the article to the research paper

My research paper considers country-level data. The values of the variables vary across countries. The share of merchandise exports considers many exporting firms. My analysis shows that the firms do not have control over the factors that impact productivity. Furthermore, my data section (section 5.4) provide the degree of heterogeneity across countries and time. We observe heterogeneity for all variables. The country dummies illustrate the difference in TFP across 15 OECD countries.

3.8 North-South and South-South Trade-related Technology diffusion: How important are they in improving TFP growth?

Schiff and Wang (2006) in their study stress the importance of the likelihood of the endogeneity problem in the study of TFP and technological diffusion. Specifically, the endogeneity problem between total factor productivity and explanatory variables that impact innovation processes. According to Schiff and Wang (2006) endogeneity is driven by "cyclical considerations". Cyclical considerations are that the productivity is being affected by actual economic growth.

3.8.1 The relevance of the article to the research paper

Similarly, to our paper, the authors use the ANBERD (2000) dataset. The explanatory variables that Wang and Schiff (2006) use are R&D in telecommunications, education (average total schooling), the capital stocks are derived from investment series using perpetual inventory model with a 5 percent depreciation rate and labor share. The perpetual inventory method features inventory quantities that are updated continuously. My research paper will use a similar data collection approach; however, with more recent data. Schiff and Wang (2006) use the fixed effects in their methodology. The inclusion of country fixed effects allows for the isolation of the potential differences across countries in trade and innovation policies that may affect the trading decision. Industry fixed effects account for differences in factors like the level of competition, market demand and trade intensity which can affect the relationship between trade and growth. Moreover, fixed effects can control for the possible effects of differences in the macroeconomic environment and changes in international trade. Most importantly fixed effects are robust with respect to problems related to unobservables. Our research paper contains a special case of fixed effects. The random effects method will be used to obtain the estimates of the variables. The random effects consider the unobserved heterogeneity and in-between variation across sectors within the countries. Similarly, we are constructing the R&D stocks with a 5% depreciation rate. Schiff and Wang (2006) has differenced the TFP in the regression model. Our model consists of TFP as a dependent variable and lagged TFP as an explanatory variable. The inclusion of TFP and the lagged dependent variable differentiates the TFP variable.

4. Descriptive Statistics

The descriptive statistics consider data that show the trends R&D expenditures, and variables such as educational quality and proxies for human capital (earnings rate), relevant for transformation of R&D in actual increases of the TFP. The descriptive statistics shows simple graphic analysis of the variables that will be used in the methodology section. In this section, we are presenting and visualizing raw data. The descriptive statistics section does not consider inferential statistics. Inferential statistics is used in the data, methodology and results section.

4.1 Expenditures on R&D

In figure 1, we will compare expenditures on research and development and the education quality of different countries.

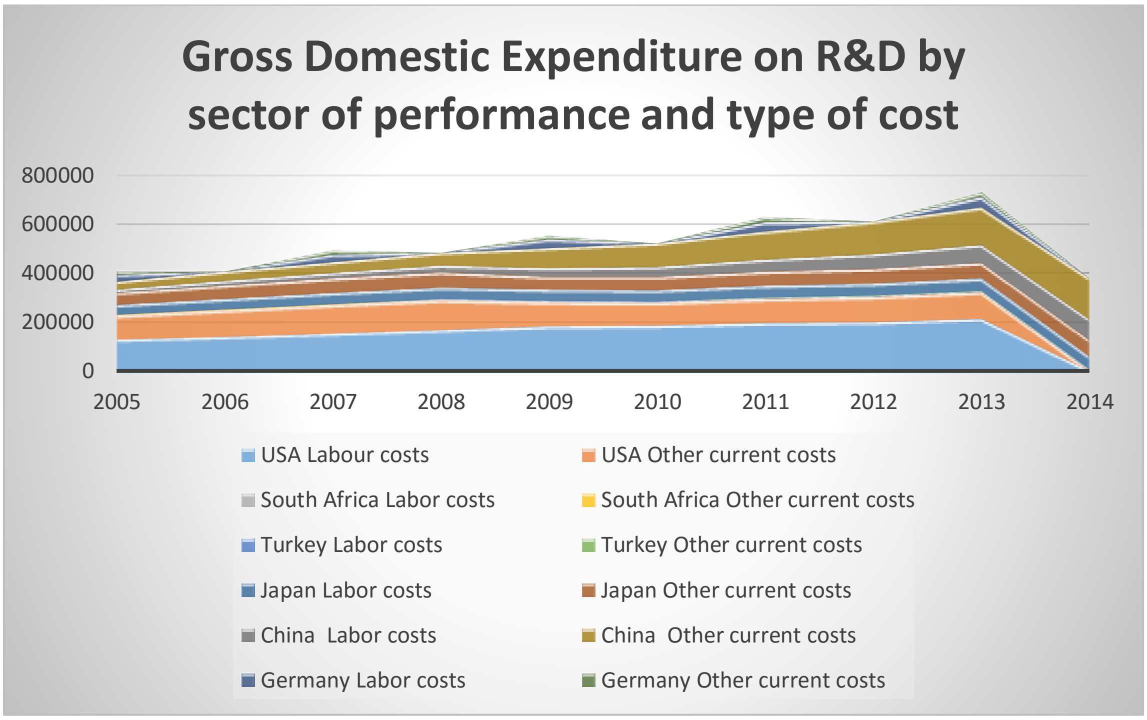

Figure 1: Gross domestic expenditure on R&D by sector of performance and type of cost from 2005-2014 in current prices US dollars (OECD data).

The sudden decline in 2014 is caused by the missing data. The types of costs are sub-total current costs, which are labor costs and other current costs. The sector represents business enterprise. The graph indicates that there is a gradual increase in investment for research and development. Especially in 2013 Turkey has seen a dramatic increase in current costs into R&D. United States remain steady in investment levels into R&D. Germany data has been absent in years 2008, 2010, 2012 and 2014. However, in general we are seeing an upward trend of investment into R&D in developed regions (USA, Japan, Germany) and emerging regions (Turkey, China and South Africa). The graph illustrates that the surge in R&D investments.

4.2 Educational quality

The important variable in our research is educational quality. Education quality is determined by satisfaction of students, employability of graduates and competition at enrollment stage. OECD data contains graduates by field and country, educational expenditures, enrolment by age and field, enrolment data adjusted to financial year. The increase in educational expenditure do not necessarily provide or emphasize the quality of education. Simply increasing education spending may not appear to improve academic achievement and spur innovation processes. The correlation between spending and quality may be challenged. The academic outcomes depend on how money is spent, rather than on how much money is spent. Despite the complexity in evaluating educational quality, we will use the average years of schooling in each of the countries as an educational variable. We assume that students that are enrolled in universities are skilled and ready to enter the labor market.

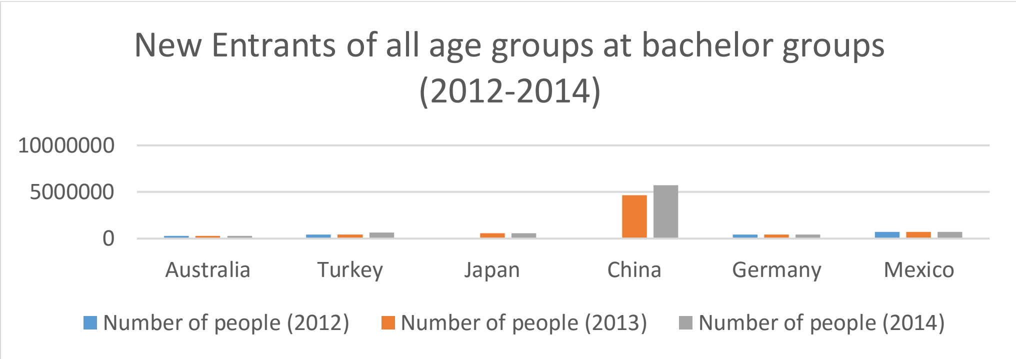

Figure 2: New entrants of all age groups at bachelor groups (OECD data)

We have not been able to receive data from Japan at year 2012 and United States. However, we can make simplistic comparison that are helpful in further research. The bachelor groups are defined via ISCED level 6 categories. Entrance at bachelor level indicates the student's ability to gather knowledge at higher level and therefore be potentially useful for contributing to innovation processes in the country. The data includes all age groups. We can see that Germany, Japan and Australia have a relatively static number of students being accepted into universities. We can see a dramatic increase of students being accepted in China. This could coincide with the increase in R&D expenditures (labor and other current costs) in China. Turkey and Mexico experience a dramatic increase in enrolment as well. Turkey's increasing number of students could also emphasize the close relationship between R&D expenditures and number of students being accepted in bachelor levels. The funding for the universities are mainly coming from the government. The data section provides a correlation table presenting a relationship between R&D and education (human capital variable).[3]

[3] The data section provides an explanation for the construction of the human capital variable (Section 5.2.4).

4.3 Human capital and innovation

The important elements of R&D are the knowledge, creativity and the ability to convert these resources into innovation. Specifically, the endogenous growth theory treats human capital as an important determinant in economic development. In such scenario, we are dealing with people that have graduated and entered the labor market. The cost of production of human capital comprises of living, health care and education expenses. The educational expenses are a determinant that influence the efficiency of the economy. Czajkowski (2014) has provided different approaches on analyzing the linkages between human capital and innovation. These approaches are based on costs of production, income levels in different countries and approaches based on educational parameters. Educational parameters are adult literacy rates and school enrollment rates.

4.3.1 The impact of Total Factor Productivity on workers' earnings

Workers should benefit from productivity growth as there are positive effects on real earnings. One can examine the increase in total factor productivity with an increase in earnings. In this paper, we should expect a strong positive correlation between these two variables. Hornbeck and Moretti (2015) estimated TFP by classifying workers into more-educated workers and uneducated workers. The author has estimated that TFP growth generates greater increases in the local number of more-educated workers and larger local wage increases for less-educated workers. Thus, the author justified that the local increases in TFP compresses inequality. More specifically Julian Messina, Oskar Nordstrom Skans and Mikael Carlsson (2016) have noted in their insights that workers' wages are responsive to TFP shocks that are shared with other firms in the same industry than to shocks that hit a single firm in isolation. In addition, when the TFP shock is shared across firms within which worker mobility is high, the wage of workers is more prone to changing. Harris and Holmstrom (1982) show that in a competitive market without worker commitment firms continue to insure against risk, but must increase the wages whenever productivity increases to retain the worker. More importantly, the impact on productivity shocks is skewed towards more-mobile high-skilled workers. In the long-run increases in worker's living standards is naturally linked to productivity growth. Productivity is not geographically uniform within a country and there are productivity differences within countries in the cross-section and in changes over time. These differences are reflected through R&D investment, education, trade and local economic policies.

4.4 Linkage between access to technology innovation and productivity

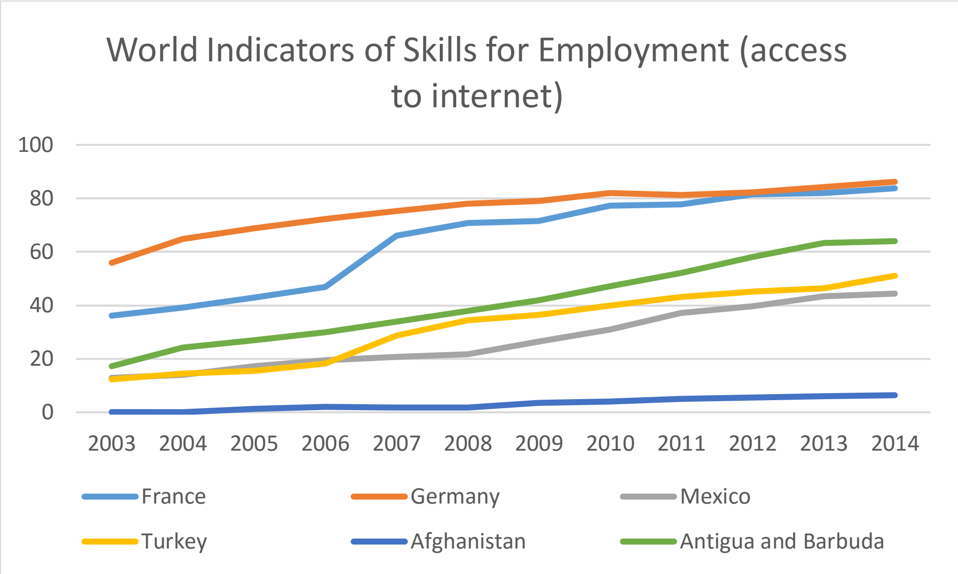

Figure 3: World Indicators of Skills for Employment in access to internet measured in per 100 inhabitants (OECD data)

Access to internet is an important determinant that impacts the performance of many firms. Shahram Amiri (2013) studied the correlation of GDP growth and internet penetration. The author stated that the Nordic region has some of the highest internet adoption, but also some of the highest GDP levels per capita globally. Connections to information become more prevalent and the access to information will begin to drive economies, productivity and efficiencies. Andres, Cuberes, Diouf and Serebrinsky (2010) have focused specifically on the introduction and growth of ICT in developing countries and its impact on GDP. The findings illustrated that the degree of competition in the provision of internet service contributes positively to its diffusion and that there are positive externalities associated with the increase in internet usage.

4.4.1 Access to technology and its use by manufacturing industries

The information and communications technology sector has been a powerful catalyst in addressing the needs of low-income countries. Only in the past twenty years the ICT sector's role in expanding economic opportunity has emerged. The rate of technological innovation in ICT has accelerated dramatically. William J.Kramer, Beth Jenkins, and Robert S.Katz (2007) stresses that technology only increases productivity when lots of people share access. An increase in access of technology reduces transaction costs, increases choice in the marketplace and channels knowledge and information of all kinds. Business that have access to technology can widen up their economic scope and opportunities. Manufacturing industries are responsible for spreading “know-how” and knowledge spillover. Therefore, having access to ICT accelerates the knowledge spillover across regions and countries.

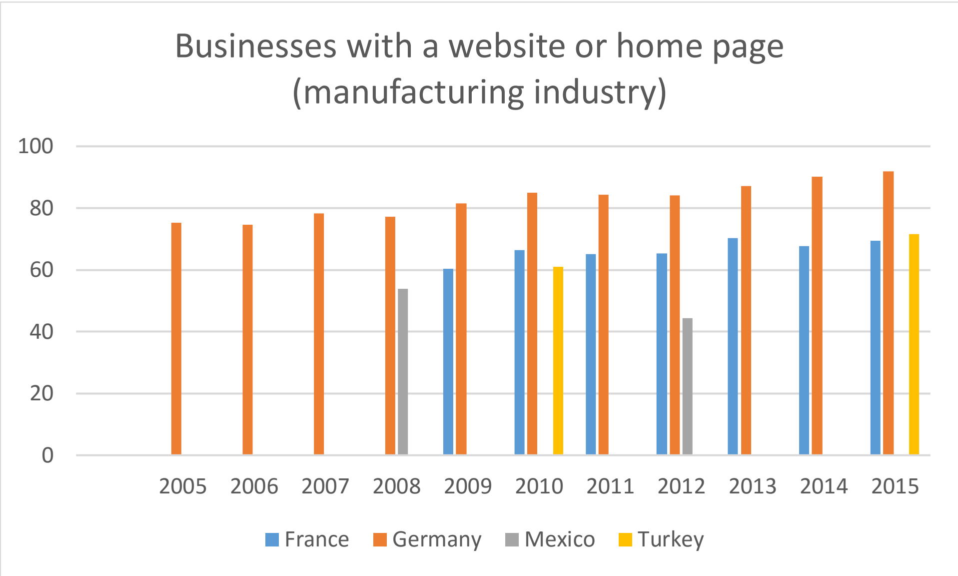

Figure 4: Businesses in manufacturing industry with a website or home page in percentages (OECD data)

Germany, France and Turkey have an increased rate of ICT access used by manufacturing industry. The challenge is that the OECD database lacks data coming from developing countries.

4.5 Linkages between trade and productivity

This section is important as it relates to the hypothesis regarding the positive relationship between exports and technological innovation. The dataset on export in goods consists of firms that are assumed to be the most productive in the country. Joachim Wagner (2005) noted that there are additional costs when selling goods in foreign countries. The range of extra costs include transportation costs, marketing costs or production costs in modifying current domestic products for foreign consumption. These costs are regarded as entry barriers of firms that are less successful and therefore less productive. We assume that OECD data on export in goods are related to many domestic firms that have high productivity and therefore have an impact on the economy and innovation process in the country.

5. Data

5.1 Description of data

The panel data includes 15 OECD countries from 1996-2009. The countries are selected according to the complete data availability on multi-factor productivity, R&D expenditures, human capital and share of merchandise exports. The selected sectors in our dataset are Agriculture and Fisheries, Manufacturing, Electricity, Machinery, Mining, Communications and Wholesale retail and repairs. The sector-level variables are multi-factor productivity and R&D stocks. The country-level variables are share of merchandise exports and human capital. The exports shares could not be obtained at a sectoral level. The human capital variable combines educational information regarding additional year of schooling and earnings of an average worker. The panel dataset is strongly balanced.[4]

5.2 Exploring panel data

Exploring the dataset involves summary statistics (number of observations, mean, standard deviation, min and max) time trends for TFP, export, R&D stocks and HC in the selected countries and their sectors. Furthermore, the paper examines the different standard deviations of TFP across countries. This section elaborates on the symmetry plots, histograms and normal Q-Q plot to indicate that we are dealing with dynamic panel data. This section also provides a correlation table.

5.2.1 Summary statistics

Variable	Obs	Mean	Std.Dev	Min	Max
TFP	1486	2.078	6.2237	-37.3	27.8
Human capital	1904	3.22	0.2922	2.56	3.68
Exports	1904	0.44	0.2541	0.084	1.39
R&Dstock	1266	6.90	2.5827	-0.015	14.38

Table 1: Summary statistics (Stata)

The summary statistics includes the information regarding mean, standard deviation, minimum and maximum. The total factor productivity has a significant variation between the minimum and maximum value. On the other hand, the human capital variable (HC) that includes education and earnings has relatively a low gap between its minimum and maximum value. The earnings rate in the dataset do not fluctuate and are relatively similar

[4] STATA has described the dataset as strongly balanced from 1996-2009. There are minor gaps in the dataset.

across countries. Additional year of schooling contributes to a higher rate of earnings across all 15 OECD countries and therefore one does not expect significant differences across the countries. Higher education does lead to higher levels of earnings.

5.2.3 R&D expenditures

Research and development expenditures are measured by using total costs of R&D. The total costs consist of basic research, applied research and experimental development. The data are obtained from OECD. The dataset does not contain data on many developing countries. The data represent current domestic R&D and gross domestic R&D expenditures by sector of performance (business enterprise). The ANBERD database incorporates industrial R&D expenditures. The current ANBERD database is broken down across 100 manufacturing and other industry groups. Most of the R&D is conducted in developed countries. Specifically, my research paper collects the data on 15 developed OECD countries. The data on R&D expenditures will be used to derive a measure of R&D stocks. The positive relationship between R&D and TFP should indicate an improvement in innovation processes in the country.

5.2.4 Human capital and education

The sector involves both public and private institutions and all educational programmes. Schiff and Wang (2006) has used average total schooling as an education variable. Average total schooling might not represent higher skills and knowledge that are needed for innovations to take place. Tertiary education is an important aspect in impacting TFP and innovation. It is assumed that people that are in tertiary education learn complex and challenging methods in conducting research and are applying them in practice. The complexity and difficulty in obtaining tertiary education should spur productivity and innovation. The education aspect in the data is incorporated in the human capital variable (HC). The human capital variable measures the rate of earnings in relation to 1 more additional year of schooling. The data on the human capital has been obtained from the Penn World database.

5.2.4.1 The construction of the human capital variable by using the Mincer equation

The human capital index is based on the average years of schooling from Barro and Lee (2013) and an assumed rate of return to education, based on Mincer equation. Helle Bunzel

(2008) states that the Mincer equation provides a relationship between schooling, earnings and post school investment in human capital. One such application of Mincer equation involves explaining earnings as a function of schooling and labor market experience. The Mincer equation provides estimates of the average monetary returns of one additional year of education. The information based on Mincer equation is important for policymakers who must decide on education spending and prioritization of schooling levels. Patrinos (2016) has stressed that recent studies that have used the Mincer equation indicate that tertiary education may now provide the greatest returns to schooling.

5.2.4.2 The issues related to using Mincer equation and constructing data on the average years of schooling

Patrinos (2016) has elaborated on three issues related to using the Mincer equation. Firstly, the relationship between schooling and earnings do not necessarily imply causality. Secondly, as economies become more complex and technological developments alter the demand for education, decades-old-cross sectional data may not be informative about returns to current investment decisions. Thirdly, earnings functions provide private returns to schooling, whereas public costs and other benefits are needed to estimate the social rate of return. The challenge in constructing data on the average years of schooling in the population is to combine information from population censuses with information on school enrolment, in the face of inconsistencies in classification systems between sources and censuses. De La Funte and Domenech (2006) and Cohen and Soto (2007) have argued that the data from Barro and Lee contain undesirable features related to inconsistent use of source data. Depending on the results it may be necessary separate the earnings and education aspect in the human capital variable.

5.2.5 Trade - related aspects of data

The frequency of the data is on an annual basis. Annual data allows for long-run analysis of TFP. The annual data have been used due to availability. The share of exports are weighted by GDP. The share of merchandise exports has been obtained from the Penn World database. The export variable is analyzed through the country level since the share of exports includes manufactured products obtained from all the sectors. The exports are sector-invariant. The positive relationship obtained from the share of merchandise exports and TFP will be reflected in estimates obtained from the random effects model. This would suggest that the export promote growth in general using aggregate data for countries and industries.

5.2.6 Trends in TFP in relation to country and sector

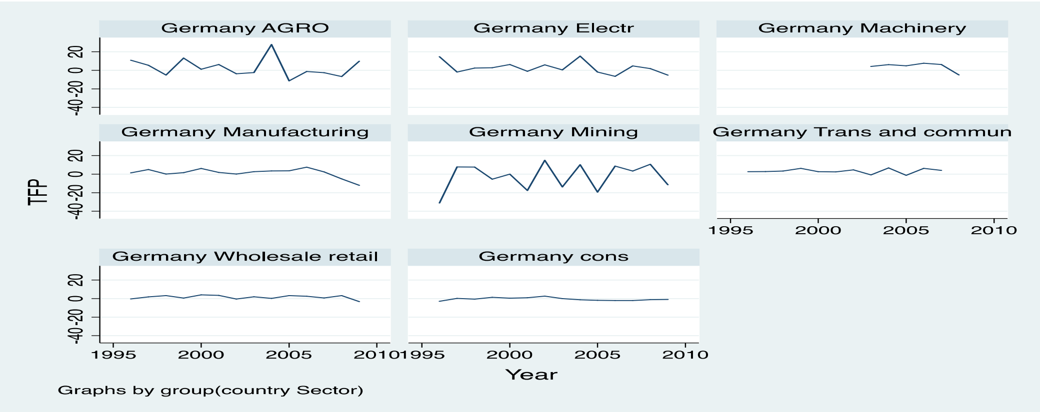

Figure 5: The trend of TFP in Germany across sectors from 1996-2009

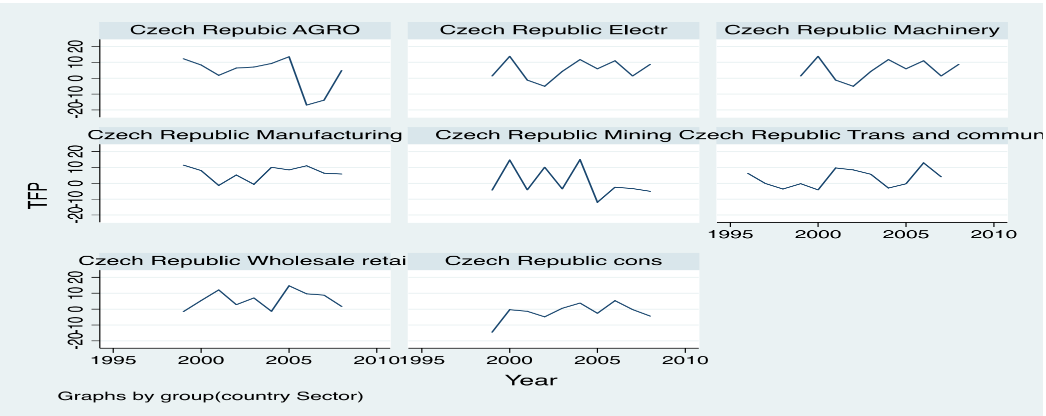

Figure 6: The trend of TFP in Czech Republic across sectors from 1996-2009

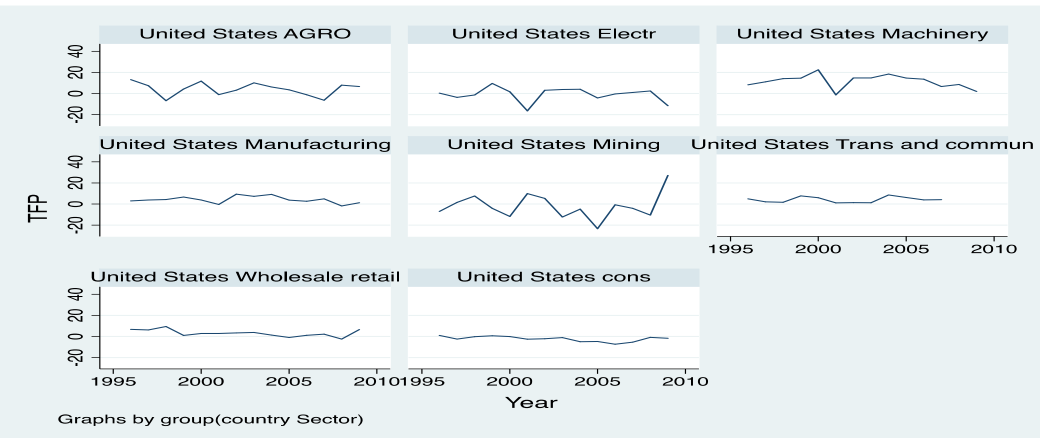

Figure 7: The trend of TFP in the United States across sectors from 1996-2009

Figures 5,6,7 presents the total factor productivity for 3 countries and 8 sectors[5]. The trend for TFP in Germany, Czech Republic and the United States behave in a random manner. The construction of TFP time plot graphs allows for the identification of non-linearity of the dependent variable. The TFP for the mining industry in Germany and the United States fluctuate very frequently. The TFP for Czech Republic fluctuate across all sectors. The OECD database did not have complete data on multi-factor productivity and therefore some of the values are missing. The missing information on multi-factor productivity can contribute to some degree of fluctuations in the TFP trends represented in Figure 7,8,9. The next section of exploring the data will involve the symmetry plots, histograms and the normal Q-Q plot for the variables included in this paper.

5.2.7 The symmetry plot for TFP

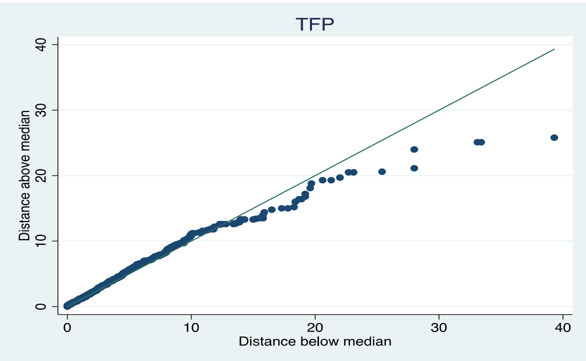

Figure 8: Symmetry plot for TFP (STATA)

The inference regarding the symmetry of TFP suggests that the data is weakly symmetric and light tailed. Light tailed distribution implies a small variance. The TFP variable takes its extreme values (both high and low) less frequently.

5.2.9 Histogram for TFP

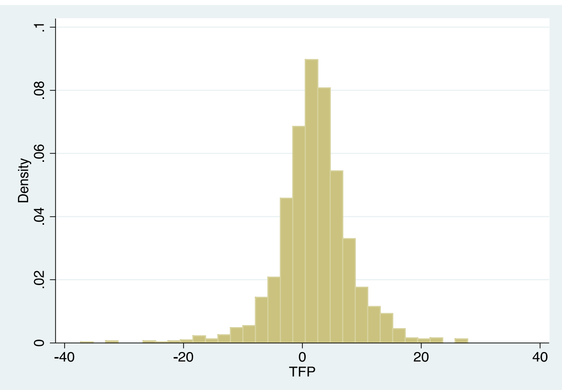

Figure 9: Histogram for TFP (STATA)

[5] The full representation of TFP trend across all countries and sectors are present in the Appendix figure 1. The 3 selected countries for TFP trends allow for clearer visualization.

The histogram for TFP illustrates that right tail of the distribution is longer than the left tailed distribution The TFP variable has a weakly skewed to the right.

5.2.10 The normal Q-Q plot for TFP

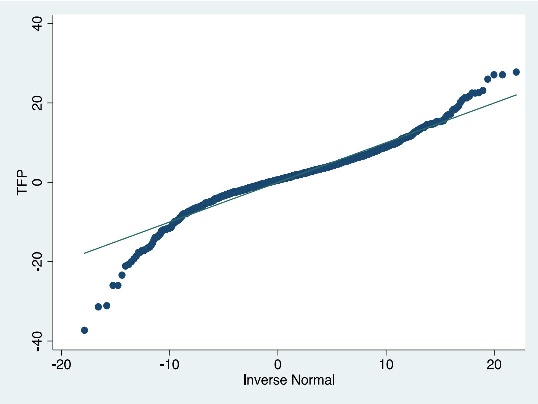

Figure 10: Normal Q-Q plot for TFP (STATA)

The normal Q-Q plot provides a graphical way to determine level of normality. The dots fall on the line indicating that the data for TFP are normal.

5.2.11 Standard deviation of TFP across countries

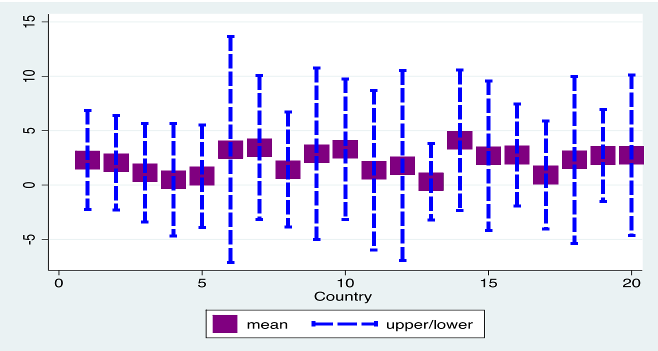

Figure 11: Standard deviation of TFP across countries

The standard deviations across countries differ from country to country. In my research paper, the degree of convergence depends on the selected countries. The standard deviation of TFP are similar within a selected group of countries. Similarly, Ascari and Di Cosmo (2004) have elaborated on the differences of TFP across Italian regions. The authors have constructed a standard deviation graph across Italian regions from 1980-2000. The authors have found that there is mixed evidence on convergence. The degree of convergence depended on the selected years.

5.2.12 Trends in share of merchandise exports in relation to country and sectors

Figure 12: Trends in the ratio of merchandise exports in Germany. (STATA)

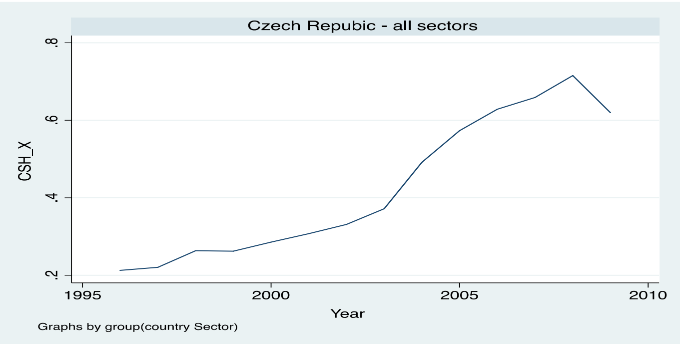

Figure 13: Trends in the ratio of merchandise exports in Czech Republic

Figures 12 and 13 shows an increase in the share of merchandise exports from 1996-2010 indicates that the growth rate of exports contributes to the progress of an economy in expanding economic activity into international markets.

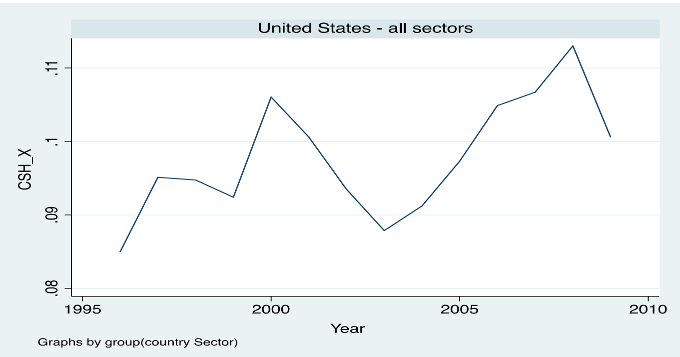

Figure 14: Trends in the share of merchandise exports in the United States

The share of merchandise exports weighted by GDP (CSH_X) is obtained by country-level data. The data on merchandise exports are sector-invariant. Figures 12,13,14 indicate that the exports data are linear and more predictable than the data on TFP. The model specification in the methodology section contains partly linear coefficients. Germany and Czech Republic have experienced an increase in the share of merchandise exports from

1996-2009. The United States experience fluctuations in their export levels. The trends for all countries indicate a rather steady rate of exports during that time[6].

5.2.13 Symmetry plot for merchandising exports

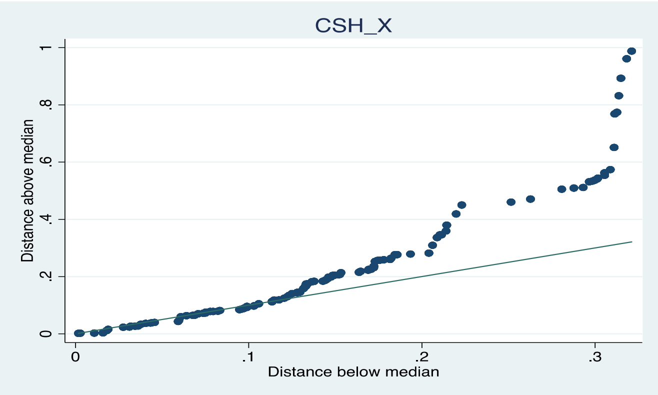

Figure 15: Symmetry plot for the ratio of merchandise exports

The symmetry plot for merchandising exports illustrates that the data are weakly symmetric and skewed to the right. The skewness is illustrated by its heavy right tail. The most extreme points are getting further away from the line. The weak symmetry could reflect the relationship between volatility and export diversification. The presence of weak symmetry may refer to the amount of uncertainty about the impact of changes or shocks on export productivity.

5.2.14 Histogram for merchandising exports

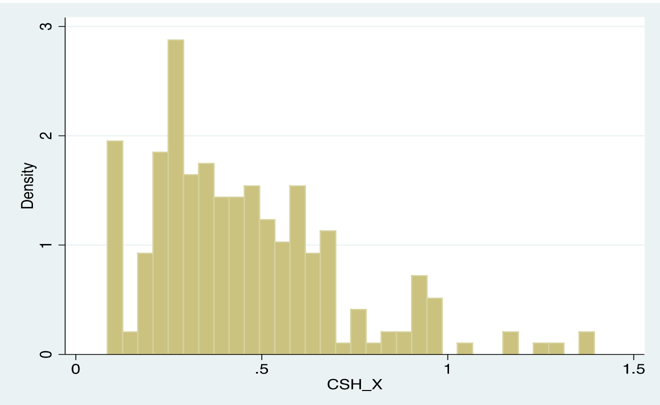

Figure 16: Histogram on the ratio of merchandise exports (STATA)

Figure 16 illustrates that the histogram is skewed heavily to the right. Much of the data are located on the right side of the histogram. The peaks represent the most common values. The most common values are between 0 and 0.5 indicating the values of 0-50% share of merchandising exports. The variable contains some outliers as indicated by the isolated bars at the end of the graph.

---

[6] The trends for merchandise exports for all 15 OECD countries are in appendix, figure 2.

The Shapiro-Wilk test

The Shapiro-Wilk test indicates whether the sample has a normal distribution. The table illustrates the Shapiro-Wilk test for normal data.

Variable	**Obs**	**W**	**V**	**z**	**Prob>z**
Exports	1904	0.92129	89.259	11.405	0.00000

Table 2: Shapiro-Wilk test for share of merchandise exports (CSH_X)

The null hypothesis of the test is that the sample is normally distributed. The p-value is zero, which indicates that the null hypothesis is rejected and therefore the sample size is not normally distributed. If the assumption of normality is violated, then the interpretation and inference may not be reliable. The violation of normality may be attributed to the unequal sample sizes between the variables. Given a relatively large sample size of 1904 observations, then the test may be more accurate. The skewness and the presence of outliers in some of the variables indicate the usefulness of non-parametric methods. My paper uses the Lowess smoother (section 5.3.4) as a non-parametric method in establishing a relationship between the variables. Nevertheless, the violation of normality assumption should not cause major problems in our specification. Despite the indication of non-normality Ghasemi and Zahediasi (2012) have stated that some researchers recommend the Shapiro-Wilk test as the best choice for testing the normality of the data.

5.2.15 The normal Q-Q plot for merchandise exports

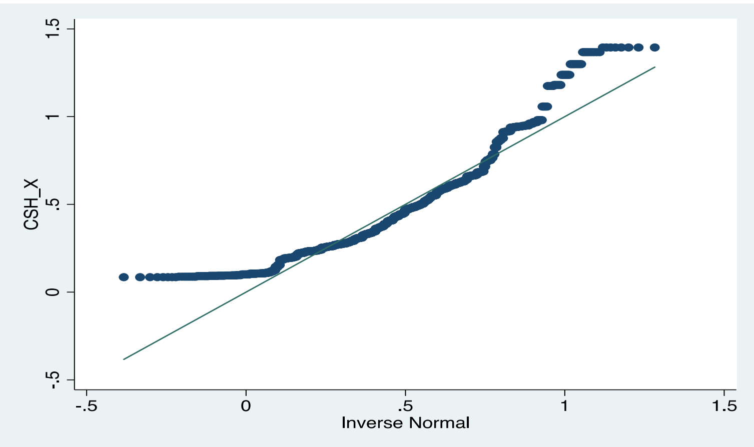

Figure 17: Normal Q-Q plot for share of merchandise exports (STATA)

In figure 17, the points fall along a line in the middle of the graph, but curve off in the extremities. The plot that exhibits this behavior mean that the data have more extreme values than would be expected. This is likely to be caused by the nature of the data as the values are increasing in time. The plot does not support normality of the sample.

5.2.16 The methodology used in calculating R&D stocks

Research and development has proven to be an important element of economic growth. Griliches (1981) has shown that R&D investment is an important source of productivity growth. The R&D stock of a county is not directly observable and therefore appropriate techniques have to be applied to construct measures of the capital stock. Michael Berlemann and Jan-Erik Wesselhoft (2014) have constructed R&D stock data based on the Perpetual Inventory Method. In this paper we are using the same method to construct R&D stocks for each of the countries that have been selected. The stock of inventory increases with investment. The amount by which the capital stock falls per period, is the depreciation rate. The equation that has been used to construct the capital stock is as follows:

$$K_t = K_{t-1} + I_t$$

Adding assumed geometric depreciation at constant rate δ, we can rewrite the capital stock as:

$$K_t = K_{t-1}(1-\delta) + I_t$$

For the calculation of R&D stocks we have chosen the depreciation rate of 5%. The following elements in the equation are:

$K_t =$ the stock of capital at current year

K_{t-1} = the stock of capital at previous year

δ= the depreciation rate at 5%

$I_t =$ the R&D expenditure at current year (investment at current year in US million dollars)

In addition one needs to calculate the initial capital stock. The initial capital stock is calculated using the formula:

$$K_0 = {}^{I_t}/_{(\delta + g)}$$

K_0 = the initial capital stock

g = the growth rate of R&D expenditures

The stock of R&D capital can be regarded as the proxy for knowledge capital. However, R&D capital is not exactly equal to knowledge capital. Other sources such as "learning by doing" or “education” can generate knowledge as well. Therefore, the R&D stock can be a good proxy for knowledge stock.

5.2.17 The specification of the depreciation rate

In practice, it is very difficult to accurately estimate asset-life length because directly observed data on life-length are not readily available. Dey-Chowdhurry (2008) states that the rate of depreciation varies by asset type and can also change over time. This would indicate that the depreciation rate would differ among products that are produced within industries and across industries. The size of the investment would also indicate different levels of depreciation. For simplification, many studies on public infrastructure considered to use a uniform depreciation rate. Ferraresi, Rizzo and Galmarini (2017) have stated that many studies that estimated the stock of public infrastructures considered linear depreciation rates of 2%,3%,4% and 5%. Baffes and Shah (1993) have examined the composition of public spending and its implications for economic growth. In their data description, the authors have constructed infrastructure capital stocks using the perpetual inventory method using a depreciation rate of 5%. My research paper constructs the R&D stock using the perpetual inventory method of 5%. The R&D stocks may be regarded as infrastructure capital stocks.

5.2.18 Limitations in calculating R&D stocks

Ning Huang (2007) reflected on some of the issues related to the calculation of R&D stocks. Firstly, one issue can arise from the un-observability of R&D output. Shanks and Zheng (2006) pointed out that the future expected yields accrued from newly created knowledge are generally not observable. It is quite challenging to observe the prices of the same knowledge assets of different ages at the same time. Due to such limitation of the information and the special features of knowledge assets, we use the input-based measure of R&D capital stocks. The information about R&D expenditures give us some degree of information that can be derived, even if the method does not account for fluctuations in the economy.

Secondly, there is a problem of incorporating two opposite forces. The two opposite forces are up-scaling and depreciation. Depreciation reduces knowledge stock and up-scaling increases the stock. Depreciation deals with the fact that as knowledge capital accumulates over time, old knowledge becomes obsolescent due to emergence of new knowledge. The outdated knowledge causes the depreciation of knowledge capital and in the meantime, new knowledge increases the stock of R&D stock (up-scaling).

Third, Ning Huang (2007) reflected on the problem associated with knowledge diffusion. The knowledge diffusion is related to spillover effects. R&D investments is an important source of funds that can help firms gain higher level of technological efficiency. There are however, other firms that can possess high technology, by investing far less or almost zero to R&D. The methods involving gaining new technology can be done through borrowing, purchasing or even stealing. The knowledge diffusion is related to spillover effects. In this case, the spillover effects arise when the firms that undertake R&D are unable to fully benefit from their research results due to imitations or competition pressures.

Lastly, there is a problem of knowledge similarity. There are several firms within a sector that may create similar knowledge. Knowledge stock reflects technological efficiency of knowledge. The issues lie on methods incorporating aggregate similar knowledge into the aggregate knowledge capital stock.

5.2.19 Trends in R&D stocks in relation to country and sector

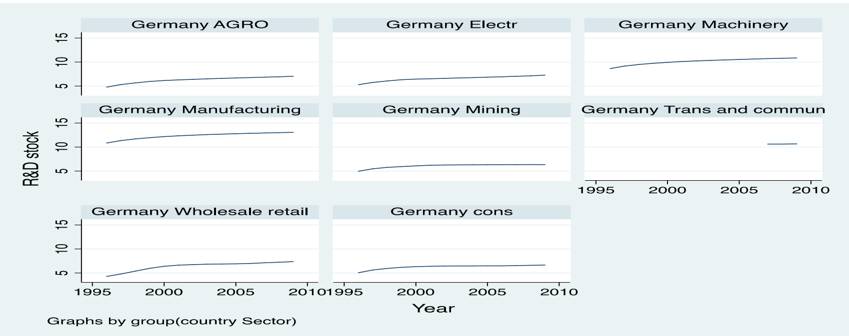

Figure 18: Trends R&D stocks in Germany and across sectors (STATA)

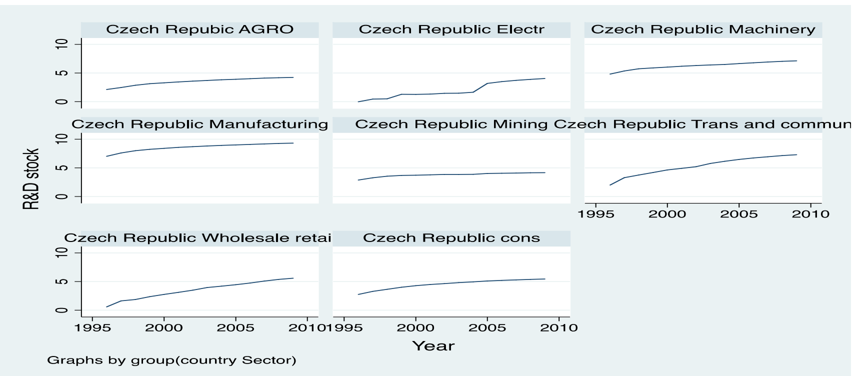

Figure 19: Trends in R&D stocks in Czech Republic and across sectors (STATA)

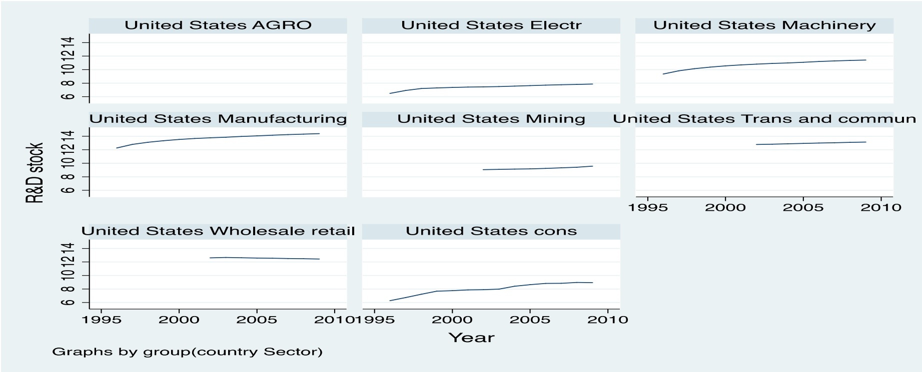

Figure 20: Trends in R&D stocks in the United States and across sectors (STATA)

Figures 18,19,20 exhibits relatively mild increases of R&D stocks in countries from 1996 to 2009. The manufacturing sector in the Germany, Czech Republic and the United States contain the highest value for R&D stocks. The data on R&D stocks have been missing on Denmark, France, Ireland and Sweden. The data on United Kingdom's machinery sector has been lacking as well.[7]

5.2.20 Symmetry plot for R&D stocks

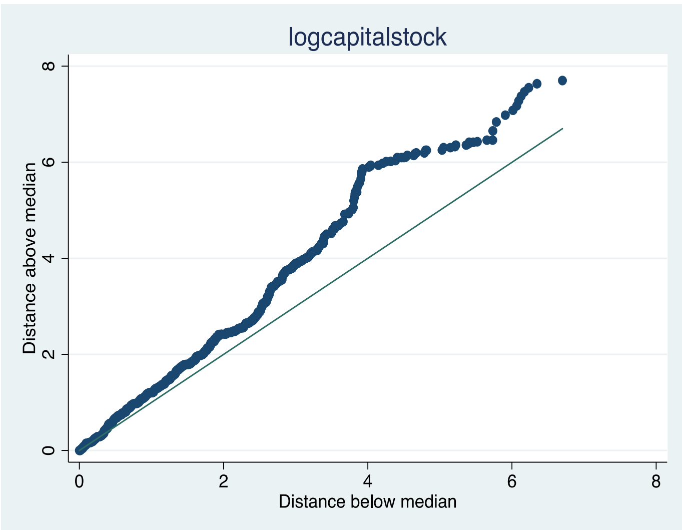

Figure 21: Symmetry plot for R&D capital stocks

Figure 21 indicates that the straight line corresponds to a symmetric sample. The data on R&D stocks can be characterized as symmetric and light tailed. The most extreme points are not getting further away from the line.

[7] See appendix, figure 3.

5.2.21 Histogram for R&D stocks

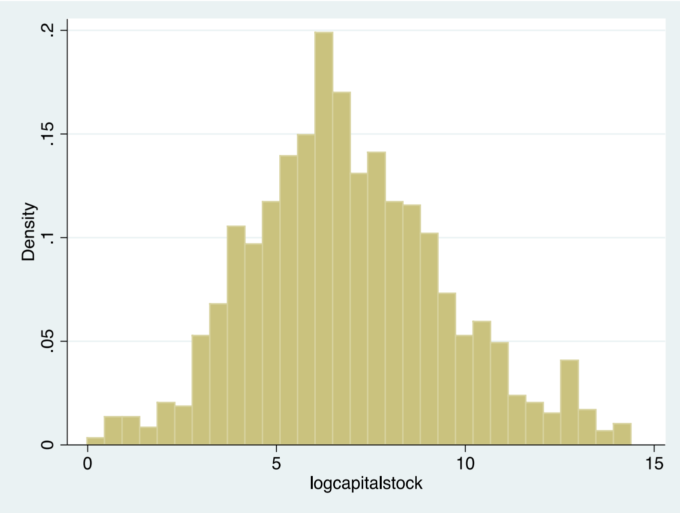

Figure 22: Histogram for R&D stocks (STATA)

Figure 22 illustrates a symmetric sample indicating normality of the data. The most frequent values are close to the mean. The normality of data will be illustrated by normal Q-Q plot.

5.2.22 The Normal Q-Q plot for R&D stocks

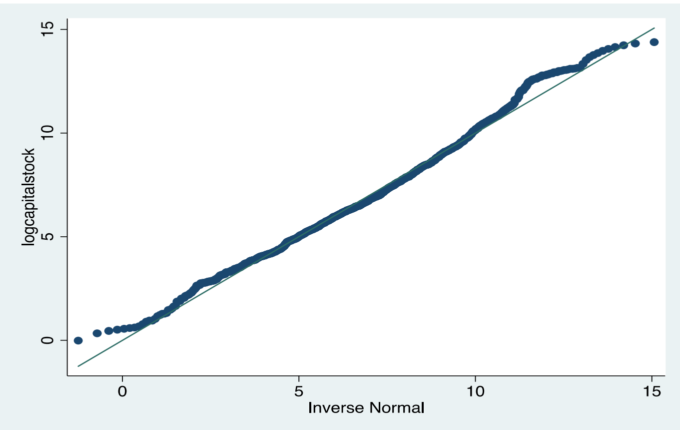

Figure 23: The normal Q-Q plot for R&D stocks (STATA)

The points for along the whole line indicating normality of the data. The points do not curve off indicating that the R&D stocks do not contain any significant outliers. The R&D stocks seem to behave in a predictable manner.

5.3 Exploring the relationship between the variables

The relationship between the variables will be explored in the correlation table. The relationship in the correlation table assume linearity of the variables and therefore the table illustrates a representational and simplistic approach at analyzing the relationships between the variables. The relationships between the variables will be explored in the methodology section of the paper involving panel data regressions. The correlation coefficients are not able to tell us the causality between the dependent and independent variables. David M. Lane (2013) points out that the correlation table does not give information regarding the slope of the line; it only illustrates whether there is relationship between the variables[8]. Section 5.3 will illustrate classical correlation table, residual Q-Q plots, establishing a relationship between the variables by using the Lowess smoother and Spearman's rank order coefficient.

5.3.1 The correlation coefficient table for TFP, merchandise exports and R&D stocks

Variable	TFP	HC	CSH_X	R&D stock
TFP	1			
Human capital	0.0511	1		
Exports	-0.0297	-0.0031	1	
R&D stock	0.0650	0.1715	-0.1780	1

Table 3: The correlation coefficients of each of the variables (STATA)

Table 3 illustrates a simplistic relation between the variables through the estimation of correlation coefficients. In relation to our first hypothesis regarding the relationship between productivity and R&D, one can see a small positive correlation coefficient between total factor productivity and R&D stock. On other hand with regards to our second hypothesis, the correlation coefficient between productivity and exports are slightly negative. An interesting aspect is the positive correlation coefficient between R&D and human capital. This could coincide that an increase in tertiary education enrolment will lead to higher inflow of skilled labor on the labor market. The input of skilled workers should contribute to the enhancement of productivity and R&D. The correlation coefficients are small and therefore the results do not verify or explain the causality between the variables. There is a positive relationship between productivity and human capital, indicating that additional years of schooling and earnings contribute to an increase in the economy's productivity.

[8] The correlation coefficients are between -1 and 1. The value of -1 indicating a perfectly negative relationship and 1 a perfectly positive relationship. The value of 0 indicates no linear relationship.

5.3.2 The residual Q-Q plot on merchandise exports weighted by GDP

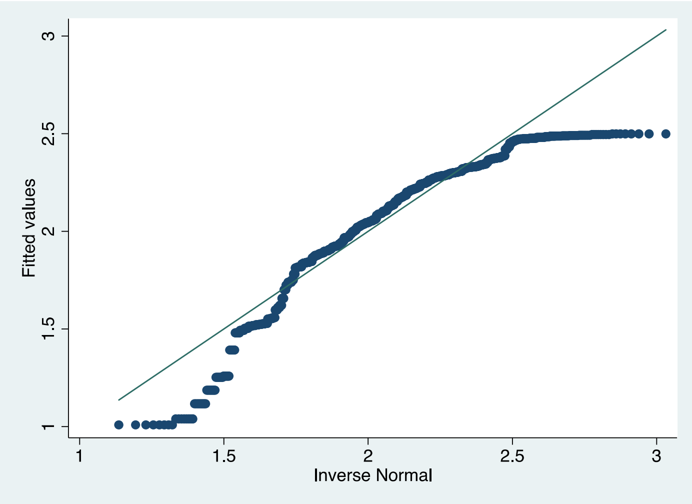

Figure 24: Normal Q-Q plot of residuals after regressing TFP on merchandise exports (STATA)

Figure 24 illustrates that the residuals do not indicate normality. The Q-Q plot indicates that the error terms are not normally distributed after regressing TFP on merchandise exports.

5.3.3 The residual Q-Q plot on R&D stocks

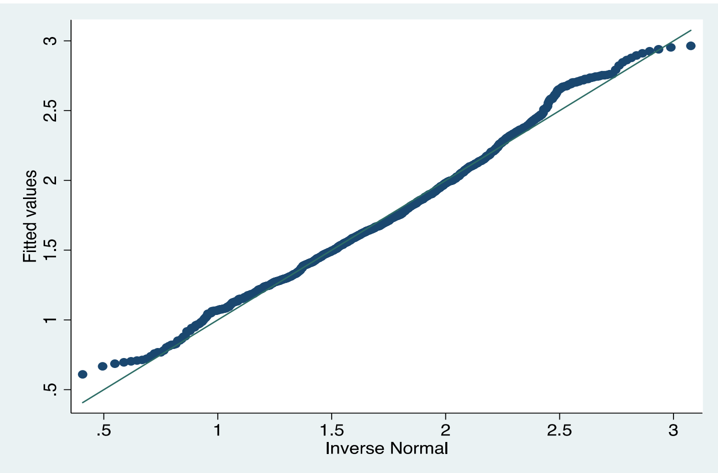

Figure 25: Normal Q-Q plot of residuals after regressing TFP on R&D stocks (STATA)

Figure 25 illustrates the normality of the error terms after regressing TFP on R&D stocks. The points fall along the whole line, with few extremities on the left side of the graph. Previous figure (Figure 24) emphasize that the non-normality of the error term in the share of merchandise exports indicate that the relationship is not well described by a straight line. Since, we are partly dealing with a linear dataset, the method for constructing relationship between variables requires a different method that will be outlined in the methodology section.

5.3.4 Constructing the relationship between TFP and its variables using Lowess smoother

The Lowess smoother is typically used for fitting a line in time plots where noisy data values or weak interrelationships. The smoothing is a non-parametric strategy aimed at smoothing the curve to data points. The benefits of non-parametric smoothing are that it provides a flexible approach at representing the data. Lowess smoother is a data technique used for smoothing the "noisy" relationship between 2 variables. The method captures the major trend of the data and the relationships between the variables. Cleveland (1979) noted that the smoothing is a way of depicting the "local" relationship between a response variable and a predictor variable, which may differ from a "global" relationship determined using the whole dataset. In our case, we provide the relationship between the variables from a country and sector perspective. The country and sector perspective suggests the local relationship between the variables.

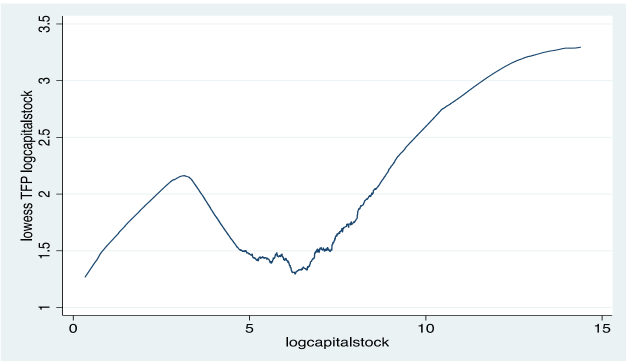

Figure 26: The relationship between TFP and R&D using a Lowess smoother (STATA)

Figure 26 illustrates the relationship between TFP and share of merchandise exports. TFP is on the vertical line and R&D stock is on the horizontal line.

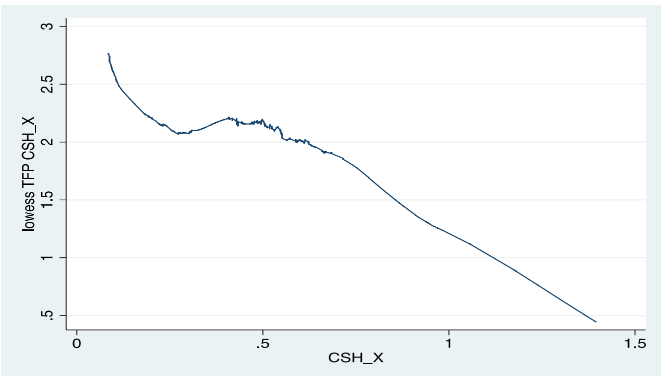

Figure 27: The relationship between TFP and share of merchandise exports using a Lowess smoother (STATA).

Figure 27 indicates a negative relationship between TFP and share of merchandise exports. The negative relationship between TFP and the share of merchandise exports contradicts our hypothesis. Cleveland (1979) has stated that the method makes no assumptions about the form of the relationship and allows the form to be discovered using the data itself. The Lowess-enhanced scatterplots reveal the relatively complex relationships, that could easily be overlooked with traditional statistical modelling procedures. Our hypothesis based on the relationship between TFP and exports call for “linearity” and “predictability”. Beck and Jackman (1998) have noted that “linearity by default” creates a problem because a detailed theory or hypothesis suggest nonlinear relationships. Thus, a nonparametric technique like Lowess smoothing should be useful for discerning such nonlinearities. We recognize that the exclusive focus on exports leaves the import part of the trade and productivity relationship unexplored. The hypothesis focuses on the relationship between exporting and productivity.

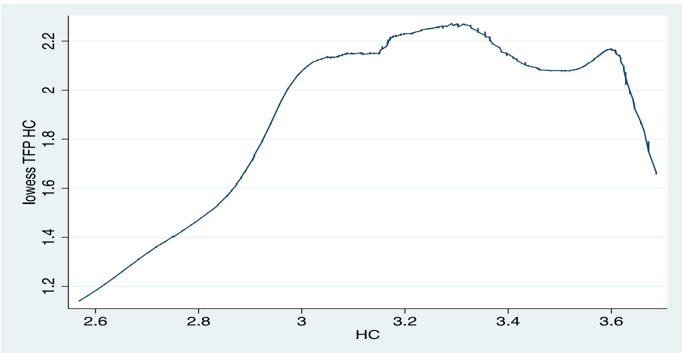

Figure 28: The relationship between TFP and human capital using a Lowess smoother (STATA).

The relationship between TFP and human capital is non-linear. The overall impact of TFP on human capitals seems to be relatively positive. But, with no further information, it is not possible to provide any more detail about the exact nature of this relationship from the visual information alone.

5.3.4.1 The Lowess line vs. linear regression analysis

The fitting line in the ordinary regression analysis represents the data in an optimal way, where the parameters are determined using all the data, meaning they are globally determined. Lowess line could be thought of as a line, where local maxima happen to be arranged along a straight line. The Spearman’s rank order correlation coefficients (section 5.3.5) show weak strength of linearity and therefore my research paper illustrates the importance of showing the local relationship between the variables. The locality and non-linearity of the relationship between TFP and its variables is emphasized through the cross-country and cross-sectoral study of this paper.

5.3.5 Spearman's rank order correlation coefficient

The data we have obtained are not linearly related and some variables are not normally distributed as illustrated by histograms and normal Q-Q plots for each of the variables. Furthermore, the Lowess smoother has illustrated non-linear and non-parametric trend between the variables. The relationships between variables across countries and sectors are non-monotonic. The relationship between TFP and R&D (figure 26) and the relationship between TFP and human capital (figure 28) are not monotonic Specifically, the relationship between TFP and share of merchandising exports across countries and sector emphasize a monotonic behavior (figure 26). Gale Thompson (2008) has presented that the Spearman's correlation coefficient is a statistical measure of the strength of the monotonic relationship between the variables. The interpretation of the Spearman's rank order is similar the linear correlation coefficients. The closer the correlation coefficient is to -1 or 1, the stronger is the monotonic relationship. The weak coefficients of Spearman's estimates indicate a weak strength of linear association between trends. The fluctuating and "bumpy" relationship between TFP and its determinants strongly indicates that we are dealing with a dynamic panel dataset.

Spearman's correlation table

Variable	TFP	HC	CSH_X	R&D stock
TFP	1			
Human capital	0.0551	1		
exports	0.1345	0.0964	1	
R&D stock	0.2769	0.1612	-0.1873	1

Table 4: Spearman's correlation table (STATA)

Table 4 illustrates that in case of Spearman's correlation, the coefficients in many cases are positive, but close to 0. The relationship between TFP and the rest of the variables are positive. The strength of the relationship between TFP and share of merchandising exports could be described as weak (0.13). On the other hand, the correlation coefficient of 0.27 between TFP and R&D stock can be regarded as moderate. In general, the monotonic relationship between these variables remain weakly positive. The weak strength of the relationship between the variables indicate the non-monotonic relationship between TFP and its determinants.

5.4 The degree of heterogeneity among variables

In the previous section, we have described the variables and illustrated the relationships between the dependent variable (TFP) and independent variables (human capital, share of merchandise exports and R&D stocks). We will construct graphs illustrating heterogeneity for TFP, exports and R&D stocks and human capital across countries and years. We assume that heterogeneity for the variables is not constant over time. The degree of heterogeneity across country and time and the high R^2 for in-between groups leads to the selection of the random effects model. Higgins, Thompson and Spiegelhalter (2009) have noted that the presence of unexplained heterogeneity is often undertaken by using a random effects model.

5.4.1 Heterogeneity of TFP across countries, sectors and years

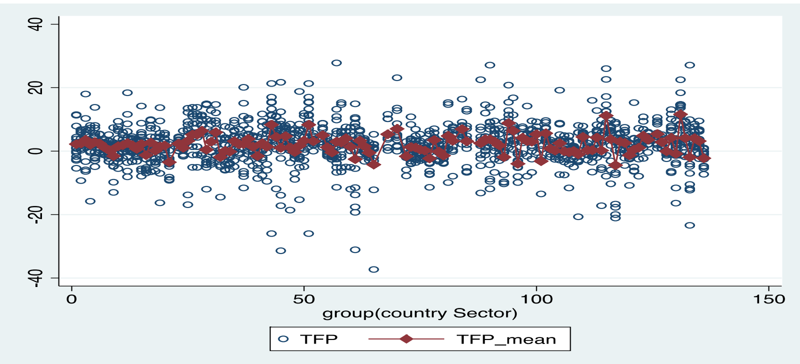

Figure 29: Heterogeneity of TFP across countries and sectors (STATA)

The TFP has similar trends among countries and sectors. The red line fluctuates and revolve around the mean and therefore the unobserved variable does not change over time.

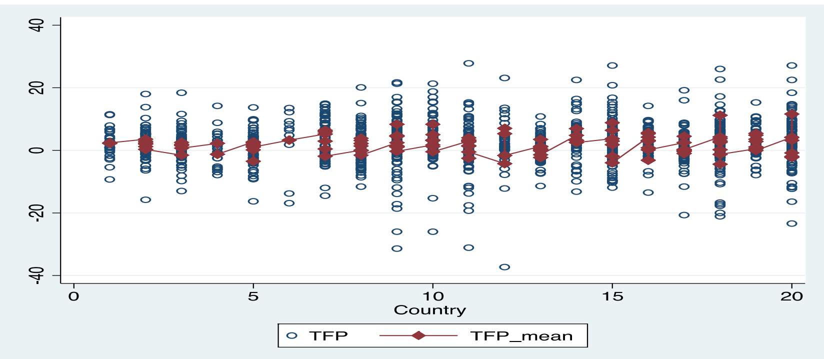

Figure 30: Heterogeneity of TFP across years 1996-2009

Figure 30 illustrates that heterogeneity is not constant over time. The TFP contains random and non-continuous fluctuations across the years. The time-fixed effects are not significant in the random effects model. The model does not include a linear time trend. There are many local properties of the data and therefore the trend will be mingled with local cycles. The TFP growth rates are different from year to year, given also the different growth rates for each of the sectors.

5.4.2 Heterogeneity of merchandise exports across countries and years.

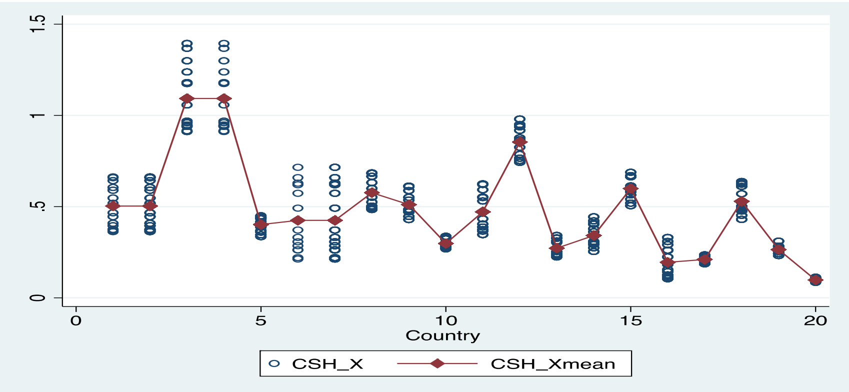

Figure 31: Heterogeneity of merchandise exports across countries (STATA)

The merchandising exports are country-level data regressed on a cross-sectoral panel. The share of merchandising exports account for all sectors included in our analysis. The share of merchandise exports experience non-constant heterogeneity across the selected countries.

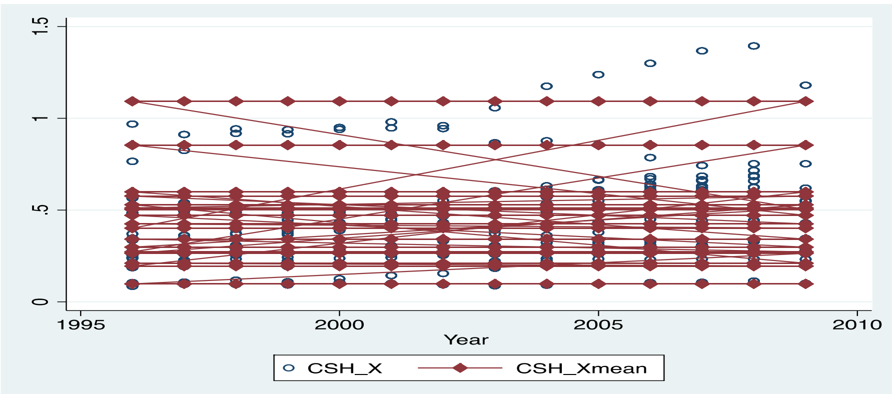

Figure 32: Heterogeneity of merchandise exports across years (STATA)

The heterogeneity is not constant across time. Thus, changes in the explanatory variable reflect sensitivity and abrupt changes across time. In this case, we assume no contemporaneous correlation of the errors and the explanatory variables. The heterogeneity across time suggests that the data contain between-unit variation.

5.4.3 Heterogeneity of R&D stocks across countries and years

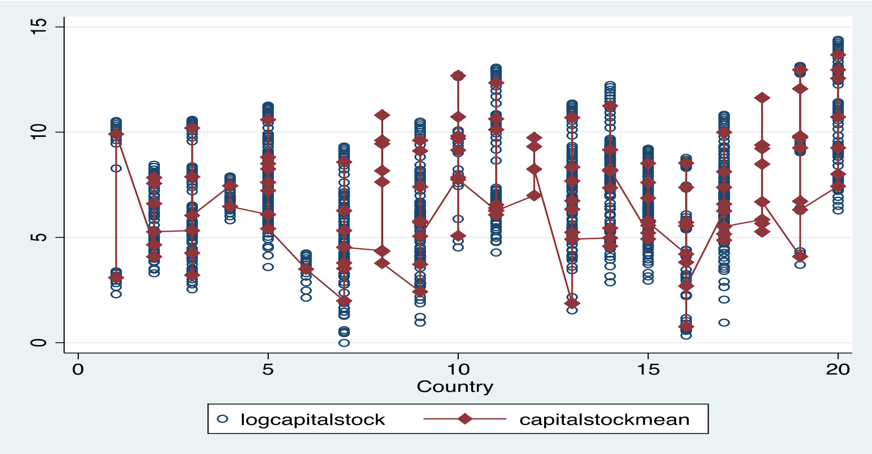

Figure 33: Heterogeneity of R&D capital stocks across countries (STATA)

The heterogeneity is not constant across the countries**.** Figure 33 suggests that the heterogeneity is derived from different level subsidies that the firms obtain across countries. The presence of heterogeneity suggests the different innovation policies that are undertaken across the selected countries. Dirk Czarnitzki and Cindy Lopes Bento (2010) have noted in their study that one would expect that the optimal policy mix varies across countries with different industry structures. One of the selected countries like Belgium is regarded as a small open economy and therefore applies different innovation policies than Germany or United States that are regarded as bigger open economies.

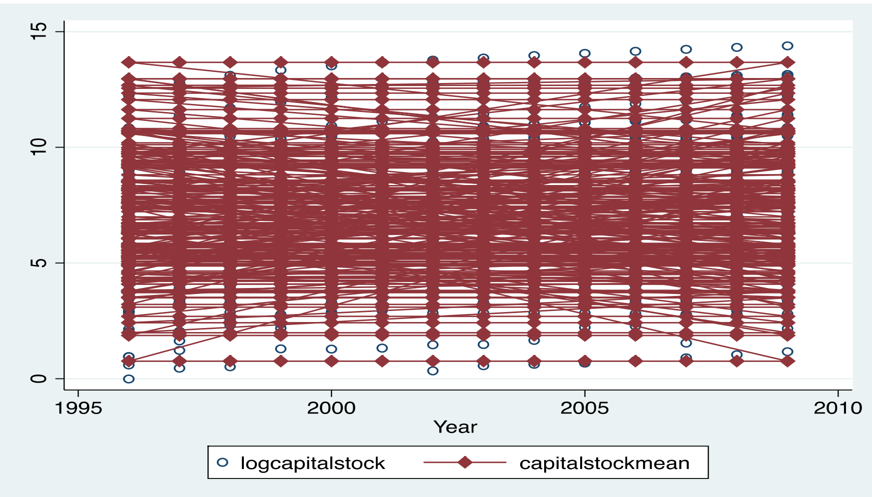

Figure 34: Heterogeneity of R&D capital stocks across years (STATA)

Figure 34 illustrates that the results are stemming from actual differences across countries and years. There is no time trend of R&D stocks across years.

5.4.4 Heterogeneity of human capital across countries and years

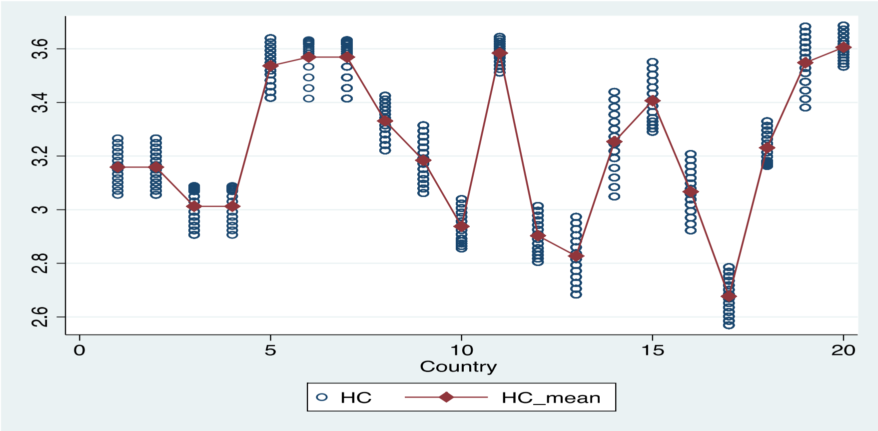

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Figure 35: Heterogeneity of human capital across countries (STATA)

The heterogeneity is observed across countries. The workers from different sectors obtain different kind of schooling and specialization. Heterogeneity is reflected through the different specializations of workers across sectors and countries. The heterogeneity also reflects a difference in the number of graduates in each of the countries. Joseph G. Altonji, Erica Blom and Costas Meghir (2012) noted that the estimated return differs across individuals with different choice history of courses. The heterogeneity of returns is driven by the differences in experiences and expectations of the ability and preferences. Moreover, different countries have different labor market conditions.

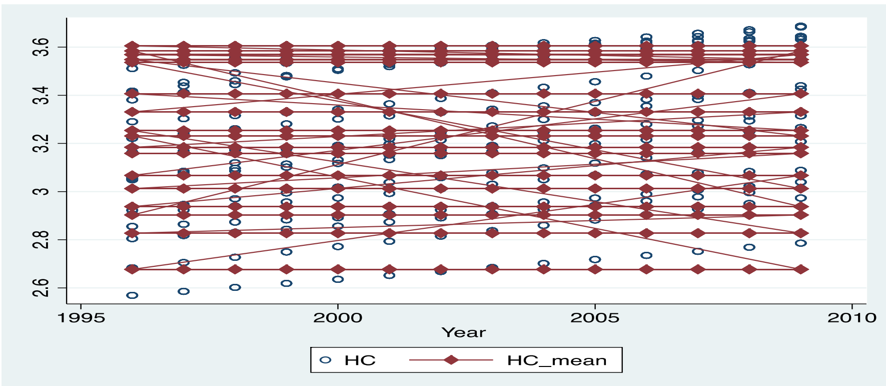

Figure 36: Heterogeneity of human capital across years (STATA)

Figure 36 shows the random nature of heterogeneity across time. Longitudinal data sets contain observations on various countries, each observed at several points in time. Assuming many time periods, one can expect the possibility that the data are not linear across time. The non-linear behavior in the time series allows for the existence of different regimes across countries.

6. Methodology

Spearman correlation coefficients suggested that the variables are weakly or moderately correlated with each other. We use random effects when controlling for heterogeneity. Byrne, Fazio and Piacentino (2009) have noted that the fixed effects estimation is potentially inconsistent when using dynamic equations under cross-sectional heterogeneity. In my research paper the significant limitation for fixed effects model is that one cannot assess the effect of variables that have small within-group variation. The indication that the time trend is not constant may imply that the data is not linear and there are "bumpy" cyclical annual patterns involved across time. The country variations are significant and therefore in-between variations among countries should be considered. All independent variables (exports, human capital and R&D stocks) have a lot of variation across countries, but little variation over time. The heterogeneity among entities have a significant impact on the dependent variable (TFP). The OECD database constructs data on different countries and therefore "country" may be a random effect. In addition, we will use the Arellano – Bond estimation to control for endogeneity. My research paper will compare the estimates obtained from Random effects and Arellano – Bond methods.

6.1 Random effects model

We test for correlation instead of causality between the covariates and outcomes. The group-varying intercepts help avoid possible bias stemming from the correlation. The differences across entities (countries) have influence on the dependent variable (TFP). The random effects model is illustrated as:

$$Y_{it} = \beta X_{it} + \alpha + u_{it} + \varepsilon_{it}$$

where:

Y_{it} = dependent variable measured across countries *i* and time *t.*

βX_{it} = the coefficient of the explanatory variable across countries *i* and time *t*.

α = constant

u_{it} = Between-entity error

ε_{it} = Within-entity error

The sector-invariant variables are share of merchandise export and human capital. These variables are containing country-level information across different sectors. The two variables, therefore do not vary across time and sectors, but do vary across countries. The sector variant variables are the lagged value of TFP and R&D stocks. The variation of R&D and exports reflect the heterogeneity between the countries. The heterogeneity illustrates the differences in trade policies and R&D policies.

6.2 The specification of the model

The specification includes the dependent variable (TFP) and the explanatory variables (exports, human capital and R&D stocks). The results will be obtained from the given specification of the model, which is illustrated as follows:

$$TFP_{tcs} = \beta_0 + \beta_1 LTFP_{tcs} + \beta_2 HC_{tc} + \beta_3 exports_{tc} + \beta_4 logRDstock_{tcs} + \beta_5 DC + u_{ct} + \varepsilon_{ct}$$

where:

TFP_{tcs} = total factor productivity (dependent variable)

$LTFP_{tcs} =$ lagged dependent variable across time, country and sectors (total factor productivity)

$HC_{tc} =$ human capital variable across time and country

$exports_{tc} =$ the share of merchandise exports across time and country

$logRDstock_{tcs}$ = the logarithm of R&D stock obtained across time, countries and sectors

u_{ct} = Between-entity error

ε_{ct} = Within-entity error

$DC =$ Dummy for countries

The random effects are applied for sectors within the countries and the dummies are applied to countries. The model specification for random effects are used for in-between variation among countries and sample size discrepancies among sectors. An added benefit of random-effect models is to allow group-level estimates for a response. The overall model estimate is known as the marginal estimator for a response variable (Breslow & Clayton 1993; Begg & Parides 2003; Skrondal & Rabe-Hesketh 2004). By accounting for these relationships among samples, including correlation, random effects provide more robust inferences.

6.3 Relevance of model specification to literature

My methodology specification indirectly follows the specification proposed by Wang and Schiff (2006). The differences are that my specification does not consider the diffusion and FDI aspects in the paper. The similar aspects in the specification are the inclusion of education variable which is represented by the average years of schooling. In addition, the authors construct the country dummies to consider possible heterogeneity across countries. Similarly, to my research paper the authors have constructed R&D stock from R&D flow data, using a perpetual inventory method with a 5% depreciation rate. They are using a more complex approach with the inclusion of IO tables that evaluate indirect access to R&D via trade in related sectors. The authors have concluded that human capital generates large positive effects in increasing its TFP growth. The positive value for the human capital occurs due to the inclusion of developing countries and spillover effects. We have arrived at different conclusions regarding the relationship between TFP and human capital. Instead of analyzing spillover effects, my research paper focused on trade-related aspects (exports) and domestic R&D. In my research paper, the data on domestic R&D were available, since the selected countries are 15 developed countries. The authors included developing countries and therefore lacked data on domestic R&D. Most of the R&D in developing countries are financed by foreign countries. The authors have included the developing countries for the analysis of technological diffusion. In my research paper, the positive link between TFP and R&D stocks may indirectly indicate positive spillover across countries.

6.4 The inclusion of the lagged dependent variable

The lagged dependent variable should be significant in our model. There are several implications for including the lagged variable. The significance of the lagged variable implies that the lag term has some casual power. Luke Keele (2005) mentioned that the lagged dependent variable eliminates autocorrelation present in the regression that only includes the current state of the economy. Luke Keele (2005) concluded that given the results, the lagged variable should be included on the right-hand side. Dynamic regression models are a component of panel data analysis, which frequently makes use of lagged dependent variables to model processes where the current values of the dependent variable are a function of its prior values.

6.5 The inclusion of country dummies in the random effects model

Dummy variables are practical when the number of observations are not too large. The country dummies allow for the inclusion of different intercepts in each country. In my research paper, the sectors across countries are the random effects and the countries are the fixed effects. Irwin (2006) has noted that the interactions involving random and fixed effects are random effects interactions. In addition, Bell, Jones and Fairbrother (2016) have concluded that the hybrid model of random effects and fixed effects is essential a random effects model. The authors have stressed that the hybrid model allows for the possibility of different relations at each level; it models between effects, which are substantively interesting. The authors have indicated that describing the hybrid model under the fixed effects framework is misleading about its value and capabilities. Under the random effects framework unexplained variances are modelled, meaning that we can find out more about the differences. Allison (2014) prefers to name the hybrid model as 'within-between RE'. In my paper, we control for partially fixed effects in a random effects model. The random effects model with the inclusion of fixed effects allows us to model important complexities such as heterogeneity. The random effects allow for the modelling of within-group-invariant variables that are often of substantive interest. Within-group-invariant variables in my research are sector-invariant such as human capital and share of merchandise exports.

6.6 Wooldridge test for autocorrelations

In order to conduct test for autocorrelations, one can use the Wooldridge test for autocorrelation in panel data. A relatively new test discussed by Wooldridge (2002) is very attractive because it requires few assumptions and is easy to implement. David M.Drukker (2003) notes that the test is very flexible and is found to have a good size and power properties with sample of moderate size. The central procedure of the Wooldridge test is that the residuals are not serially correlated. The method uses the residuals from a regression in first-differences. First-differencing the data in the model removes the individual-level effect. Baltagi and Li (1995) addressed the problem of jointly testing for serial correlation and individual effects. The joint statistic involves multiple regression coefficients Wooldridge test for autocorrelations can be conducted on data based on random effects designs. The null hypothesis states that there are no first-order autocorrelations. In case we reject the null hypothesis, one can obtain the robust standard errors from the random effects model. The estimates obtained from robust standard errors are shown in the results section. In my research paper, we reject the null hypothesis and therefore our model contains autocorrelations[9]. The alternative hypothesis states that there may be serial error correlation. The issue arising from the Wooldridge test comes from the fact that individual effects are removed through differentiation of the equation. The approach in dealing with autocorrelation involves the use of robust standard errors. In the results section, we will provide the coefficients obtained using the normal standard errors and robust standard errors.

6.7 Testing for stationarity of variables

The augmented Dickey-Fuller test can be used with serial correlation. The test based on Dickey and Fuller (1979) states that under the null hypothesis, unit root exists. In case of unit root the data is non-stationary. If we reject the null hypothesis, we obtain stationarity of the data. In the case of stationarity, we mean a relatively flat looking time series, without trend and constant variance, a constant autocorrelation structure over time and no periodic fluctuations. In case of non-stationarity, we assume that the variables vary across time. Non-stationarity allows for distinguishing the points by the values of the parameters. Since, we have autocorrelation, we will conduct the test using minimum number of lags. Philips (2017) provided an exemplary scenario of a time series that contains a unit root and has used an augmented Dickey-Fuller test. The exemplary time series contains 500 observations. Philips (2017) has observed that there is a clear drop in the proportion of simulations that are able to reject the null hypothesis as the number of lags increase. The number of lags should be minimized to reject the hypothesis. In my research paper, the higher number of lags would dramatically reduce the size of observations and therefore provide an incorrect inference regarding the complete picture of stationarity. The stationarity and non-stationarity of variables will be reflected in the results section. In the case of non-stationarity of TFP exports and R&D stocks may imply strong causality.

6.8 Literature on stationarity and TFP

Byrne, Fazio and Piacentino (2009) have employed panel root tests to investigate convergence in TFP among Italian regions. The tests provide an inference valid in the presence of heterogeneity. The results obtained from the unit root tests add a further

[9] The STATA command is xtserial and results obtained from the Wooldridge test for the the autocorrelation of residuals was *prob > F = 0.000*. We reject the null hypothesis.

dimension to the view on growth dynamics. The paper conducts the augmented Dickey-Fuller test to test convergence and divergence of TFP across Italian regions. If the null hypothesis is not rejected, it is possible to conclude that all the series in the panel are non-stationary and do not exhibit the tendency to converge. The rejection of the hypothesis does not need to indicate that all panels (regions) are stationary. The authors have stressed that the augmented Dickey-Fuller test has shown that there is substantial evidence against the usual portrait of convergence within geographical areas. The authors have used additional types of unit root tests to test for regional convergence of TFP. My research paper has opted for a quick and simple method of testing stationarity because the ADF method did not seem to be an issue for Byrne, Fazio and Piacentino (2009) as well. My research paper uses the ADF on the determinants of TFP to examine if the determinants of TFP converge or diverge within countries. The authors have noted that to address the estimation of convergence, a natural step would be to look at the determinants of TFP and to try to explain which factors may have convergence or divergence. In my results section rejecting the null hypothesis, does not indicate convergence across 15 OECD countries.

7. Results

In this section, the results of the data analysis are presented. The data were collected and then processed in response to the problems posed in first section of this paper. The goal of this paper is to test the two hypotheses and determine the long-term technological dynamics in the selected 15 OECD countries. In this section, we will show the results of each country obtained from country dummies. Countries were selected based on the full availability of data on total factor productivity. The differences between countries were obtained from using the country dummies in the regression.

7.1 Estimates obtained from Random Effects

TFP	**Coefficient**	**Std.Error**	**P >|z|**
LTFP	0.079	0.033	0.019***
HC	-18.809	4.42	0.000***
Exports	5.142	2.82	0.069***
R&D stock	0.386	0.09	0.000***

Table 5: Random effects model coefficients (STATA)

Table 5 provides the coefficients, standard errors and p-values obtained from using the random effects model. Table 5 illustrate the estimates using classical standard error coefficients and the table 6 illustrates robust standard error coefficients.

The dependent variable (TFP) is regressed on the lagged dependent variable, human capital, share of merchandise exports and R&D stocks obtained from using the perpetual inventory method. The increase in the export share by 1 percentage increases the TFP by 5.14 units. At the aggregate level, exports are positively associated with total factor productivity. The exports have a very low p-value indicating significance and impact on TFP. Similarly, a 1 percentage increase in the R&D stocks increases the TFP by 0.386 units. Interestingly, we have obtained a negative coefficient on the human capital variable. The result seems to be counterintuitive as earnings from additional year of schooling should contribute to a higher level of productivity.

Various factors can contribute to the wrong sign of the human capital variable. Haider and Solon (2006) demonstrate that the association between current and lifetime earnings vary systematically. Furthermore, they show that regression models, using current earnings as a proxy for lifetime earnings, will produce inconsistent estimates. The critical elements in identifying the returns to schooling is to assess the role of life-cycle bias in earnings regressions. For example, the current earnings gap between college and high-school educated workers early in their careers may understate the lifetime earnings gap.

TFP	**Coefficient**	**Robust std.error**	**P > |z|**
LTFP	0.0797	0.08	0.323
HC	-18.808	5.31	0.000***
Exports	5.12	3.62	0.095*
R&D stock	0.386	0.09	0.000***

Table 6: Random effects with robust standard errors (STATA)

In this case, the robust standard error method in table 6 produces bigger standard errors than in table 5. The share of merchandise exports is significant at 10% significance level, whereas in table 6, share of merchandise exports are significant at 5%. In this paper, we consider the 10% significance level as a benchmark for categorizing significance of variables. The R&D stocks have retained their significance. The classical and robust standard errors estimates are approximately similar, given the fact that the coefficients of the variables have not varied in table 5 and table 6. In both cases the between R^2 is 0.46. In this regard, much of the variation of the dependent variable (TFP) is explained by the variables that consider the difference between the countries and sectors. The presence of autocorrelation does not necessarily lead to biased estimates. The standard errors are corrected using robust standard errors. The robust standard errors do not improve the model. The coefficients have not altered and the robust standard errors estimates have slightly increased.

7.2 Interpreting confidence intervals of the variables

TFP	95% confidence interval
LTFP	0.013 – 0.146
HC	-27.47 - -10.145
Exports	-0.39 – 10.6
R&D stock	0.19 – 0.58

Table 7: 95% confidence intervals obtained from random effects model (STATA)

The confidence intervals are obtained from classical standard error estimates. The lagged dependent variable (LTFP) and R&D stock retain a narrow confidence interval. The human capital variable and share of merchandising exports retain a significantly wider confidence interval. The broad confidence interval can be explained by the variability of values across countries. Both variables contain cross- country data.

7.3 Interpreting country coefficients and regional comparison

Country	Coefficient	Std.Error	P > |z|
Austria	-0.1158	1.47	0.937
Belgium	-7.2847	2.56	0.004***
Canada	5.3177	2.28	0.020**
Czech Republic	9.0401	3.14	0.004***
Finland	0.6862	1.41	0.629
France	-5.9626	2.61	0.022**
Germany	6.4248	2.37	0.007***
Italy	-7.6904	1.92	0.000***
Korea	3.1078	1.69	0.067*
Norway	4.0804	1.66	0.014***
Poland	1.0977	1.81	0.546
Spain	-9.5131	2.27	0.000***
Sweden	-3.5874	1.91	0.061*

United Kingdom	5.8267	3.24	0.072*
United States	8.9341	3.18	0.005***

Table 8: Country coefficients obtained from random effects (STATA)

The 15 OECD countries are represented above. The countries are included in the table to represent between-entity effects. The coefficients represent the effect of countries on TFP. The coefficients between countries are different. The coefficients are level effects which implies that the regression function has a different intercept for each of the countries. One can observe the unequal patterns between countries and in most cases the differences are significant. Poland and Finland contain coefficients that are not significant. The differences across the countries are substantial. North America continent (Canada, United States) seem to be positively influencing the TFP. The TFP of the United States have risen by 8.93 units in comparison to 5.31 units by Canada. The Scandinavian region have (Sweden, Norway) different responses. The TFP for Norway has risen by 4.08 units, whereas Sweden's TFP has decreased by 3.58 units. The Eastern European region (Czech Republic, Poland) has a positive response to TFP. The TFP in the Czech Republic has risen by 9.04 units. The southern European region (Italy, Spain) have had a negative response towards TFP. The TFP for Spain and Italy have declined by -9.51 and -7.69 respectively. Western European region (United Kingdom, Belgium, France, Germany, Austria) have had positive and negative response towards TFP. For United Kingdom and Germany the TFP has risen by 5.82 units and 6.42 units respectively. For Austria the TFP has decreased by -0.11 units respectively. The TFP for Belgium and France has decreased by -7.2 units and -5.96 units respectively. The Asian region (Korea) is positively influencing the TFP. The TFP for South Korea has risen by 3.10 units. Interestingly, Czech Republic has the biggest positive value for TFP and Spain has the biggest negative value. The differences in TFP reflect the different intercepts. The intercepts are different because some additional variables are not included in the model. Moreover, growth rates are uncorrelated, which reflects long period stability of country rankings by absolute productivity despite the great variability in the productivity growth rates.

7.4 Intuition behind the results of cross-country study

The study made by Md. Rabiul Islam (2009) contained results that R&D seems to have significant impact strong positive impact in OECD countries. Moreover, human capital is found to be significant and robust in OECD countries. The disparities of the growth rates are observable in table 8. We have used domestic R&D capital stocks since the endogenous growth theory assumes that the rate of technological progress in one country depends on domestic research intensity in that country. Gerschenkron (1962) noted that technologically backward countries may have the potential to generate rapid growth than that of more advanced countries. The Eastern European region is catching up to technologically to their Western European counterparts. My results indicate that the differences in knowledge investments may explain a significant portion of TFP differences across countries. The unobserved differences in TFP can be attributed to institutional quality and investment climate. We include the country-specific fixed effects to control for the unobserved time invariant country specific effects. Krueger and Lindhal (2001) argue that education is significant and positively associated with growth only for the countries with low level of human capital.

7.5 Issues related to cross-country studies

Limitation for interpreting the country specific effects is the lack of data on developing countries. Therefore, ignoring the missing data may not represent the true variation of TFP across the countries. The sign of the human capital coefficient could possibly change to the positive and influence the value for TFP, if there is the inclusion of less developed countries, where human capital plays a significant role. Krueger and Lindhal (2001) argue that education is significant and positively associated with growth only for the countries with low level of human capital.

7.6 The intuition behind cross-sectoral studies

The impact of TFP in the manufacturing sector can be reflected through the number of people that are employed for foreign final demand. The employment for foreign final demand can act as a proxy for the share of merchandise exports. The number of people that are employed for foreign final demand work for exporting companies.[10] The pie charts indicate that in all selected countries from the sample, the most number of people work in the manufacturing sector. The number of people reflected in the manufacturing sector reflects the contributions towards the TFP and hence the impact on TFP. Czech Republic contains the largest share of people working for foreign demand.

[10] Appendix, figure 4 showing pie charts for the share of people working for foreign final demand across sectors

Additional pie chart reflects the share of R&D expenditures across sectors.[11]The R&D spending is focused primarily in the manufacturing sector, the machinery sector and the communications sector. The manufacturing and machinery sector are significant sectors in impacting the TFP. The countries increased its share in output via higher investments and increased productivity. The manufacturing, machinery and communications sector encompasses ICT aspects as it involves the production of high-tech products. The ICT aspect and the shift into more-skill intensive output, have had profound implications for production structures. Misallocation of resources can arise if the movement of factors between heterogeneous sectors can give rise to persistent rates-of-return differentials across sectors, that may undermine TFP growth. Restuccia and Rogerson (2013) and Hopenhayn (2014) have confirmed the presence of misallocation of factor inputs as well as cross-country differences leading to large losses in aggregate productivity. The differences and variability across countries imply that there is a need for a more effective resource allocation.

7.7 Arellano – Bond estimation

Arellano – Bond estimator may be useful because our model includes a lagged dependent variable, which gives rise to endogeneity. The relationship between the explanatory variables and the dependent variable may be bidirectional and therefore the explanatory variables may be correlated with the error term (endogeneity). Endogeneity would imply that traditional panel methods would give inconsistent estimates. Arellano and Bond (1991) derived a consistent generalized method of moments estimator of this model. The GMM estimator uses the lagged differences of the dependent variable as instruments for the equations in first difference. The first difference eliminates the individual effects from the model and may eliminate endogeneity. The dynamic panel data model allows disentangling heterogeneity (as reflected by the country effects in random effects model). Mileva (2007) has noted that using deeper lags reduced the sample size and if the number of countries is large enough, one may use all the available lags for instruments. In my research paper, the number of countries are small and therefore increasing the lags would significantly limit the number of observations. Table 9 provides the estimates of the Arellano – Bond estimation.

[11] Appendix, figure 5 showing the pie charts regarding the R&D expenditures across sectors in millions of dollars

TFP	Coefficient	Std. Error	P > |z|
L1	-0.39	0.035	0.000***
HC	-19.353	9.73	0.047*
Exports	14.01	4.13	0.001***
R&D stock	-1.30	1.04	0.214

Table 9: Arellano – Bond estimates

The lagged differenced variable of TFP (L1) is significant and negative. The negative coefficient may indicate that the TFP fluctuates from positive to negative growth rates and vice versa from year to year. These fluctuations are random across years. The human capital variable estimate is similar to the estimate obtained from the random effects model (Table 5). The estimate for R&D stock obtained from the random effects is different than the estimate obtained from the Arellano – Bond estimate. The R&D stocks also lose their significance in the Arellano – Bond model. The possible explanation behind the loss of significance in R&D is that R&D could be picking up some strong autocorrelation of the TFP series, working then as a proxy for the lagged value of TFP. The significance of R&D stocks in the random effect model may be due to spurious regression. The exports retained their positive significance on TFP. Furthermore, the differenced equation eliminates the individual effects and therefore does not consider the variation between the countries. The correlation between the covariates and the outcome variables is eliminated by considering the differences across regions.

7.8 Relevance of Arellano-Bond estimation to the literature

Ascari and Di Cosmo (2004) have presented an Arellano - Bond procedure in their study of TFP across Italian regions. The authors have used the estimation to control for the potential problems due to the presence of endogenous explanatory variables, by using as instruments the lagged values of the explanatory variables and TFP. The authors have obtained somewhat different results in comparison to their LSDV method. The R&D variable has retained its significance under the Arellano- Bond estimation, however their education variable lost their significance in comparison to the LSDV method. The different estimates obtained from Arellano-Bond estimation are present in our paper as well.

7.9 Random effects vs. Arellano – Bond estimation

Wansbeek (2012) noted that the interest in the precise value of the coefficient of the lagged dependent variable appear meager. The potential of using exogenous variable as instrument is a matter deserving more attention. The critical issue here is that random effects and Arellano-Bond estimates arrived at a different conclusion (Table 5 and Table 9). Wansbeek (2012) noted that many studies that were using lagged values of dependent variables as instruments lead to superior results. On other hand the author stressed the issue of residual autocorrelation. The author has noted that 24 out of 31 studies failed to reject the null-hypothesis of no autocorrelation involving Arellano-Bond estimation. Despite the popularity of Arellano-Bond estimator, one cannot ignore the variations and heterogeneity among countries. The random effects are relevant in observing the variations among countries and verification of our two hypotheses. Moreover, the significance of R&D in the random effects model intuitively illustrates that the R&D does impact TFP.

7.10 Stationarity

The descriptive statistics provided the relationship between TFP and other variables across sectors. We have multiple panels across our data and therefore we are conducting a Fisher-type unit-root test for variables based on augmented Dickey-Fuller test. The null hypothesis states that all panels contain unit roots and the alternative hypothesis states that at least one panel is stationary. Based on augmented Dickey-Fuller test we have obtained the following results. The test is regressed on one lag.

	Statistic	**p-value**
Inverse chi-squared	503.9025	0.0000***
Inverse normal	-6.1365	0.0000***
Inverse logit t(684)	-5.1263	0.0000***
Modified inv. chi-squared	9.9427	0.0000***

Table 10: Fisher-type unit-root test for human capital (STATA)

Table 10 indicates that we reject the null hypothesis and therefore we achieve stationarity for human capital. The mean and the variance are invariant across panels. The earnings rate obtained from the additional year of schooling do not vary across panels. This could indicate that the heterogeneity across countries do not vary. Logically, the earnings are higher for individuals that obtain tertiary or higher education. The next table contains the results for share of merchandise exports.

	Statistic	p-value
Inverse chi-squared	84.1217	1.0000
Inverse normal	14.8685	1.0000
Inverse logit t(684)	15.0679	1.0000
Modified inv. chi-squared	-8.0552	1.0000

Table 11: Fisher-type unit-root test for share of merchandise exports (STATA)

Table 11 illustrates that we fail to reject the null hypothesis and therefore it is more likely that all panels contain unit roots. The statistical property of non-stationarity is that the variable contains deterministic functions of time. The non-stationarity is reflected through the heterogeneity of merchandising exports across countries. One can look at figure 26 and observe whether the mean changes over time. The quantities from different countries look different and this provides some evidence of non-stationarity. The next table contains the results for R&D stocks.

	Statistic	p-value
Inverse chi-squared	905.6983	0.0000***
Inverse normal	-10.1227	0.0000***
Inverse logit t(684)	-20.4538	0.0000***
Modified inv. chi-squared	37.0125	0.0000***

Table 12: Fisher-type unit-root test for R&D stocks (STATA)

In this case, we reject the null hypothesis of unit root. The alternate hypothesis states that some panels are stationary, but not necessarily that all panels are stationary.

7.11 The verification of the first hypothesis (establishing a link between R&D and productivity)

The first hypothesis deals with the relationship between R&D and productivity. Table 8 shows that a 1 unit increase in R&D stocks increases the TFP by 0.38 units. The positive coefficient obtained from the random effects model indicate positive link of R&D and productivity. Shanks and Zheng (2006) discussed the reasons for the empirical difficulty in pinning down a magnitude on the effect that R&D has had on productivity. They have elaborated on the issue of the construction of R&D stocks as a proxy of the stocks of knowledge. One such issue is that the R&D stocks do not only take the form of knowledge accumulation. Various economic theories have highlighted the role of education and learning by doing. The second issue deals with the fact that the R&D stocks are intangible and unobservable. There are other R&D output measures, specifically patents, but they have limitations, especially for measurement of knowledge on national scale. The measurement difficulties provide a fundamental problem in establishing a link empirically between R&D and productivity. Nevertheless, the positive link between R&D and productivity suggests that the countries do indirectly benefit from R&D spillover. The more open they are and in the quality of their institutions. The positive value across countries should be attributed to favorable investment conditions and governance.

7.12 The verification of the second hypothesis (establishing a link between productivity and exports)

The sensitivity of exports to productivity growth indicates a strong positive relationship between these two variables. Giles and Williams (2000) presented a comprehensive survey of more than 150 applied papers on the relationship between exports and economic growth distinguishing between cross sections and time series. In most cases with regards to cross sectional studies they find support for a positive relationship between economic growth and TFP. In addition, they have presented that earlier studies have assumed that the regression parameters are constant across countries and that the variables involved are statistically stationary. A more recent strand of literature applies various time series techniques to examine the export-productivity growth relationship and avoid potential problems with cross-sectional methods. We cannot reject the hypothesis for the period 1996-2009 and for 15 OECD countries. The microeconomic heterogeneity within sectors, related to the distribution of productivities across firms, and to the concentration of activity among small subset of firms, may affect the reaction of aggregate exports to external shocks such as exchange rate movements or foreign demand. The non-stationary of exports might reflect the vulnerability of exports towards external shocks. From a macroeconomic perspective, the aggregate exports can be supported by the presence of few highly productive firms, which are able to operate in a highly competitive environment. Especially for firms that are involved in the manufacturing, machinery and communications sector. The significance and the positive coefficient obtained in table 5 for the share of merchandise exports indicate that exports are an important determinant in productivity growth.

8. Conclusion

The two hypotheses cover the trade-related and innovation aspects of determining the TFP. The export data include the importance of trade to economic development and productivity. The significance of exports illustrate that the impact of trade has many channels. The channels include informational efficiency and interdependence of economies. The R&D output was significant and had a positive impact on the TFP using the random effects model. The human capital variable needed to be included in the paper to cover educational aspects of the paper.

The hypothesis does not cover the relationship of human capital and TFP. Nevertheless, the human capital variable plays an integral part in covering the "education" aspect of my model. We have compared the estimates obtained from the random effects and Arellano-Bond estimation. Intuitively, the random effects were preferred because the model provided significance for all variables. In addition, we have obtained the estimates using the random effects with robust standard errors. The estimates obtained from robust standard errors were not used for verifying the hypothesis due to inflated standard errors and non-significance of R&D stock. In the end the random effects with country dummies provided the intercepts for the countries that were worth interpreting.

Economic development is essentially an endogenous process. The spread of new knowledge represents a non-rival and non-scarce resource and therefore policy-makers need to create such incentives and assume an active role in facilitating economic and technological change. Endogenous growth theory states that internal factors influence the growth of the economy. Such internal factors that promote growth are exports and domestic R&D. In this paper, the selected countries are open and developed economies. The internal processes within the countries suggest heterogeneity across countries, since each country possess different internal processes on how to invest in R&D and promote exports.

Appendix

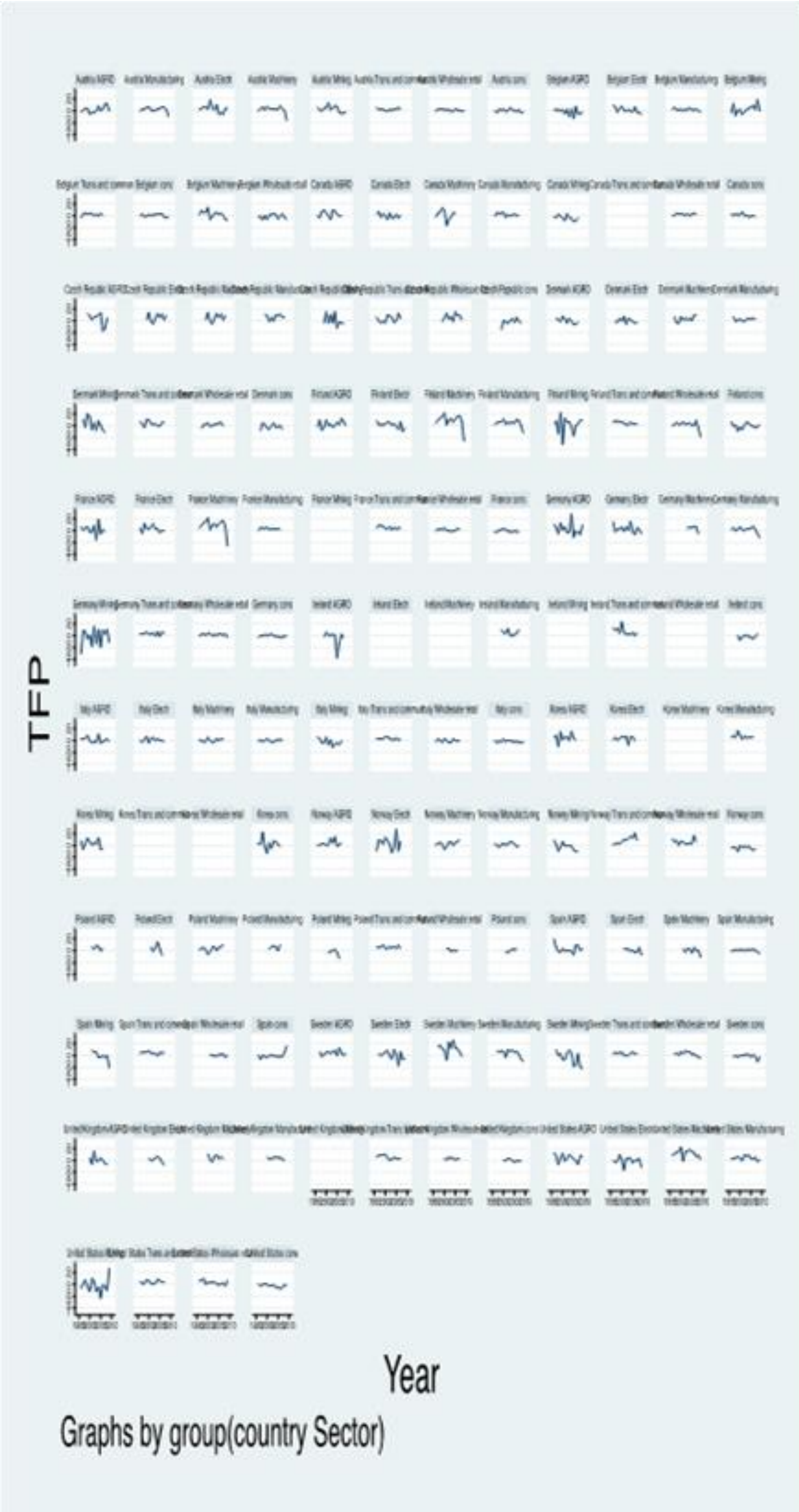

Figure 1: Trends of TFP across all countries and sectors

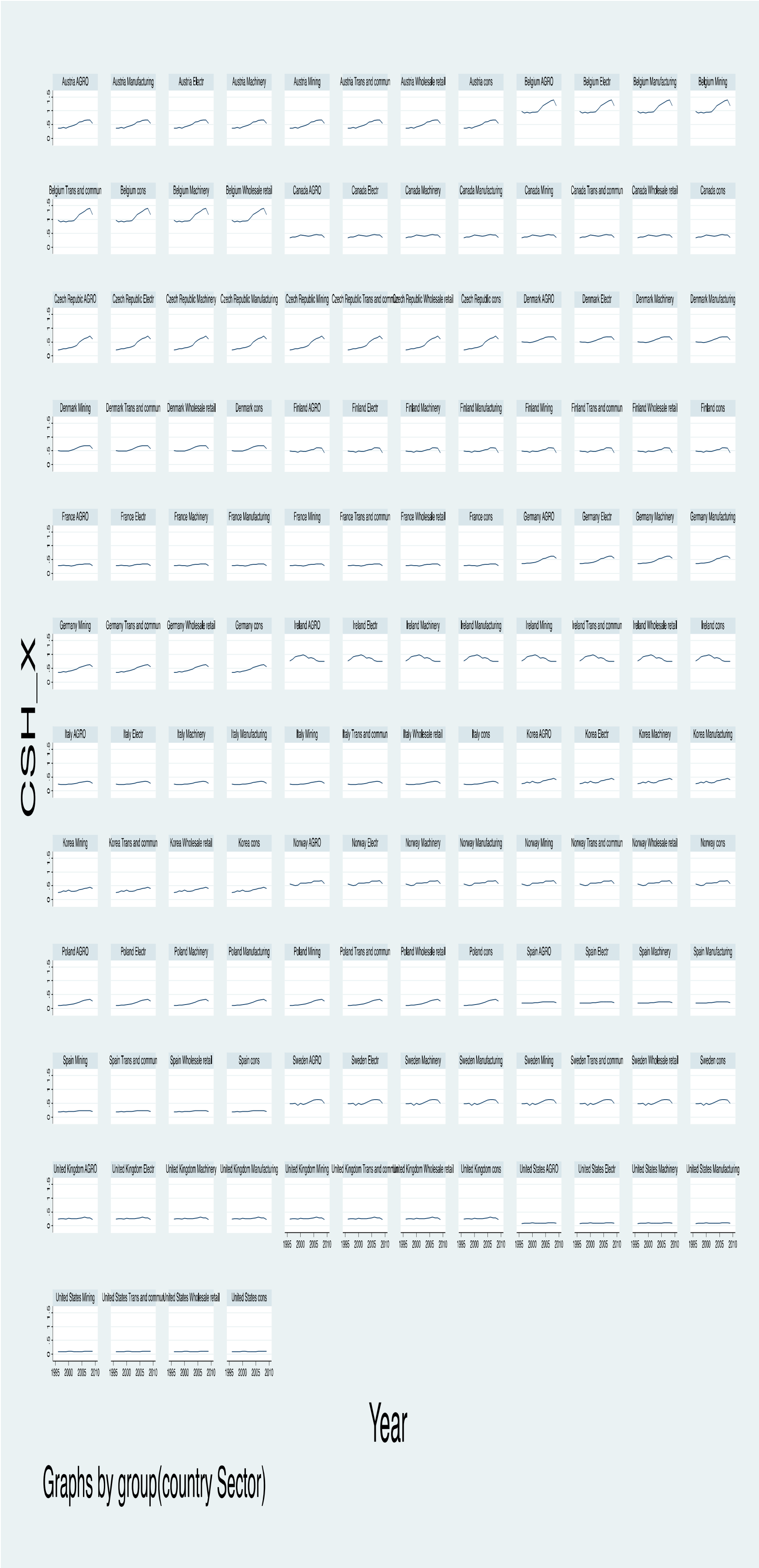

Figure 2: Trends of merchandise exports across countries and sectors from 1996-2009.

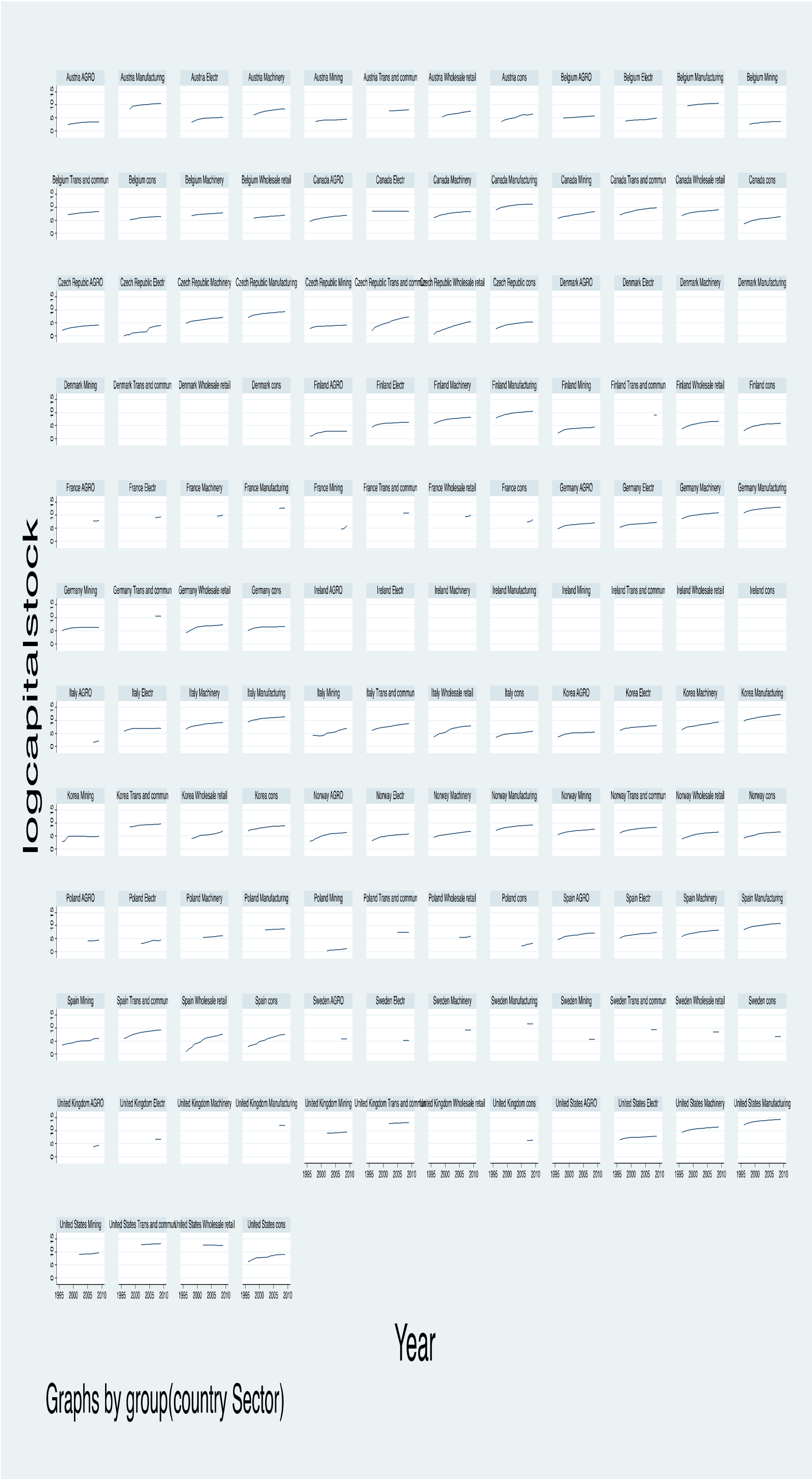

Figure 3: Trends R&D stocks in relation to country and sector from 1996-2009

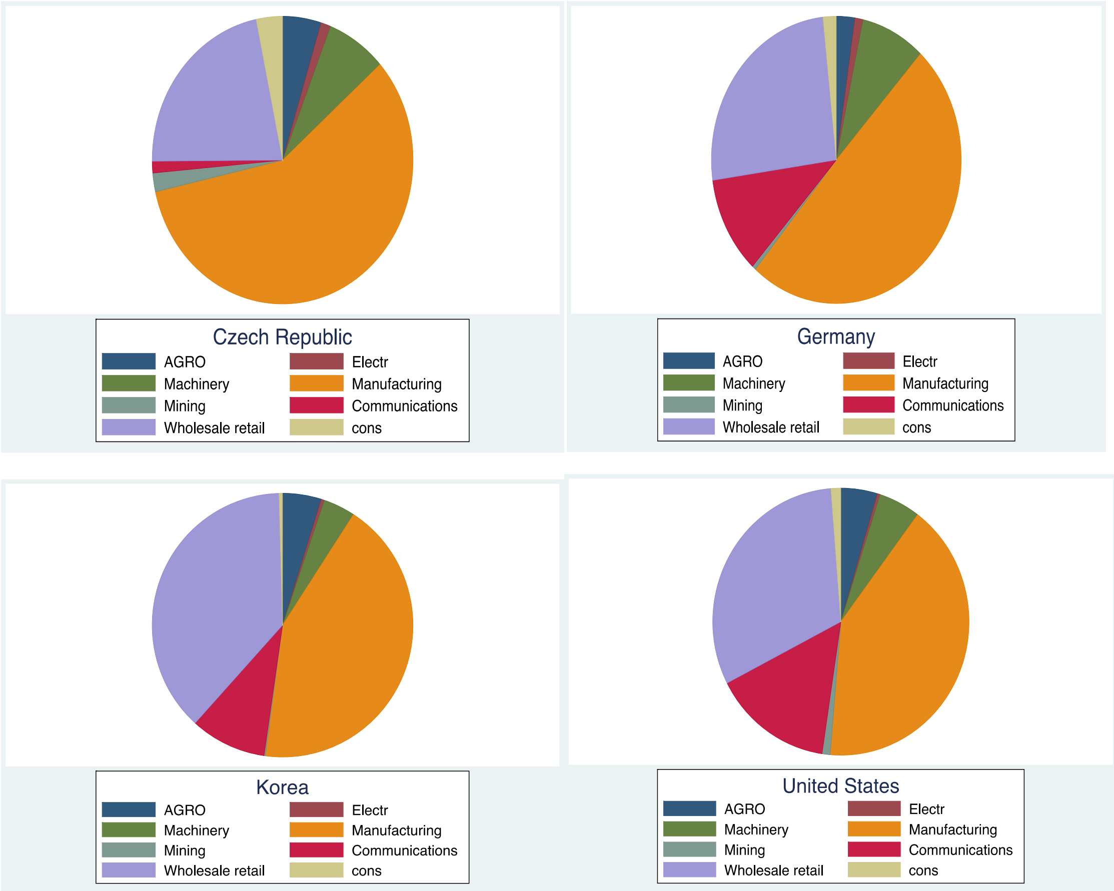

Figure 4: Pie charts indicating the share of people working for foreign final demand across sectors (STATA)

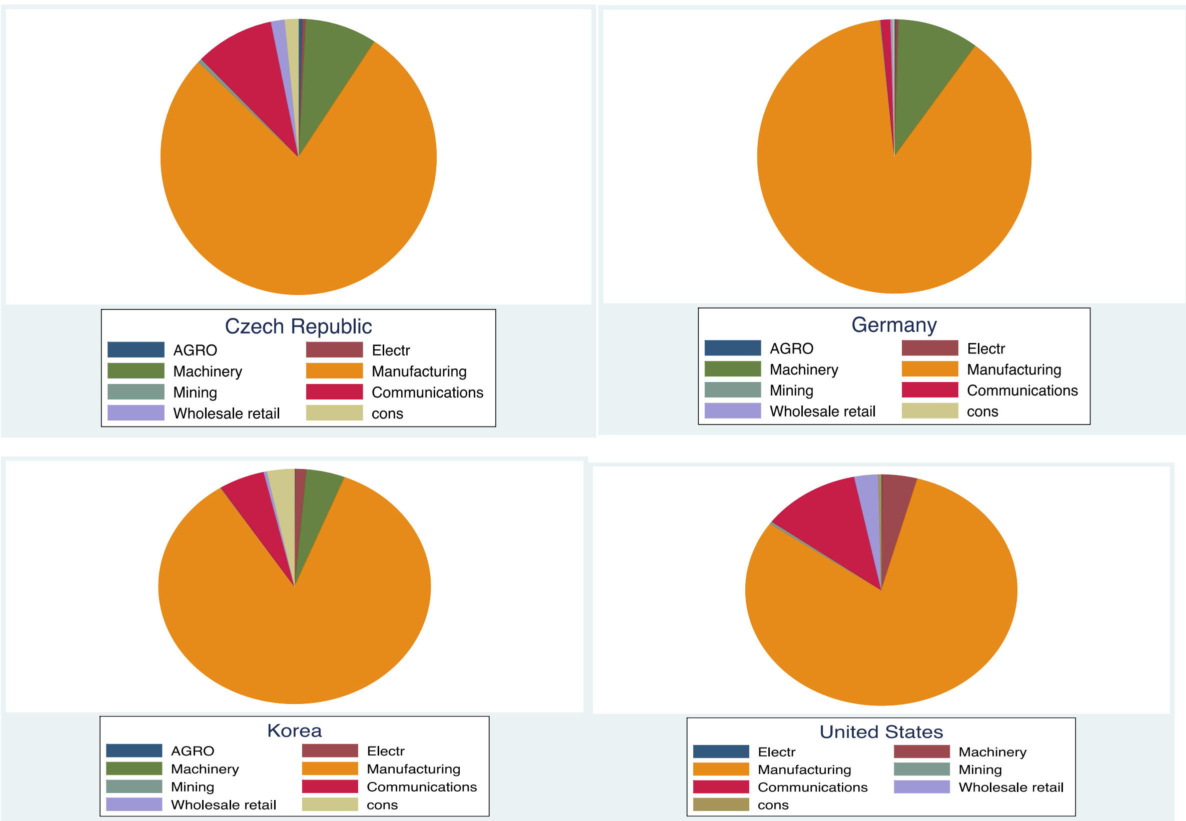

Figure 5: Pie charts indicating the share of R&D expenditures across sectors

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