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EVIDENCE OF THE GREAT DECOUPLING AND IDENTIFYING ITS CAUSES

DOCTORAL THESIS

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Abstract

During the 20th century, changes in economic growth have been mainly driven by technology and globalisation, causing fundamental shifts in the business landscapes and labour market.
Research showed that four factors that used to move in union are now decoupling: *labour productivity*, *median household income*, *private employment* and *GDP growth*. This phenomenon is called the Great Decoupling, a study that has been in the focus of the work done by Erik Brynjolfsson and Andrew McAfee. Why are *productivity* and *GDP growing*, but *private employment* and *wages* lagging behind? In this research, an interpretation is given with factors that likely affect the phenomenon. In the first part of this research, evidence of the presence of the Great Decoupling is given. In the second part of the research, a new modified model is built with variables representing the effects of economics of AI-driven automation and globalisation. Selected countries as major economic areas are analysed based on the period 1975-2014. It is important to further understand how an economy may effectively respond and benefit as a society from these trends.

Keywords

Macroeconomics, Great Decoupling, Panel Data, AI-driven automation, Globalisation, Human capital

Extended Abstract

Changes happening in the last's centuries are reflecting, mostly, technological advancements. Many books and papers have been written on this matter and the majority's strategies were quickly outdated by the exceptionally fast paced rhythm of technology progress and daily changes. Can countries operate with those changes without a deeper understanding to where will these trends lead and shape future generations? One of the biggest motivations for this research was the work done by Erik Brynjolfsson and Andrew McAfee (2013) about the Great Decoupling. They analysed four key measures of an economy's health that started to grow decoupled: *GDP per capita*, *labour productivity*, the number of jobs in *private employment* and *median household income*. Is the Great Decoupling real? If this phenomenon is happening, what are the crucial indicators that are affecting it? After conducting a relevant literature survey that provide the necessary understanding of the Great Decoupling, a review of academic journals and government papers was carried. Sources on models used to explain economic growth in times of technological change and globalisation were reassessed.

The research was divided in two parts. In the first one, a two means test is conducted between growth rates of every and each of the variables in the model. The conducted test was used to show is the variables were growing in union or if the divergence occurred. The second part consists of a panel data analysing the influence of globalisation and AI-driven automation. In the model, the *globalisation index* (*KOF Globalisation Index*) was used as an indicator for globalisation, while *total factor productivity* was used as an indicator for AI-driven automation. One of the many reasons for using total factor productivity in the model was (i) Comin (2010) who suggested that total factor productivity can indicate the endogenous level of technology and innovation decisions such as endogenous technology acceptance processes which are significant in developing economies and (ii) Solow (1956) who underlined that cross-country differences in technology may generate important cross-country differences in income per capita.

This analysis was performed on four major economic areas using annual data: United States, Japan and the United Kingdom and the euro zone (Bergeaud, Cette and Lecat, 2017). Countries elected for the euro zone are Sweden, Finland and Germany, based on Bernstein and Raman (2015).

The most serious challenge was the one of data unavailability. Two of the four mentioned variables that Brynjolfsson and McAfee (2013) used in their framework for the country of the United States of America are *labour productivity* and *GDP per capita*. Because of data availability of the two remaining variables for the five countries of Japan, United Kingdom, Sweden, Finland and German, the variables number of jobs in *private employment* and *median household income* needed a replacement.

The variable *private employment* was replaced by the variable of *employment*, while the variable *median household income* is replaced with the index of the *top 10% share of income inequality* - income share held by highest 10% in a country. Both of the variables stay, mostly, constant over time; in *employment*, the number of employees in the government do not change significantly, so unusual trends in employment are mostly caused by transitions in private employment. The index of the *top 10% share* of the people with the highest income are a solid indicator of income inequality and of maximisation of profit. If the share of the "richest" is rising, it means that income is not distributed evenly trough society and that the "poorer" are sharing the decreasing piece of cake that is left behind just as median household income describes.

Findings suggested that for the two means test, a trend between the rate of growth of the variables the variables of *GDP per capita*, *labour productivity*, *employment* and *top 10% share of income* was found, confirming the high possibility of the presence of the Great Decoupling in the countries of Germany, Japan, Sweden and the United States of America. Data of the variable's private employment and median household income that were included in the original model were not available, so further research to implement the best possible replacement for mentioned variables is needed.

In the second part of the research, findings suggest that, based on the panel data model, there exists a positive impact on economic growth of technological advancement through AI-driven automation that can be represented with the variable *total factor productivity*. The negative impact of globalisation on economic growth can be represented through the *KOF Globalisation Index*.

In the model analysis, financial crisis of 2009 and the one of 1991,1992 and 1993 were included in order to prevent possible interference in the econometric model. With the elected variables of *GDPpc*, *total factor productivity* and *globalisation index*, results connoted that longer-term global trends such as technological change like AI-driven automation have a positive impact on economic growth while globalisation a negative.

Educational institutions, businesses, education innovators and policy-makers should intensely collaborate to provide skills and knowledge to shape future generations of workers - ensuring that they have a high standard of living. Changes in technology helped explaining a constant growth in productivity throughout the 1990s (Basu, Fernald and Shapiro, 2001), but why keep the richer getting rich? Why are inequalities not shrinking at a needed pace? Why do governments fail at protecting the working class and do not simulate a more even distribution? Emergences of new innovations and altered forms of competition are changing the structure of economy and the countries' progresses are uneven. New efficient strategies to prepare future generations to come are needed.

Keywords

Macroeconomics, Great Decoupling, Panel Data, AI-driven automation, Globalisation, Human capital

Contents

1. Introduction

This dissertation investigates the challenges that the exponential advancement in technology is bringing. One of the main strategies used in this research to overcome this problem is to build on the work of Erik Brynjolfsson and Andrew McAfee (2013). The authors conducted a research and analysed four key measures of an economy's health that started to grow decoupled: GDP per capita, labour productivity, the number of jobs in private employment and median family income. The phenomenon that represents this divergence is called the Great Decoupling.

Analysing structural changes, preliminary results theorized that both globalisation, proxied by measures of openness, import penetration and export intensity at the sectoral level, and digitalisation, proxied by ICT capital intensity at the sectoral level are all linked with higher wage divergence. They do tend to strengthen the link between productivity and wage dispersion within sectors and countries over time (Berlingieri et al., 2017).

The main focus of this thesis is evidence of the existence of the phenomenon of the Great Decoupling and the dynamic relationship between technology, globalisation and economic growth. An investigation of the presence of the Great Decoupling as well as the influence of economics of AI-driven automation and globalisation is conducted. Reinforcement of their influences during periods of the occurrence of the phenomenon the Great Decoupling is offered.

1.1. Hypothesis

The intention is to provide evidence of the existence of the Great Decoupling in the four major economies. For selected countries of the EU and Japan, it is possible to replace private employment with employment while median household income can be replaced with the top 10% share of income due to data unavailability.

The research is built on the main hypothesis that the existence of the Great Decoupling is proven by applying the variables of labour productivity, employment, index of the top 10% share of income inequality and GDP per capita in the model. The Great Decoupling model is modified by applying the following variables: total factor productivity, globalisation index and GDP per capita. Labour productivity is indirectly used to calculate total factor productivity, because of its high correlation, makes total factor productivity a fit replacement for labour productivity. Factor productivity is going to represent automation in the form of technological innovations, and replace private employment. Globalisation index is a replacement family median income since it reflects educational attainment. Important factors affecting the Great Decoupling are globalisation and economics of AI-driven automation. Technological change can be better handled by panel data than by pure cross-section or pure time series data. The first auxiliary hypothesis is that the KOF Globalisation Index has a negative impact on economic growth. The second auxiliary hypothesis is that the total factor productivity has a positive impact on economic growth. The recessions of the years 1990-1993 and 2009 have significant impact on the results of the model which was the reason why were left in order to receive accurate results.

1.2. Motivation

Assuming that the factor of globalization and significant technological progress (economics of AI-driven automation) are significantly affecting economic growth and so fuelling the Great Decoupling, a model is built with elected variables. The same model is applied to countries members of four major world economies, USA, Japan, United Kingdom and European Union. It is interesting to interpret possible impacts and future trends of the largest economies that are shaping today our world of tomorrow. The largest economies carry the responsibility that the acknowledgements and strategies of today will echo through the rise of the next generation of world economy shapers.

1.3. Challenges

Two of the four variables that Brynjolfsson and McAfee (2013) used for their framework are Labour productivity and GDP per capita. Because of challenges of data availability of the two remaining variables, the number of jobs in Private employment and Median household income, other variables for the chosen countries had to be elected as replacement. Below is given an understanding of why the elected variables are appropriate for the model.

In the first part of this research, evidence of the presence of the Great Decoupling is given. In the model, variables with available data were used for each country during a given period of time. As already mentioned, data for the United States of America was fully gathered while for the other countries were not. As a substituent for the variable private employment, employment is used, while the variable median household income is replaced with the index of the top 10% share of income inequality - Income share held by highest 10% in a country. Both of the variables that are acting as replacement stay, mostly, constant over time; in employment, the number of employees in the government do not change significantly, so unusual trends in employment are mostly caused by transitions in private employment. The index of the top 10% share of the people with the highest income are not only a good indicator of income inequality, but also one of maximisation of profit. If the share of the "richest" is increasing, it means that income is not distributed evenly trough society and that the "poorer" are sharing the decreasing piece of cake that is left behind just as median household income describes.

A research from the World Inequality Lab (2019) found that citizens of the EU are more unequal today than they were four decades ago. Results suggested that between 1980 and 2017, the top 1% grew more than two times faster and captured as much growth as the bottom 50%. The share of national income captured by the richest 10% Europeans increased from 29% to 34% between 1980 and 2017. A worrisome data is that about 20% of citizens lived below the European poverty line in 1980, compared to 22% in 2017. In the United States of America, the situation is worse than in Europe: average income of the poorest half of Europeans was 40% higher in 2017 than in 1980, while it was essentially the same as in 1980 (+3%) for the poorest 50% Americans. Trends are illustrated in Figure 1.

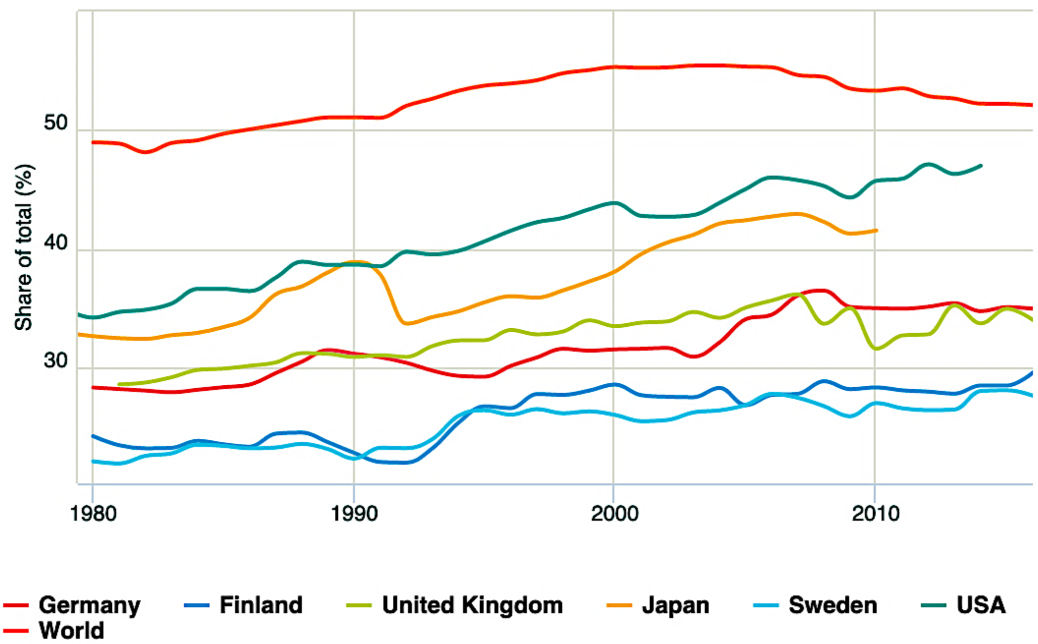

Figure 1. Top 10% income for Germany, Finland, United Kingdom, Japan, Sweden and United States of America (World Inequality Lab, 2019)

In the second part of the dissertation, that is built on the main hypothesis, after a thoroughly evaluation of literature review and critical thinking a new model can be found. The variables used in the model are GDP per capita, Total factor productivity and Globalisation Index. GDP per capita is used as a measure for economic growth, while Total factor productivity is used as a variable that influences AI driven automation that fuels the effect of the Great Decoupling. The variable KOF Globalisation Index is elaborated and described as the second variable that significantly impacts the Great Decoupling. Below is given an explanation on why were the variables elected.

Bergeaud, Cette and Lecat (2015), showed that there is an overall convergence process among advanced countries relying also on total factor productivity. Changes in technology helped explaining a constant growth in productivity throughout the 1990s (Basu, Fernald and Shapiro, 2001) and it sure had a role in the 21st century. Comin (2010) suggested that total factor productivity can indicate the endogenous level of technology and innovation decisions such as endogenous technology acceptance processes which are significant in developing economies. He pointed out that this may be an important ingredient to understanding high and medium-term fluctuations in developing economies. Solow (1956) underlined that cross-country differences in technology may generate important cross-country differences in income per capita. He continued with Klenow and Rodriguez-Clare (1997) and Hall and Jones (1999) who have confirmed that a majority of the gap in income per capita between rich and poor countries is associated to large cross-country differences in total factor productivity. Those are the arguments in favour of choosing total factor productivity as a variable that represents growth in technology, innovation and automation.

Furthermore, it is shown that numerous factors can influence GDP per capita growth and convergence (Baumol, 1986, Barro, 1991). Institutions and education, linked to innovation and technological progress, are the one with the highest influence. Acemoglu et al. (2001) showed the significant impact of human capital on long-run development. The measurement of human capital is also reflected through Globalisation Index. Drivers of globalization are the forces that lead towards closer economic integration (Bang and Markset, 2011). The index analyses the contributors and inhibitors to the development and deployment of a healthy, educated and productive labour force and is one of the variables in this research. It reflects inequalities and knowledge sharing. The Globalisation Index measures the economic, social and political dimensions of globalisation and is possible to replace family median income since it reflects educational attainment. The returned investment of educational attainment is a response to changes in globalization. Higher educational investments influence national economic growth.

1.4. Approach

In Chapter Four, a method is presented in order to suggest if the phenomenon of the Great Decoupling exists. A two means test is conducted between growth rates of every and each of the variables. If results can reject the hypothesis that there is no difference in means, then we can conclude that the variables grew in union. If not, results can point in the direction that divergence is present. Additionally, a mean test was used to display if significant increase (or decrease) were recorded in growth. All the variables were tested on time series method for the period that data availability allowed.

As Gujarati listed in his book Basic of Economics (2003), phenomena such as technological change can be better handled by panel data than by pure cross-section or pure time series data. Panel data analysis combines time series and cross sections, allowing greater flexibility in modelling differences.

The econometric analysis is based on panel data estimation, using the Gretl software.

The first step in Panel data models is to test whether the data series can be estimated through a panel data model or through a pooled OLS. A simple probability test has the null hypothesis the OLS model and the alternative hypothesis the fixed effects model (FEM). The next step would be to decide whether a fixed effects model or a random effect model (REM) is more appropriate for the data series. There will be types of panel data analytic models (1) constant coefficients (pooled regression OLS) models, (2) fixed effects models (FEM), and (3) random effects models (REM). Data for each country are available for the period 1975-2014. Thus, we have a balanced panel with 6 cross-sectional units covering the period 1975-2014.

This analysis is performed on our four major economic areas using annual data. Analysed countries are three developed countries: United States, Japan and the United Kingdom and the euro zone (Bergeaud, Cette and Lecat, 2017). The euro zone was narrowed to three countries that was affected by the Great Decoupling: Sweden, Finland and Germany, all of it mentioned in the interview by Bernstein and Raman (2015).

1.5. Contributions

The main contribution of this research is to provide evidence of the existence of the phenomenon and to explain factors affecting the Great Decoupling in order to give solid grounds for policy makers. Taking into account globalisation and economics AI-driving automation variables, it can help understand the implications of the Great Decoupling. It can help as a conceptual framework to identify and understand changes in economic growth. It is clear that technological shocks significantly reduced the share of 20th century GDP growth, but after many debates and discussion, a lot is still left unexplained. Nevertheless, this underscores the importance of further research to better measure the implication of economics AI-driving automation and globalisation. The Great Globalisation is not only changing the way we work but the way we live. As William Gibson (1993) once wrote, “The future is here, it’s just not evenly distributed yet.”

1.6. How to Read this Dissertation

The dissertation is aimed at offering an insight into the phenomenon of the Great Decoupling.

As an introduction, thoughts of the author and the perspective at the beginning of the research journey are presented. A sketch of the motivation and challenges encountered is given, but also a new approach that will shape the contributions of the research. The chapter *An insight into the great decoupling* is devoted to describe the phenomenon itself and the literature. It contains the strong connection between Total factor productivity (TFP) and growth of Labour productivity (LP) that were used in the econometric models. It also incorporates the nexus between the KOF Index of Globalisation and Household income. Chapter Three, *Statistical insight of Germany, Finland, United Kingdom, Japan, Sweden and United States of America* displays analysis of the Index of Economic freedom and general statistical overview of history and predictions of the economic development of the selected countries. The *Wh(a)ys of Germany, Finland, United Kingdom, Japan, Sweden and United States of America* it the Fourth Chapter that provides methods that are used to explain and prove the existence of the phenomenon in four major economies: United States, Japan, United Kingdom and European Union. The Fifth chapter *Panel Data Analysis* presents an examination of the methodology of Panel Data Analysis, with emphasis on the Fixed effects model (FE) and Random effects model (RE). Chapter six *The Wh(a)ys of Globalisation and Economics of AI-Driven automation* adds to the literature that assesses the impact and effects of globalisation and AI-driven economics on economic growth, underlining the importance of employment and competitiveness. Chapter Seven discusses related results, and concludes.

2. The Great Decoupling

The last several decades have been defined by an increasing pace of change and uncertainty in the world. One of the main trends that are marking this change is the global shift toward liberal economic policy, which was made possible especially through globalisation. The other trend is entering the digital era through enormous technology advancements and AI improvements. Both of those trends are fuelling the effects of the Great Decoupling, the phenomena that is in the focus of study done by Erik Brynjolfsson and Andrew McAfee (2013). They analysed four key measures of an economy's health: GDP per capita, labour productivity, the number of jobs, and median household income and found that they were not growing in a union like they used to - and should. In the study it is shown that productivity growth and employment growth started to become decoupled, all of it contributing to the stagnation in average incomes in the United States and to the dissolution of many middle-level jobs. McAfee (2013) explains how an American household at the 50th percentile of income distribution earns less today than it did in 1998, which can be seen in the graph below.

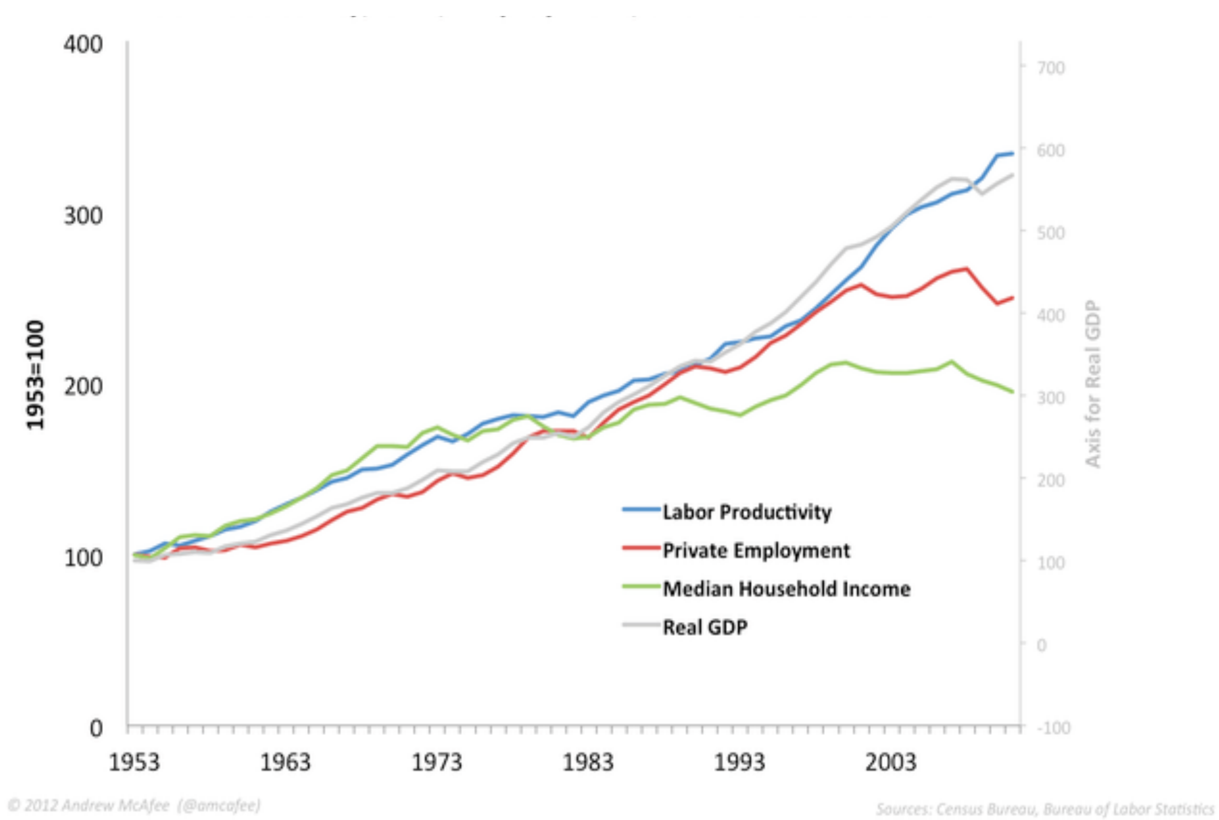

Figure 2. The Great Decoupling: When workers began falling behind (Bernstein and Raman, 2015)

Technology has been one of the main drivers of productivity growth. The application of AI and the automation of activities can boost productivity growth and other benefits not just for businesses on a micro scale, but entire economies. Technological advances have historically varied impacts on the labour market. New technologies may substitute for some skills while complementing others and these trends change over periods of time (Acemoglu and Autor, 2011).

Van Biesebroeck (2015) suggested that there are three principal means for assessing the tightness of the link between wages and productivity. First, one is that experimental and real-world indications suggests that employers have monopsony power that they are allowed to operate to pay their workers below the corresponding marginal productivity. Second, such system highlights the existence of large youth unemployment. Firms, for not arbitraging between older and younger workers and not compensating particular worker characteristics, was given as an example.
The second mean and the compensation below someone's productivity level is confirming the first one. The third one is the falling share of labour in national income over time. This has been combined to the increased relevance of entrepreneurship and human capital relative to pure labour input. Ford (2015) and Cowen (2015) argue that weak wage growth for large groups (in the US) is only the beginning of wage polarization in the labour market.

Bivens and Mishel (2015) covered the reason why did the Economic Policy Institute launched Raising America's Pay - an initiative that explains the role of labour market policies in wage and benefit patterns and identifies policies that will generate broad- based wage growth by tilting bargaining power back toward low- and moderate-wage workers. As EPI's Agenda to Raise America's Pay (2015) explains, these policies include:

- Raising the minimum wage
- Updating overtime rules
- Strengthening collective bargaining rights
- Regularizing undocumented workers
- Providing earned sick leave and paid family leave
- Ending discriminatory practices that contribute to race and gender inequalities
- Supporting strong enforcement of labour standards
- Prioritizing very low rates of unemployment when making monetary policy
- Enacting targeted employment programs and investing in public infrastructure to create jobs Reducing our trade deficit by stopping destructive currency manipulation

- Using the tax code to restrain top 1 percent incomes.

In their paper, Berlingieri, Blanchenay and Criscuolo (2017) covered and conducted a preliminary and suggestive analysis where conditional correlations rather than causal effect of policies are shown. A positive link between higher minimum wages, unionisation, EPL (Employment protection legislation) and reduced wage inequality exists. When it comes to the case of the minimum wage, there is evidence of a strong nexus between productivity and wages dispersion over time.

Gil-Alana and Škare (2018) in their work "Testing the great decoupling: a long memory approach" analysed the works of individual country study such as van Soest and Stancanelli (2010) for France, group country studies Mistral (2011) for the OECD countries, Kodama and Odaki (2012) for Japan and Meager and Speckesser (2011) for 25 countries over 1995-2009 and suggested that limited evidence on the presence of the Great Decoupling is given. Further research is needed in order to explain factors affecting the phenomenon to give solid ground for policy makers.
A systematic overview on productivity-wage-employment has been given in *Is the Great Decoupling real?* (Škare and Škare, 2017).

Table 1. Overview on productivity-wage-employment link studies (Škare and Škare, 2017)

Author(s)	**Study description**	**Results**
Harris and Todaro (1970)	Impact of migration on productivity and wages	Rural-urban wage gap is maintained by labour market frictions
Mincer (1974)	Wage premium over marginal productivity depends on workers' characteristics	Human capital causes marginal wage rise
Shapiro and Stiglitz (1984)	Efficiency wage policy	Unemployment and efficiency wages induce workers' productivity

Krueger and Summers (1988)	High-wage industries and wage differentials	Sectors with high industry profits pressure wage level upward
Abowd, Kramarz, and Margolis (1999)	Impact of workers' individual characteristics on wages	More productive workers earn higher wages
Spence (2002)	Wage differentials and asymmetric information	Asymmetric information influence productivity and wages
Heckman, Lochner, and Todd (2006)	Returns on education depends on the level of uncertainty	Human capital-wage link depends on associated uncertainty
Helpman (2006)	Trade, FDI and production location influence wage rate and productivity	Global trade and firms' location determine country efficiency wage level
Oreopoulos (2007)	The link between investments in education and marginal wage	Productivity gain is now always following investments in education
Staiger, Spetz, and Phibbs (2010)	Monopsony power and wage differentials	Labour costs are higher under Monopsonistic labour market
Konings and Vanormelingen (2010)	Association between productivity and wage differentials	Productivity differentials drive wage differentials
Manning (2011)	Bargaining mechanism and wage level	Bargaining mechanism control wage and productivity divergences

van Biesebroeck (2011)	Bargaining power impact on wage level	Bargaining power can maintain wage above productivity levels
Fox and Smeets (2011)	Human capital impact on productivity level	Human capital has low impact on productivity differences
Oreopoulos (2012)	Demand for labour and unemployment affect equilibrium wages	Equilibrium wage is not always associated with productivity alone
Brummund (2012)	Firms' market power impact on wage level	Firms' with high market power have limited control on the labour market and wages
Brynjolfsson, Mcafee (2013)	The great decoupling theory	The divergences between productivity, wages and employment are due to technological advancement
Elgin and Kuzubas (2013)	Wage-productivity gap interaction with unemployment and unionization rate	Wage-productivity gap is higher in time of unemployment and lower on unionized markets

Back in the day, after watching the movie The Fifth Element, people used to imagine the future full of flying cars and super-fast makeup appliers - which today we know it is not the case. That innovation was an expectation that technological advancement has not been able to originate by now. The clash of expectations and statistic was described by Brynjolfsson, Rock and Syverson (2017). What does come true, are the effects of globalisation and economic AI-driven automation whose benefits of technological change and economic growth are not necessarily shared equally.
The paradox of globalisation is that it has probably helped to decrease inequality between countries but increased it within nations. The paradox of productivity is that the productivity is decreasing

although the implementation of AI and automation is present in our everyday life more than it has ever before.

Many companies have difficulties adopting new skills and technologies, those that successfully implemented the capabilities are capturing disproportionate benefits. Such disproportions have deep implications for the economy consequently for society as a whole.
This is changing the foundations of competition. Automation technologies can achieve substantial performance gains and take the lead in their respective industries, even as their efforts contribute to economy-level increases in productivity.

The pace of innovation will determine whether new sectors or tasks will be created to counterbalance the decline of routine and automated jobs as technology costs decline. Meanwhile, whether the cost of labour remains low in emerging economies in relation to capital will determine whether firms choose to automate production or move elsewhere.

2.1. The nexus between Total factor productivity (TFP) and growth of Labour productivity (LP)

Comin and Mestieri (2008) stated that little is known about the drivers of cross-country differences in income growth over protracted periods of time. They mentioned Klenow and Rodrıguez-Clare (1997) and Clark and Feenstra (2003) whose investigation showed that factor accumulation of physical and human capital accounts only for roughly 10% of cross-country differences in growth over the protracted periods they study which are 1960 to 1985 and 1850 to 2000, respectively. The study presented that the remaining 90% of cross-country variation is driven by differences in the growth rate of the Solow residual. The Solow residual is interpreted as a measure of the productivity of production factors or total factor productivity (TFP).

In their model, they evaluated twenty-five technologies and 139 countries and did a research on the evolution of individual technological adoption. They came to the conclusion that there exist two distinct trends over the last two centuries: adoption lags have converged across countries and that the intensity of use has diverged. Results suggested that differences in the evolution of adoption margins in Western and non-Western countries account for around 75% of the income per capita divergence observed between 1820 and 2000. Comin (2010), as mentioned before, stated that total factor productivity can indicate the endogenous level of technology and innovation decisions such as endogenous technology acceptance processes which are significant in developing economies.

Yuan (1991) thought that the total factor productivity included:

1. Science and technological progress. It offered a material basis to make capital and labour reach the appropriate efficiency level.
2. Policy. It had a significant impact on the efficiency of capital and labour by influencing the enthusiasm of laborers.
3. Market. Supply of raw materials, fuel, outsourcing, etc., and products sales would directly impact the using efficiency of capital and labour.
4. Natural and other random factors. Factors that could affect the efficiency of capital and labour.

2.1.1. Building to the New Growth theory

Economic growth is one of the most important concepts in the global economy. Despite the presence of much criticism that the level and rate of growth does not always reflect the real level of a population's living standards, it is still used as the primary measure of prosperity.

Many development theories attempt to explain the necessary conditions that would create a sustained and growing economy, highlighting the importance of particular conditions. At the United Nations Conference on "Environment and Development" that was held in Rio de Janeiro in 1992, representatives from 176 countries signed Agenda 21, where it were determined the principles of sustainable development and laid out a strategy for its achievement.

It was Adam Smith (1723-1790) who said that there are natural harmonies in economic life and described them as the force of the invisible hand, which stabilizes the market (Smith, 1954). In his book the Wealth of Nations (1776), Smith argued that the wealth of nations was based not on gold, but on trade. He thought that the main driving force behind increased productivity was the division of labour and improvement of technology, perceiving competition as the core of economic sector and the national economy as a whole. He stated that the economy can grow rapidly due to technological advances, part of which is the division of labour.

Smith's belief was that population growth is endogenous and that it depends on the available provisions for survival. He also recognized investment as endogenous, depending on the work and savings of the capitalists (Sharipov, 2015). The output growth from land was linked to the geographical discoveries and technological improvements in existing land fertility (Lavrov and Kapoguzov, 2006). The view he presented was further succeeded by classical economists, such as David Ricardo (1772-1823), Thomas Malthus (1766-1834), Karl Marx (1818-1883), John Stuart Mill (1808-1873), Jean-Baptiste Say (1767-1832) and others. The theory developed by these economists is known as classical theory of economic growth.

Views of Thomas Malthus and David Ricardo on the economic growth was more pessimistic, stating that the population would grow faster than the world's capacity to feed itself, not taking into account factors as migration and technological advancements. Ricardo's most important legacy is his theory of comparative advantage, where a country should focus its economic growth the most by focusing on the industry in which it has the most substantial comparative advantage. A very significant contribution to growth theory was the one by Joseph Alois Schumpeter (1883-1950). In 1911, he published his work "Theory of Economic Development", where he introduced the term "innovation". He did not consider the accumulation of capital as the main driving force of economic growth but the "hero of development" - the innovation and creativity of entrepreneurs. He perceived and in a new way considered the significance of the entrepreneur in terms of economic growth. Following the introduction of an innovation an entrepreneur receives great profits, but over time the competition copies the invention and the profits begin to decline (Piętak, 2014). Schumpeter proposed the theory of economic growth which was based on the assumptions of private property, competitive market and the efficient financial markets that would be able to support the production of new inventions. Unfortunately, the theory is suitable and effective only in a democratic system and economically developed countries.

In 1936 the book "The General Theory of Employment, Interest and Money" written by John Maynard Keynes was published. On Keynes work was built Keynesian and neo-Keynesian growth theories with the main following representatives of John Maynard Keynes (1993-1946), Roy Harrod (1900-1978), Evsey Domar (1914-1997), Joan Robinson (1903-1983), Nicholas Kaldor (1908-1986), Luigi Pasinetti (1930 –till now), James Meade (1907-1995).

Keynesian growth theories were based on the main posit by John Keynes that the expansion in effective aggregate demand will contribute to economic growth. As the main factor of economic growth is considered investment, introducing the term "multiplier effect".

Post-Keynesian (Neo-Keynesian) theory of economic growth has been structured mainly by Evsey Domar and Roy Harrod whose results were very similar. They agreed that the technical conditions of production, economic growth is determined by the marginal propensity to save, and that the dynamic equilibrium in the market system is inherently unstable, so that maintaining it at full employment requires active and purposeful actions of the state (Sharipov, 2015). Limitations of their theory were that they did not take into account technological progress, the growth of a capitalist economy at the guaranteed rate of growth with full employment is not possible and that in a capitalist economy there is no convergence towards equilibrium.

The new technology, improving productivity and improving the organization of production were all introduced by the first neoclassical growth theories emerged in 1950s –1960s. The main representatives of this school are Alfred Marshall (1842-1924), Carl Menger (1840-1921), Friedrich von Wieser (1851-1926), John Bates Clark (1847 –1938), Irving Fisher (1867-1947), Robert Solow (1924-present) and others. The economists were against government's intervention in the economy and believed that it should be allowed for large firms to achieve their growth potential in a competitive market. They strongly criticized the neo-Keynesian growth theory because they focused only on capital accumulation, ignoring other factors like technological improvement, education and skills. A second point that they criticized was the belief of permanency of the capitals share in income, without taking into consideration different combinations of resources. They also disagreed on the fact that market mechanism does find its balance. Solow created the "golden rule of accumulation", which mostly affected the optimal level of capital intensity and formulated a neoclassical growth model. He suggested that to achieve economic growth, investments, increase in the number of employees and technical progress are fundamental. It was Robert Solow (1956), who suggested that the long-run growth in income per capita in an economy is mostly driven by growth in total factor productivity (TFP).

A new chapter in economics began with the development of the theory of economic growth occurred in the 80-90s. A new contribution to growth theory emerges in the works of Paul M. Romer (1986), S. Rebell (1991), R. E. Lucas (1988). Growth in the Romer model (1990) was based on research and development, led by technological progress arising from investment decisions of economic entities that maximize profits (Cortright, 2001). Paul Romer recognized that technology differs from all other goods and recognized technological advances as endogenous. Lucas (1988) has shaped a growth model based on externalities, which stemmed from the process of accumulation of human capital through education or learning.

A central proposition of New Growth theory is that, unlike land and capital, knowledge is not subject to diminishing returns. It can be perceived that the development of knowledge is a key driver of economic development. Government do have a crucial role, they should boost and invest in human capital, in the development of education and skills. Private sector research and development needs also financial support in order to encourage inward investment, resulting in new knowledge. Cortright (2001) outlines that 'public' investment in social capital is subject to market failure and recognized that the New Growth theorists argued that government should allocate resources to compensate for this failure. The accumulation of private capital, like energy or water, does also depend on the correct level of expenditure by government. Additional care should be directed to building new infrastructure that would in return have many benefits, from higher quality of life for society to attracting tourists as a form of a returned investment.

We can perceive the New Growth Theory by implementing two important points. First, technological progress as a product of economic activity. It should not be treated as a given, which is one of the reasons why New Growth Theory is also called "endogenous" growth theory. Second, the endogenous growth theory believes that knowledge and technology are characterized by increasing returns, and these increasing returns drive the process of growth. Those are all assumption that have to be taken into account when talking about total factor productivity and the impact it has on the economic growth.

2.2. The nexus between KOF Index of globalisation and household income

Globalisation is a tool that helps to create and form more wealth and stability in developing countries. Unfortunately, the gap between the world's poorest countries and the world's richest does not seem to get smaller fast enough. The within-country income inequality is increased (Dreher, 2006).

Inequality is one of the main negative consequences of globalisation and is one of the key measurements to how globalisation affects the world. The paradox of globalisation is that it has probably helped to decrease inequality between countries but increased it within nations. One of the possible reasons for it is that it increased the demand for and the returns to higher-skilled work but decreased the expected income for people that are relatively low-skilled and have low-knowledge occupations. A more detailed description of the possible reasons delivers Mills (2008). In her work where she linked globalisation to inequality and build a theoretical model that illustrates how globalisation generates increased inequality within industrialized nations and decreased inequality within developing economies. In Figure 3, Mills(2008) defined globalization in four interrelated structural shifts that roughly occurred since the 1980s of: (i) internationalization of markets and declining importance of borders for economic transactions, (ii) tougher tax competition between countries, (iii) rising worldwide interconnectedness through new Information and Communication Technologies (ICTs), and (iv) the growing relevance and volatility of markets that was discussed in Mills and Blossfeld (2005).

GLOBALISATION

Internationalization of markets	Increased competition between nations	New ICTs & increased interconnectedness	Rising relevance and volatility of markets

⬇️

INCREASE IN

Financial openness	Trade	Foreign Direct Investment	ICT capital investment & use	Migration and mobility of workers

⬇️

NATIONAL INSTITUTIONAL FILTERS

Education systems	Employment & industrial relations systems	Welfare regime	Migration restrictions

⬇️

INDUSTRIALIZED COUNTRIES DEVELOPING ECONOMIES

• Deindustrialization • Weaker bargaining position of labour • Capital flight/ international relocation of jobs • Increased premium on higher skills for knowledge-based industries • Shift from higher wages in industrial sector to lower wages in service sector • Rise in higher-skilled workers' incomes	• Industrialization • Capital arrival/new jobs • Increased premium on lower skills for labour-intensive industries • Increase in wages for lower-skilled workers • Reduction in higher-skilled workers' incomes

⬇️

INCREASE IN INEQUALITY	DECREASE IN INEQUALITY
AGGREGATE OBSERVATIONS OF INEQUALITY	

Figure 3. Mechanisms linking globalization to inequality (Mills, 2008)

Berumen and Pérez-Megino (2015) found that globalization reduces the gap between developing and developed countries. One of the reasons is because offshoring raises the demand and the wage of developing countries' workers. They conducted a research where Sweden's level of inequality remains practically constant since 1945 while in the United States the level of inequality has risen to get back to levels of 1910s. The conclusion was that the approach with which the government faces globalization matters enormly.

Shopina, Oliinyk and Finaheiev (2017) conducted an analysis of trends of the world economy in the period of 2000–2017. They indicated that there is an aggravation of economic problems and a decline in economic growth rates in all regions of the world, more precisely in developed economies – by 0.4%, in the EU countries – by 0.3%; in developing countries – by 0.1%. They stated that the growing threat of terrorism, socio-economic instability, and geopolitical uncertainty are one of economic consequences of the negative impact of globalization on the global economy.

Investigating the influence of short-run dynamics and long-run equilibrium relationships between globalization and the growth of ASEAN countries in the period between 1970 and 2008., Ying, Chang and Lee (2014) established that the economic globalization has a positive influence on economic growth, but social and political globalization a negative impact on the growth of ASEAN countries that Titalessy (2018) confirmed.

Acemoglu, Gallego and Robinson (2014) revisited the relationship among institutions, human capital accumulation, and long-run economic development. The weight of evidence suggests that a 1 percent increase in school enrolment rates has led to an increase in GDP per capita growth of between 1 and 3 percent (Wilson and Briscoe, 2004). One view, proposed by Acemoglu et al. (2001) and Acemoglu & Robinson (2012), and inspired by North & Thomas (1973), focuses on institutions as the fundamental determinant of development. They stated that the Great Divergence in levels of prosperity that has occurred over the past 250 years is a consequence of societies having very different types of institutions.

Globalisation Index measures the economic, social and political dimensions of globalisation. Globalisation in the economic, social and political fields has been on the rise since the 1970s, receiving a full increment after the end of the Cold War.

When it comes to globalisation, it is very important to enhance the social segment and what does it represent for society. The social internal rate of return indicates the costs and benefits to society when investing in education. Such a cost includes the opportunity cost of having people not participating in the production of output and the full cost of the provision of education rather than only the cost borne by the individual. The social benefit consists of the raised productivity that is directly connected with investments in education and a host of possible non-economic benefits, such as lower crime, better health, more social cohesion and more informed and effective citizens (OECD, 2002). One of the negative sides that it brings is the lack of competitiveness in the market. As it will be analysed in later chapters, it is common that international companies with wider economies of scale drive local companies out of business, causing increasing income inequality and unfair competitive advantage.

The index is used in order to follow changes in the level of globalisation of different countries over a long period. The current Index is available for a total of 195 countries and covers the time period from 1970 to 2016. The Index measures globalisation on a scale from 1 to 100 and 42 different variables are used.

3. A statistical insight of Germany, Finland, United Kingdom, Japan, Sweden and United States of America

Identifying potential countries where the effect of the phenomenon is the strongest was an important selection. The countries were elected based on the available historical data taking into account related articles and other publications. This analysis is performed on four major economic areas using annual data. Analysed countries are the developed countries of United States, Japan, the United Kingdom and the euro zone (Bergeaud, Cette and Lecat, 2017). The euro zone was narrowed to three countries that was affected by the Great Decoupling: Sweden, Finland and Germany, based on Bernstein and Raman (2015). The macroeconomic trends in these six countries are of great importance for the past and future development of the world economy.

For all the countries, a short statistic description will be given using the latest data from the United Nations Conference on Trade and Development (UNCTAD, 2019). Since the main focus of this dissertation is the impact of globalisation and AI driven automation, the countries will be also analysed through the Index of Economic Freedom 2019 (The Heritage Foundation, 2019) that was created in 1995. Economic freedom is the fundamental right of every human to control his or her own labour and property. In an open market, individuals are free to work, produce, consume, and invest in the way they choose to. All data are taken from Miller, Kim and Roberts (2019). The Index of Economic Freedom has provided powerful insights that economic freedom, measured by the Index by factors related to the rule of law, limited government, regulatory efficiency, and open markets can help answer questions about wealth and prosperity of an economy. It documents the positive relationship between economic freedom and other social and economic goals. A strong correlation with healthier societies, cleaner environments, greater per capita wealth, human development, democracy, and poverty elimination is present (The Heritage Foundation, 2019). It is calculated based on 12 quantitative and qualitative factors, grouped into four broad categories of economic freedom:

1. Rule of Law (property rights, government integrity, judicial effectiveness)
2. Government Size (government spending, tax burden, fiscal health)
3. Regulatory Efficiency (business freedom, labour freedom, monetary freedom)
4. Open Markets (trade freedom, investment freedom, financial freedom)

Each of the twelve economic freedoms within these categories is graded on a scale of 0 to 100.

3.1. Germany

Population 82.114 Millions	Exchange rate 0.887 EUR/US$	GDP 3 693 204 Millions current US$
Land area (n) 349 360 km²	CPI growth 1.74 %	GDP growth 2.16 %

A short overview of the main statistical results for Germany is presented. This country is the world's fourth-largest economy following the United States, China, and Japan.

Table 2. Total merchandise trade in Germany (The Heritage Foundation, 2019)

Total merchandise trade **(millions of US$)**				
	2005	**2010**	**2015**	**2017**
Merchandise exports	970 914	1 258 924	1 326 206	1 448 190
Merchandise imports	777 073	1 054 814	1 051 132	1 162 907
Merchandise trade balance	193 842	204 110	275 074	285 283

From Table 2. can be seen that the merchandise exports growth rate in 2017 had a total growth of 8.5 %. The country has a mixed economy. It allows a free market economy in consumer goods and business services.

Top 5 partners in 2017

(exports, millions of US$)

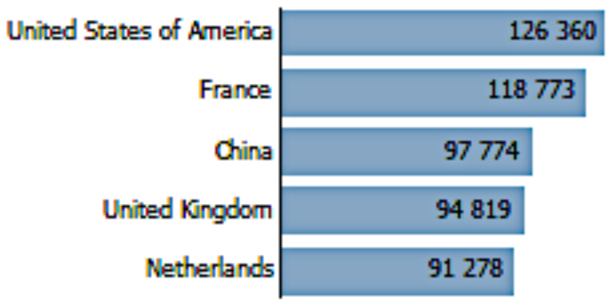

Figure 4. Top 5 partners in 2017 of Germany (The Heritage Foundation, 2019)

Germany is famous for taking the advantage of the opportunities that globalisation brings. It is known that exports of goods and services account for around half of the country's value added. One in four jobs depends on exports, and their top 5 partners, as seen in Figure 5 are the USA, France, China, United Kingdom and the Netherlands.

Table 3. Total trade in services in Germany (The Heritage Foundation, 2019)

Total trade in services (millions of US$)				
	2005	**2010**	**2015**	**2017**
Services exports	159 418	225 014	273 008	(e) 304 058
Services imports	209 867	263 280	293 639	(e) 323 647
Services trade balance	-50 449	-38 265	-20 631	(e) -19 589

It is interesting that Germany's service sector is a leading employer (72% of the workforce) and contributes to 61.5% of the country's GDP. The main reason for such a growth was the demand for business-related services and the development of new technologies, which results can be seen in Table 3. It is important to point out such investments significantly enforced new branches in the tertiary sector.

Table 4. Services exports by main category in Germany (The Heritage Foundation, 2019)

Services exports by main category (as % of total services)				
	2005	**2010**	**2015**	**2017**
Transport	23.4	24.8	20.5	(e) 20.4
Travel	18.3	15.4	13.5	(e) 13.1
Other services	53.3	56.1	60.8	(e) 61.1

Many will say that Germany is well known for mechanical engineering and its cars - which is true. In 2017 Germany became the 2nd largest exporter in the world, and the trend continues as presented in Table 4. In the period of the last five years the exports of Germany have increased at an annualized rate of 0.2%. The exports of Cars with 11.9% of the total exports are the leading category, followed by Vehicle Parts, which account for 4.81%.

Table 5. Economic indicators in Germany (The Heritage Foundation, 2019)

Services exports by main category (as % of total services)				
	2005	**2010**	**2015**	**2017**
GDP, current	2 861 339	3 417 095	3 381 389	3 693 204
GDP per capita, current US$	35 035	42 241	41 384	44 976
Real GDP growth, y-on-y, %	0.71	4.08	1.74	2.16
Current account balance, % of GDP	4.60	5.65	8.91	8.07
Exchange rate (/US$)	0.804	0.755	0.902	0.887

There was an 2.2 % increase in gross domestic product growth rate in 2017 displayed in Table 5. The GDP value of Germany represents 3.33 % of the world economy.

Table 6. Financial flows in Germany (The Heritage Foundation, 2019)

Financial flows (millions of US$ unless otherwise specified)				
	2005	**2010**	**2015**	**2017**
FDI inflows	(m) 47 449.80	(m) 65 642.99	(m) 33 276.35	(m) 34 726.28
FDI outflows	(m) 74 543.07	(m) 125 450.81	(m) 108 177.34	(m) 82 336.48
Personal remittances, % of GDP	0.24	0.37	0.48	0.46

Germany is an attractive country for foreign direct investment (FDI). The global recession and subsequent Eurozone crisis have unbalanced the influx of FDI in recent years, as seen in Table 6, while Brexit and US tax reforms made it worse. Nevertheless, there are forecasts that the FDI flows to Germany are increasing. A 2.2 % of growth of FDI outflows as % of GDP in 2017 was recorded.

A similar trend has experienced the Share of ICT goods, both in percentage of total export and import as seen in Table 7.

Table 7. Information economy indicators in Germany (The Heritage Foundation, 2019)

Information economy indicators (as % of)				
	2005	**2010**	**2015**	**2017**
Share of ICT goods, % of total exports	7.90	5.09	4.65	4.96
Share of ICT goods, % of total imports	11.50	9.16	8.44	8.78

Share of workforce involved in the ICT sector	..	(o) 4.12	..	..

The economic model is built on a network of small and medium-sized enterprises (SMEs) which are competitive in the international environment.

3.1.1. 2019 Index of economic freedom: Germany (DEU)

Germany's economic freedom score is 73.5, making its economy the 24th freest in the 2019 Index, while being placed 14th among 44 countries in the Europe region. The overall score is above the regional and world averages.
Germany is the most politically and economically influential member nation of the European Union with chancellor Angela Merkel in office since 2005. Political tensions about migration are still an issue. Germany's solid economy, which is the world's fourth largest and Europe's biggest, is based on exports of high-quality manufactured goods. The project to build a second natural gas pipeline between Russia and Germany caused many criticisms, especially coming from the US and other European countries.

German law fully protects property rights for German citizens and foreigners with secured interests in property. Germany boasts a robust regime to., and the rule of law prevails. Corruption cases are rare. The judiciary is independent, and the protection of intellectual property rights are robust.

The top personal income tax rate is 47.5 percent, the federal corporate rate is 15.8 percent and overall tax burden is 37.6 percent of total domestic income. Government spending has amounted to 43.9 percent of the country's GDP in the past three years, and budget surpluses have averaged 0.9 percent of GDP. Public debt amounts to 64.1 percent of GDP.
The efficient regulatory framework simplifies and motivates entrepreneurial activity following trend in the world. The national minimum hourly wage that was first introduced in 2015 has been increasing. A regulatory change was introduced in 2017 that applied restrictions regarding temporary employment. Monetary stability is a constant.

Exports and imports are making 86.9 percent of the overall value of GDP. The average tariff rate is 2.0 percent in Germany. The states implement a number of EU-directed nontariff trade barriers including technical and product-specific regulations, subsidies, and quotas (Miller, Kim and

Roberts, 2019). Openness to global commerce are boosting sustainable competitiveness and investments. The financial sector is one of the most developed offering a full range of services.

3.2. Finland

Population 5.523 Million	Exchange rate 0.887 EUR/US$	GDP 252 247 Million current US$
Land area (n) 303 910 km²	CPI growth 0.75 %	GDP growth 2.80 %

A short overview of Finland's economy id displayed. Finland is known for its modern welfare state, in particular high-quality education, promotion of equality, and an efficient national social welfare system.

Table 8. Total merchandise trade in Finland (The Heritage Foundation, 2019)

Total merchandise trade (millions of US$)				
	2005	**2010**	**2015**	**2017**
Merchandise exports	65 498	69 518	59 817	68 073
Merchandise imports	58 766	68 803	60 430	70 587
Merchandise trade balance	6 732	715	-612	-2 513

In Table 8, it can be seen that here was a 17.6 % growth in merchandise exports growth rate in 2017, after a significant drop in 2015. Trade is important, with exports accounting for over one-third of GDP in the last couple of years. The government is open to, and successfully proceeds with strategies to attract foreign direct investment.

Top 5 partners in 2017
(exports, millions of US$)

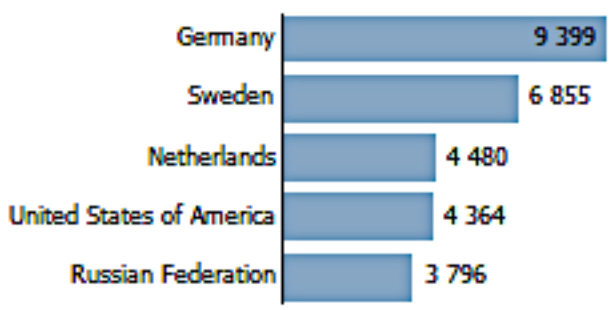

Figure 5. Top 5 partners in 2017 of Finland (The Heritage Foundation, 2019)

The top 5 partners in 2017 are Germany, Sweden, the Netherlands, the USA and Russian Federation. Finland has a high-income economy as an OECD member. It is one of the leading countries in the sector of new technologies. Because of the cold climate, it depends mostly on imports of raw materials and energy.

Table 9. Total trade in services in Finland (The Heritage Foundation, 2019)

Total trade in services (millions of US$)				
	2005	**2010**	**2015**	**2017**
Services exports	18 200	27 839	25 760	(e) 29 137
Services imports	18 922	27 317	28 836	(e) 30 920
Services trade balance	-722	522	-3 075	(e) -1 783

Its economy is mainly based on foreign trade, which accounts for 78% of its GDP in 2018 (World Bank). Finland's has exported petroleum oils, paper and motor cars. It imported crude oil, cars, petroleum oils and parts of motor vehicles. Just the forest industry products alone are responsible for 20.6% of exports. The increasing trend is shown in Table 9.

Table 10. Services exports by main category in Finland (The Heritage Foundation, 2019)

Services exports by main category (as % of total services)				
	2005	**2010**	**2015**	**2017**
Transport	-	11.6	14.1	(e) 14.5
Travel	-	10.9	10.0	(e) 10.2
Other services	-	49.8	69.1	(e) 68.4

Service exports are especially boosted by an increase in the export of ICT services, as can be noticed in Table 10. It is known that Finland's services sector employs three-quarters of the workforce, in total 59.4% of the GDP. It is the country that produces the largest number of new businesses.

Table 11. Economic indicators in Finland (The Heritage Foundation, 2019)

Economic indicators (millions of US$ unless otherwise specified)				
	2005	**2010**	**2015**	**2017**
GDP, current	204 431	247 800	232 465	252 247

GDP per capita, current US$	38 873	46 181	42 405	45 670
Real GDP growth, y-on-y, %	2.78	2.99	0.14	2.80
Current account balance, % of GDP	3.05	1.09	-0.73	0.72
Exchange rate (/US$)	0.804	0.755	0.902	0.887

A 2.8 % growth in gross domestic product growth rate in 2017 was recorded. Finland was one of the best performing economies within the EU in the period before the financial crisis in 2009. Its banks and financial markets managed to minimize the negative influences of the crisis but the world slowdown effected exports and domestic demand significantly, causing Finland's economy to deteriorate from 2012 to 2014.

Table 12. Financial flows in Finland (The Heritage Foundation, 2019)

Financial flows (millions of US$ unless otherwise specified)				
	2005	**2010**	**2015**	**2017**
FDI inflows	4 750.16	7 358.83	1 483.93	1 327.90
FDI outflows	4 222.60	10 167.18	-16 583.88	1 726.82
Personal remittances, % of GDP	0.34	0.36	0.35	0.33

The financial crisis and the Eurozone crisis significantly weakened the foreign direct investment (FDI) flows to Finland, but signs of recovery are showing. The FDI directed towards services to enterprises engaged in other service activities. FDI outflows as % of GDP increased for 0.7% in 2017.

Table 13. Information economy indicators in Finland (The Heritage Foundation, 2019)

Information economy indicators (as % of)				
	2005	**2010**	**2015**	**2017**
Share of ICT goods, % of total exports	20.29	6.36	2.46	2.69
Share of ICT goods, % of total imports	14.29	8.23	6.89	7.07
Share of workforce involved in the ICT sector	..	(o) 7.69	..	..

As already mentioned, Finland is very competitive in export of technology as well as promotion of start-ups, communications technology and biotechnology sectors. After a significant impact of the financial crisis, signs of recovery are evident in Table 13.

3.2.1. 2019 Index of economic freedom: Finland (FIN)

Finland’s economic freedom score is 74.9, making its economy the 20th freest in the 2019 Index and ranked 11th among 44 countries in the Europe region. The country's overall score is above the regional and world averages.
Finland was a part of Sweden and then part of the Russian Empire. The country became gained independence in 1917. In 1995 joined the European Union in 1995 and four years later adopted the euro.

The focus of the export has been mainly on manufacturing, principally in the wood, metals, telecommunications, and electronics industries that have been constantly growing. A relevant decision was to cut tariffs on Russian electricity imports in June 2018 and the approval of the construction of the Nord Stream II pipeline inside its exclusive economic zone which rose many controversies.

Finland regulates one of the strongest property rights protection regimes in the world and complies to many international agreements with the goal to protect intellectual property. Contractual agreements are strictly honoured. The quality of the judiciary is generally high. Finland was ranked 3rd out of 180 countries surveyed in Transparency International’s 2017 Corruption Perceptions Index (Miller, Kim and Roberts, 2019).

The top personal income tax rate is 31.25 percent while the corporate one is 20 percent. Other taxes include value-added and capital income taxes. The overall tax burden equals 44.1 percent of total domestic income. During the past three years 55.6 percent of the country’s output (GDP) was spent by the government, and budget deficits have averaged 2.0 percent of GDP while public debt is equivalent to 61.4 percent of GDP (Miller, Kim and Roberts, 2019).

Finland’s business framework is simple and motivates robust innovation and growth in productivity. The country increased the maximum length of the probationary period for permanent employees in 2017. Subsidies to Finland were expanded by the EU while the government recognizes the needed reforms in its green-energy subsidy program.

Exports and imports amount to 76.7 percent of GDP value. A large number of EU-directed nontariff trade barriers including technical and product-specific regulations, subsidies, and quotas are introduced. The average applied tariff equals 2.0 percent. Foreign investments are welcomed while the financial sector provides a broad range of services.

3.3. United Kingdom

Population 66.431 Millions	Exchange rate 0.777 GBP/US$	GDP 2 631 228 Millions current US$
Land area (n) 241 930 km²	CPI growth 2.56 %	GDP growth 1.74 %

The UK, a leading trading power and financial centre, is the third largest economy in Europe (after Germany and France) and sixth largest economy in the world. A short overview of its economy status is presented.

Table 14. Total merchandise trade in the United Kingdom (The Heritage Foundation, 2019)

Total merchandise trade (millions of US$)				
	2005	**2010**	**2015**	**2017**
Merchandise exports	384 477	415 959	459 633	441 106
Merchandise imports	513 673	591 095	626 223	643 515
Merchandise trade balance	-129 196	-175 136	-166 590	-202 409

The United Kingdom is one of the strongest players in international trade field. Results show that the United Kingdom is the fifth largest importer and tenth exporter of goods in the world, Table 14 shows an increase of 7.8 % was recorded in merchandise exports growth rate in 2017.

Top 5 partners in 2017
(exports, millions of US$)

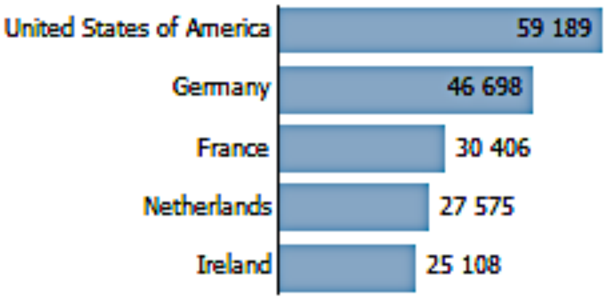

Figure 6. Top 5 partners in 2017 in the United Kingdom (The Heritage Foundation, 2019)

Figure 6. displays the main export partners which are the United States, Germany, France, the Netherlands and Ireland. Taking into account that the UK is leaving the EU, the United Kingdom will have to renegotiate its various trade agreements.

Table 15. Total trade in services in the United Kingdom (The Heritage Foundation, 2019)

Total trade in services (millions of US$)				
	2005	**2010**	**2015**	**2017**
Services exports	236 688	271 257	348 931	(e) 350 687
Services imports	174 159	184 709	217 151	(e) 214 946
Services trade balance	62 529	86 548	131 780	(e) 135 742

The UK is leader in banking, insurance, and business services - which are all the main drivers of British GDP growth. Such statement is supported by results in Table 15.

Table 16. Services exports by main category in the United Kingdom (The Heritage Foundation, 2019)

Services exports by main category (as % of total services)				
	2005	**2010**	**2015**	**2017**
Transport	14.1	10.8	11.2	(e) 10.8
Travel	13.6	12.9	13.0	(e) 12.5
Other services	72.2	76.0	73.9	(e) 75.2

The UK' imports and very similar to its exports, which are the following: vehicles and transport equipment, medicines, fuels, electronic and digital data processing devices and organic materials. Data in Table 16 show a decline in Transport and Travel exports.

Table 17. Economic indicators in the United Kingdom (The Heritage Foundation, 2019)

Economic indicators (millions of US$ unless otherwise specified)				
	2005	**2010**	**2015**	**2017**
GDP, current	2 525 013	2 452 900	2 896 421	2 631 228
GDP per capita, current US$	41 724	38 600	44 123	39 608
Real GDP growth, y-on-y, %	3.15	1.71	2.35	1.74
Current account balance, % of GDP	-2.02	-3.40	-5.19	-4.07
Exchange rate (/US$)	0.550	0.647	0.655	0.777

Although a strong economy, a big challenge ahead is Brexit and how to keep the economic growth continuous. Shown in Table 17., gross domestic product growth rate in 2017 has increased for 1.7%.

Table 18. Financial flows in the United Kingdom (The Heritage Foundation, 2019)

Financial flows (millions of US$ unless otherwise specified)				
	2005	**2010**	**2015**	**2017**
FDI inflows	182 927.94	58 200.28	32 720.42	15 090.04
FDI outflows	88 560.32	48 091.80	-83 491.52	99 613.57
Personal remittances, % of GDP	0.24	0.20	0.17	0.17

The service sector employs more than 80% of the workforce. The 80% of workforce is responsible for more than 70% of UK's GDP. As the largest financial centre in Europe, the banking sector is extremely dynamic. The capital, London, is the headquarter of many multinationals, which make it easier to attract investors. As shown as in Table 18, there was an increase of 3.8 % in FDI outflows as % of GDP in 2017.

Table 19. Information economy indicators in the United Kingdom (The Heritage Foundation, 2019)

Information economy indicators (as % of)				
	2005	**2010**	**2015**	**2017**
Share of ICT goods, % of total exports	13.48	5.78	4.10	4.25
Share of ICT goods, % of total imports	12.86	9.49	8.29	7.77
Share of workforce involved in the ICT sector	..	(o) 6.02	..	..

The UK is preparing well for the fourth industrial revolution, developing and investing in sectors as information and communication technologies, bio-technologies, renewable energies and defence. The percentages of such exports are growing - presented in Table 19.

3.3.1. 2019 Index of economic freedom: United Kingdom (GBR)

The United Kingdom's economic freedom score is 78.9, making its economy the 7th freest in the 2019 Index while it is ranked 3rd among 44 countries in the Europe region. The overall score is above the regional and world averages.

Ever since former Prime Minister Margaret Thatcher's market reforms in the 1980s, steady growth has made Britain's economy the world's fifth largest. With the referendum in 2016, the U.K. voted to leave the European Union. Services, especially banking, insurance, and business services, are key drivers of GDP growth. Large oil and natural gas reserves are decreasing.
The country has an effective rule of law, an open trade regime, and a well-developed financial sector. The liberal labour market will transform into one even more flexible after Brexit, with one of the world's most efficient business and investment environments (Miller, Kim and Roberts, 2019).

Fees related to the very secure private property rights were increased in 2018. The court system is independent, and the rule of law is well established. In the World Economic Forum's 2017–2018 Global Competitiveness Report, the UK placed 8th out of 137 countries. Bribery and corruption occur rarely, and they are prosecuted vigorously

The top personal income tax rate is 45 percent and corporate tax rate is 20 percent. Other taxes include value-added and environment taxes while the overall tax burden equals 33.2 percent of total domestic income. In the period of the past three years, government spending has amounted to a total of 41.6 percent of the country's GDP (Miller, Kim and Roberts, 2019). Budget deficits have averaged 3.2 percent of GDP and public debt is equivalent to 87.0 percent of GDP.

The efficient and transparent regulatory environment enables to takes less than a week to start a business. Regulated rates for most utilities and partial controls of prescription drug prices are maintained under price control by the government. A high possibility to reform current agricultural subsidies after Brexit is present.

Exports and imports combined are equal to 62.5 percent of the total GDP. The average applied tariff rate in the UK equals 2.0 percent. There is a chance that some EU-directed nontariff trade barriers including technical and product-specific regulations, subsidies, and quotas may be adjusted or removed after Brexit (Miller, Kim and Roberts, 2019). The United Kingdom is a country with a very well-developed financial sector and home to one of the world's most efficient investment environments.

3.4. Japan

Population 127.484 Millions	Exchange rate 112.166 JPY/US$	GDP 4 872 415 Millions current US$
Land area (n) 364 560 km²	CPI growth 0.47 %	GDP growth 1.73 %

An overview of the world's third largest economy is given. One of the main traits of Japan, is its aging population and the fact that the country is greatly affected to external impacts because of its significant dependence on exports.

Table 20. Total merchandise trade in Japan (The Heritage Foundation, 2019)

Total merchandise trade (millions of US$)				
	2005	**2010**	**2015**	**2017**
Merchandise exports	594 941	769 774	624 787	698 131
Merchandise imports	515 866	694 059	647 982	671 921
Merchandise trade balance	79 074	75 715	-23 195	26 210

An increase of 8.3 % in merchandise exports growth rate in 2017 was recorded. It is important to underline the scarcity in critical natural resources and its dependency on imported energy and raw materials.

Top 5 partners in 2017
(exports, millions of US$)

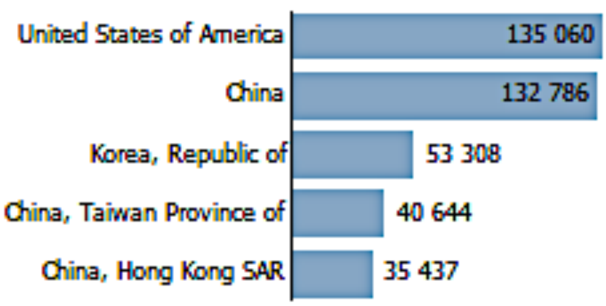

Figure 7. Top 5 partners in 2017 of Japan (The Heritage Foundation, 2019)

Japans main partners in trade are the US and all developed neighbour economies: China, South Korea, Taiwan and Hong Kong, as in Figure 7. Japan is the second-biggest trading partner in Asia, after China, with countries member of the European Union.

Table 21. Total trade in services in Japan (The Heritage Foundation, 2019)

Total trade in services (millions of US$)				
	2005	**2010**	**2015**	**2017**
Services exports	102 029	134 414	162 637	(e) 184 771
Services imports	139 030	164 704	178 587	(e) 190 889
Services trade balance	-37 001	-30 290	-15 950	(e) -8 040

The service sector is responsible for 69.3% of GDP and employs 72.2% of the total workforce. Their main services are banking, insurance, retailing, transportation and telecommunications. The increase of the trade in services is recorded in Table 21.

Table 22. Services exports by main category in Japan (The Heritage Foundation, 2019)

Services exports by main category (as % of total services)				
	2005	**2010**	**2015**	**2017**
Transport	35.1	31.4	21.8	(e) 18.4
Travel	12.2	9.8	15.4	(e) 18.4
Other services	52.4	58.3	62.3	(e) 62.5

The industrial sector excels from manufacturing products that range from basic to sophisticated technology. The country is especially well known in the automobile industry, while the potential and results in the field of robotics, biotechnology, nanotechnology and renewable energy sectors is shown in Table 22.

Table 23. Economic indicators in Japan (The Heritage Foundation, 2019)

Economic indicators (millions of US$ unless otherwise specified)				
	2005	**2010**	**2015**	**2017**
GDP, current	4 755 410	5 700 098	4 394 978	4 872 415
GDP per capita, current US$	37 054	44 341	34 342	38 220
Real GDP growth, y-on-y, %	1.66	4.19	1.35	1.73
Current account balance, % of GDP	3.58	3.88	3.12	4.03
Exchange rate (/US$)	110.218	87.780	121.044	112.166

An increase of 1.7 % in gross domestic product growth rate in 2017 is shown in Table 23. The demographic challenges that Japan is facing are serious. An ageing society and the government's expected spending on pensions and health care seems to be increasing with no sign of deceleration. The sustainability of Japan's strong economy is insecure.

Table 24. Financial flows in Japan (The Heritage Foundation, 2019)

Financial flows (millions of US$ unless otherwise specified)				
	2005	**2010**	**2015**	**2017**
FDI inflows	2 775.76	-1 251.81	3 308.82	10 429.83
FDI outflows	45 781.25	56 263.41	134 232.86	160 449.43
Personal remittances, % of GDP	0.02	0.03	0.08	0.09

In 2017, there has been an increase of 3.3 % in FDI outflows as % of GDP. Japan had been suffering lifeless growth since the 2008 financial crisis. In 2012, Shinzo Abe became the prime minister. Under the Abe Administration (2013), Japan's strategy was to open the country's economy to foreign competition and in this way generate new export opportunities for Japanese businesses, including by joining 11 trading partners in the Trans-Pacific Partnership (TPP).

Table 25. Information economy indicators in Japan (The Heritage Foundation, 2019)

Information economy indicators (as % of)				
	2005	**2010**	**2015**	**2017**
Share of ICT goods, % of total exports	16.95	10.68	8.52	8.35
Share of ICT goods, % of total imports	13.47	11.98	12.79	13.01
Share of workforce involved in the ICT sector	6.75	6.80	..	..

The ICT sector plays an important role in the Japanese economic development as well as in its culture. Although the financial crisis had an impact on the trade, as seen in Table 25, economists predict a recovery based on the Japanese strong work ethic and mastery of high technology that has helped Japan develop an advanced economy.

3.4.1. 2019 Index of economic freedom: Japan (JPN)

Japan's economic freedom score is 72.1, making its economy the 30th freest in the 2019 Index and ranked 8th among 43 countries in the Asia–Pacific region. The country's overall score is above the regional and world averages.

Prime Minister Shinzo Abe, in office since 2012 and elected to a historic third term in October 2017. "Abenomics" has provided much-needed political stability. The policy has cut deflation, but the demographic problem, its decline, as consequences of a low birth rate and an aging, shrinking population poses a major long-term economic challenge (Miller, Kim and Roberts, 2019). North Korea's nuclear and missile threats pose as a threat while China's claims of sovereignty in the East and South China Seas.

Japan's judiciary is independent and fair with good protection of contracts and of real and intellectual property. Levels of corruption are low, but close relationships among companies, politicians, and government agencies foster an internally cooperative business climate conducive to corruption (Miller, Kim and Roberts, 2019). Amakudari is common in several sectors of traditional practice which is defined as "descent from heaven", a system whereby retiring Japanese bureaucrats gain employment and executive positions from private firms.

The top personal income tax rate is 40.8 percent, corporate rate is 23.9 percent, with an important note that local taxes and an enterprise tax can increase significantly. The overall tax burden amounts to 30.7 percent of total domestic income. During the past three years, government spending has equalled to 38.7 percent of the country's output (GDP), while budget deficits have averaged 3.9 percent of GDP. Public debt is 236.4 percent of GDP (Miller, Kim and Roberts, 2019).

Bureaucracy for establishing a business can be slow although streamlined. The tendency to have a lifetime employment guarantees and seniority-based wages disrupts the development of a dynamic and flexible labour market GDP (Miller, Kim and Roberts, 2019).

Exports and imports combined equal to 31.3 percent of GDP. The implemented tariff rate is 2.5 percent (averaged value). According to the WTO as of June 30, 2018, Japan had a total of 381 active nontariff measures. The financial sector is competitive, but state involvement persists while it secures foreign investment in some sectors.

3.5. Sweden

Population 9.911 Millions	Exchange rate 8.549 SEK/US$	GDP 535 607 Millions current US$
Land area (n) 407 310 km²	CPI growth 1.79 %	GDP growth 2.10 %

An overview of Sweden's small, open, and competitive economy is presented. Its free-market capitalism and extensive welfare benefit has enabled Sweden to build a strong and stable economy.

Table 26. Total merchandise trade in Sweden (The Heritage Foundation, 2019)

Total merchandise trade (millions of US$)				
	2005	**2010**	**2015**	**2017**
Merchandise exports	130 962	158 549	140 024	153 110
Merchandise imports	111 697	148 946	138 398	154 018
Merchandise trade balance	19 265	9 604	1 625	-909

An increase of 9.9 % in merchandise exports growth rate in 2017 was noted. Timber, hydropower, and iron represents the resource base of a manufacturing economy that relies heavily on foreign trade.

Figure 8. Top 5 partners in 2017 in Sweden (The Heritage Foundation, 2019)

Germany is Sweden's top trading partner, both for imports and exports, followed by Norway, Finland, Denmark and the United States as shown in Figure 8.

Table 27. Total trade in services in Sweden (The Heritage Foundation, 2019)

Total trade in services (millions of US$)				
	2005	**2010**	**2015**	**2017**
Services exports	38 114	53 877	72 689	(e) 72 935
Services imports	39 194	50 638	61 651	(e) 68 250
Services trade balance	-1 081	3 239	11 038	(e) 4 685

The tertiary sector in Sweden is mostly based on developed telecommunications and IT equipment, and employs 80 % of the active workforce and accounts to 65 % of the total amount of GDP.

Table 28. Services exports by main category in Sweden (The Heritage Foundation, 2019)

Services exports by main category (as % of total services)				
	2005	**2010**	**2015**	**2017**
Transport	24.6	20.1	16.3	(e) 15.6
Travel	17.2	15.5	15.6	(e) 19.3
Other services	56.4	63.0	67.2	(e) 63.9

Sweden is dependent on its export who make more than 44% of its GDP. Engines, machines, motor vehicles, and telecommunications equipment arae their main exports. The country is rich in natural resources: forests, iron, lead, copper, zinc and hydroelectric energy which are also exported. As seen in Table 28, export has always been stable.

Table 29. Economic indicators in Sweden (The Heritage Foundation, 2019)

Economic indicators (millions of US$ unless otherwise specified)				
	2005	**2010**	**2015**	**2017**
GDP, current	389 489	488 909	498 118	535 607
GDP per capita, current US$	43 092	52 066	51 018	54 043
Real GDP growth, y-on-y, %	2.82	5.99	4.46	2.10
Current account balance, % of GDP	6.06	5.98	4.53	3.31
Exchange rate (/US$)	7.473	7.208	8.435	8.549

Gross domestic product growth rate in 2017 had a growth of 2.1%. Weak global demand and reduced household consumption are forecasted to challenge the economy's growth, but fiscal stimulus may boost and expand economic activity.

Table 30. Financial flows in Sweden (The Heritage Foundation, 2019)

Financial flows (millions of US$ unless otherwise specified)				
	2005	**2010**	**2015**	**2017**
FDI inflows	11 515.99	96.98	6 897.11	15 395.74
FDI outflows	28 633.00	20 729.88	14 391.85	24 302.54
Personal remittances, % of GDP	..	..	0.68	0.52

A 4.5 % increase was recorded in FDI outflows as % of GDP in 2017. Sweden is very attractive to foreign investors, because of its qualified workforce, high per capita purchasing power, strong economy and its technologies and innovation. An important role is played by its advantageous tax regime.

Table 31. Information economy indicators in Sweden (The Heritage Foundation, 2019)

Information economy indicators (as % of)				
	2005	**2010**	**2015**	**2017**
Share of ICT goods, % of total exports	11.22	9.72	6.95	6.07
Share of ICT goods, % of total imports	11.14	11.34	10.17	9.24
Share of workforce involved in the ICT sector	8.73	(o) 7.66	..	..

The Swedish ICT sector is the largest in the Nordic region, and one of the dominating sectors in Sweden. Investments for it are high and competitive in the global. The financial crisis slowed its growth, as shown in Table 31, but forecasts suggest further development and expansion of the sector.

3.5.1. 2019 Index of economic freedom: Sweden (SWE)

Sweden’s economic freedom score is 75.2, making its economy the 19th freest in the 2019 Index and 10th among 44 countries in the Europe region. Its overall score is above the regional and world averages.

Sweden has a long tradition of a stable political government. Open-market policies help to boost flexibility, competitiveness, and large flows of trade and investment, encouraging a transparent and robust entrepreneurial activity. The private sector creates wealth with no minimum wage laws. The legal system produces strong protection for property rights that in return, serves as a judicial effectiveness and government integrity support.

Sweden joined the European Union in 1995, but in 2003 voters rejected the adoption of the euro. The arrival of a large number of migrants, that started coming from 2015, a terrorist attack that occurred in 2017, and a worrisome rising gang violence have made immigration a central political issue. Sweden is well known for its outward-oriented manufacturing-based economy of timber, hydropower and iron.

Real and intellectual property rights are well protected, and the rule of law is well maintained. The judicial system is independent, impartial, and consistent with very low corruption rates. The rates of corruption are low especially because of the effective anticorruption measures that uphold government integrity.

The top personal income tax rate is 57 percent, the top corporate tax rate is 22 percent and the overall tax burden equals 44.1 percent of total domestic income. During the period of the past three years, government spending has amounted to 49.4 percent of the country's output (GDP), and budget surpluses have equalled 0.9 percent of the GDP value. Public debt makes 40.9 percent of GDP.

The government provides significant subsidies to encourage renewable energy, the regulatory framework is efficient and simplifies entrepreneurial activity. Such facilitating system allows businesses to be more innovative and creative. The nonsalary cost of employing a worker is high, on the other side, firing an employee is costly and oppressive.

The value of exports and imports combined is equivalent to a total of 86.4 percent of GDP. Sweden applies a number of EU-directed nontariff trade barriers like technical and product-specific regulations, subsidies, and quotas. The average used tariff rate is 2.0 percent. Open-market policies facilitate large flows of investment which makes Sweden more competitive. Institutions implemented successfully all financial services in the country.

3.6. United States of America

Population 328.227 Millions	Exchange rate 1.000 USD/US$	GDP 19 589 613 Millions current US$
Land area (n) 9 156 640 km²	CPI growth 2.13 %	GDP growth 2.19 %

The United States is a highly industrialised country and technologically powerful economy in the world. A quick overview of its power is displayed.

Table 32. Total merchandise trade in The United States of America (The Heritage Foundation, 2019)

Total merchandise trade (millions of US$)				
	2005	**2010**	**2015**	**2017**
Merchandise exports	901 082	1 278 495	1 502 572	1 546 273
Merchandise imports	1 732 706	1 969 184	2 315 301	2 408 476
Merchandise trade balance	-831 624	-690 689	-812 729	-862 203

Merchandise exports growth rate in 2017 was 6.6 % as seen in Table 32. Key sectors include agriculture (corn, soy, beef, and cotton); but also export of machinery, chemical products, food, and automobiles.

Top 5 partners in 2017
(exports, millions of US$)

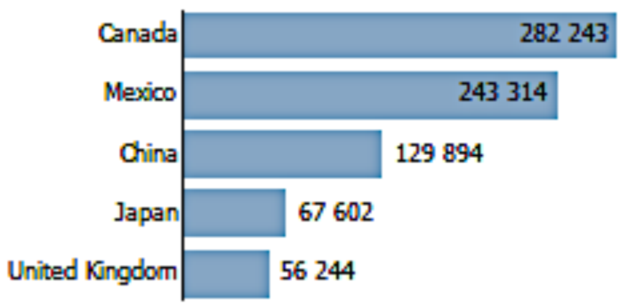

Figure 9. Top 5 partners of 2017 in the United States of America (The Heritage Foundation, 2019)

The main trade partners shown in Figure 9., are Canada, Mexico, China, Japan and the United Kingdom. Lately, President Donald Trump has put trade principles into question, announcing in

2018 that steep tariffs on steel and aluminium imports would be applied. Such decisions created tensions with China and disbalanced good relationship with other trading partners.

Table 33. Total trade in services in the United States of America (The Heritage Foundation, 2019)

Total trade in services (millions of US$)				
	2005	**2010**	**2015**	**2017**
Services exports	(e) 374 601	563 333	753 150	(e) 780 875
Services imports	304 448	409 313	491 740	(e) 538 110
Services trade balance	(e) 70 153	154 020		

The tertiary sector is alone responsible for more than three-fourths of GDP (77%) and employs in total over 79.40% of the country's workforce. The tertiary market has shown leadership in finance, insurance, real estate, rentals, and leases businesses.

Table 34. Services exports by main category in the United State of America (The Heritage Foundation, 2019)

Services exports by main category (as % of total services)				
	2005	**2010**	**2015**	**2017**
Transport	14.0	12.7	11.6	(e) 11.1
Travel	27.1	24.3	27.3	(e) 26.1
Other services	(e) 56.8	60.4	58.0	(e) 59.5

Table 34 shows the services export by main category. The US is the world leader in the automobile industry aerospace and pharmaceutical industries and production of a number of minerals.

Table 35. Financial flows in the United States of America (The Heritage Foundation, 2019)

Financial flows (millions of US$ unless otherwise specified)				
	2005	**2010**	**2015**	**2017**
FDI inflows	104 773.00	198 049.00	465 765.00	275 381.00
FDI outflows	15 369.00	277 779.00	262 569.00	342 269.00
Personal remittances, % of GDP	0.04	0.04	0.04	0.03

In Table 35 was recorded an increase of 1.8 % in FDI outflows as % of GDP in 2017. The US remained the one of the favourites destinations for FDI in 2017 mostly because to its large consumer base, transparent justice system, a productive workforce, and a strong business environment.

Table 36. Information economy indicators in the United States of America (The Heritage Foundation, 2019)

Information economy indicators (as % of)				
	2005	**2010**	**2015**	**2017**
Share of ICT goods, % of total exports	14.30	10.56	9.44	9.49
Share of ICT goods, % of total imports	13.64	14.22	13.78	14.27
Share of workforce involved in the ICT sector	..	..	..	..

Consequences of the increased costs imposed by tariffs is started to show in Table 36. Decreased economies of scale and scope are having a significant effect on both innovation and competitiveness. What comes next is hard to predicted.

3.6.1. 2019 Index of economic freedom: The United States of America (USA)

The United States' economic freedom score is 76.8 which is 12th freest in the 2019 Index. After significant improvements in scores for tax burden and government integrity far outperforming moderate decreases in fiscal health, labour freedom, monetary freedom, and trade freedom. Among 32 countries in the Americas region, the United States ranked 2nd. The score is above the regional and world averages. The United States is the world's second-largest producer of manufactured goods and leader in the field of research and development.

Property rights are guaranteed but there are problems because of an uneven protection. Although it is said that the judiciary functions independently and predictably, based on a report by Pew Research Center in late 2017, only 18 percent of Americans trust the government always or most of the time.

The top individual income tax rate is now 37 percent, corporate tax rate 21 percent while the overall tax burden is equivalent of 26.0 percent of total domestic income. During the period of the past three years, government spending covered 37.8 percent of the country's output (GDP), while budget deficits have averaged 4.1 percent of GDP. Public debt corresponds to 107.8 percent of GDP.

The new minimum wage laws have downsized low-income job opportunities in some areas although compulsory unionization have enlarged the right to work. Subsidies for agriculture, health care, green energy, and corporate welfare are responsible for billions of dollars per year to national debt of the United States of America.

Exports and imports together are equivalent to 26.6 percent of GDP. The average applied tariff rate is 1.7 percent. WTO reported that the United States in June in 2018 had 2,228 nontariff active measures. The Foreign Investment Risk Review Modernization Act and the Economic Growth, Regulatory Relief, and Consumer Protection Act came into force in 2018.

4. The Wh(a)ys of Germany, Finland, United Kingdom, Japan, Sweden and United States of America

After delivering theoretical background of the elected countries in Chapter Three, a methodological approach to the problem of the existence of the phenomenon is offered.

In the used method, the variables are converted in percentages of rates of growth and the two means test between every and each variable in the model is used. The test statistic results are shown in the table with two-tailed p-value in brackets. The null hypothesis is that the difference of means is 0. If there is no difference in the means of growth of the two compared variables, we can conclude that the variables were growing in union. In the case where the null hypothesis that the difference of means is 0 can be rejected, it will confirm that the two variables were not growing in union - they diverged in growth.

In addition, a test on each variable will be presented where the null hypothesis is that the population mean equals 0. If the null hypothesis is rejected, results suggests that there was a significant change in growth (or decrease) during the selected period of time, if not, it means that there was no significant growth (or decrease) and that the variable did stagnate. The test statistic results are shown in the table with two-tailed p-value in brackets.

Growth rates (means) of each variable will be also displayed.

4.1. The four major economies

It is important to underline that for the country of the United States of America, as in the model presented by Brynjolfsson and McAfee (2013), variables GDP per capita, labour productivity, private employment and median household income are used.

When offering evidence of the existence of the phenomenon in Germany, Finland, the United Kingdom, Sweden and Japan, a different framework is applied. Since there is no data available for the variable private employment and median household income as in the United States of America, the model had to be modified. The variables of (i) employment and (ii) the index for the top 10% share of population with the highest income (income inequality) are implemented instead. Employment is used as a good replacement for private employment since significant changes in employment are mostly linked with private employment, not with employment in government which are mostly constant over time. The top 10% share of the population with the highest income is used to demonstrate if their share decreased over time and in that way, income became more evenly distributed, or did the rich have become richer, and the poor have become poorer.

4.1.1. The case of the United States of America

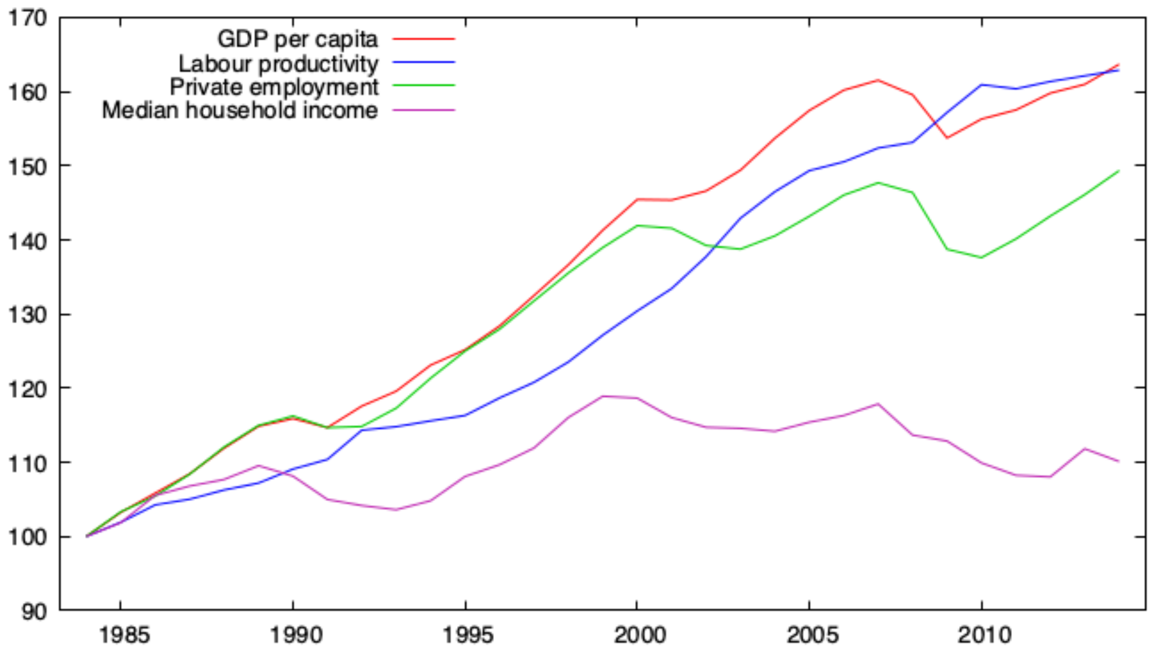

Figure 10. The Great Decoupling in the United States of America (1984-2014) (Source: Author's calculation)

Figure 10. represents the growth of the variables GDP per capita, labour productivity, private employment and median household income, the same variables that are used in the original model of the Great Decoupling for the period of 1984 until 2014. The comparison between variables and its divergences can be seen during the period of 1984 until 2014.

Table 37. Results of the 2 means test for the United States of America (Source: Author's calculation)

Variables	GDP per capita	Labour productivity	Private employment	Median household income
GDP per capita	-	0.397746 (0.6922)	0.663395 (0.5096)	3.08254 (***0.003118***)
Labour productivity	-	-	0.426357 (0.6714)	3.29873 (***0.00165***)
Private employment	-	-	-	2.23989 (***0.02888***)
Median household income	-	-	-	-

Table 37. represents the means between each and every variable in the model. The displayed results show that all the variables are growing together expect for median household income, which is not growing together with the rest of the variables. In other words, median household income does not follow the growth of labour productivity as the other variables do. In this case, an increase in labour productivity does not reflect an increase in wages. The hypothesis that the difference of means is 0 is rejected for median household income with the variables labour productivity, GDP per capita and private employment.

In the next table, Table 38, a test on each variable will be presented where the null hypothesis is that the population mean equals 0. If the null hypothesis is rejected, results suggests that there was a significant change in growth (or decrease) during the selected period of time, if not, it means that there was no significant growth (or decrease) and that the variable did stagnate.

Table 38. Results of the mean test (growth rates) for the United States of America (Source: Author's calculation)

	Sample mean	**Test statistic**
GDP per capita	0.0178529	5.72555 (***3.009e-06***)
Labour productivity	0.0164127	8.91496 (***6.185e-10***)
Private employment	0.0146742	4.03315 (***0.0003486***)
Median household income	0.00320753	0.891489 (0.38)

Table 38 presents results of the growth rates of the variables during the period of time 1984 until 2014. Results put forward that all the variables, except median household income, did not have a population mean 0 - they had a significant period of growth (or decrease). The results for median household income did not qualify to reject the hypothesis that the variable did not grow significantly in time, which confirms previous results and trends illustrated in the graph. It can be seen that median household income was growing 0.32% annually, while GDP per capita 1.78%, labour productivity 1.64% and private employment 1.46%.

4.1.2. The case of Germany

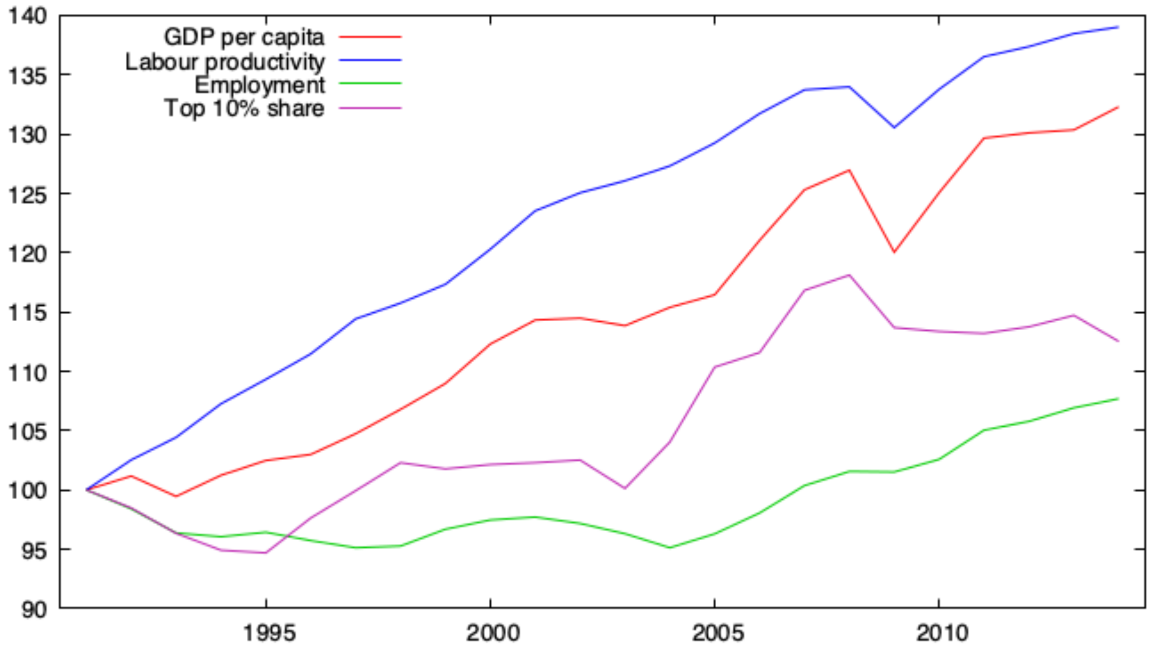

Figure 11. The Great Decoupling in Germany (1991-2014) (Source: Author's calculation)

The growth of GDP per capita, labour productivity, employment and top 10% share of income for Germany is represented in Figure 11 for the period from 1991 to 2014.

Table 39. Results of the 2 means test for Germany (Source: Author's calculation)

	GDP per capita	**Labour productivity**	**Employment**	**Top 10% share**
GDP per capita	-	0.0768355 (0.9392)	1.46083 (0.1523)	1.39544 (0.1696)
Labour productivity	-	-	2.06353 (***0.04594***)	2.10815 (***0.0405***)
Employment	-	-	-	-0.240178 (0.8113)
Top 10% share	-	-	-	-

Results in Table 39 suggest that labour productivity was not growing in union with employment and the top 10% share of income during the period of 1991 until 2014. From the graph, it is visible that labour productivity is growing faster than the other variables which is confirmed in the table below.

Table 40. Results of the mean test (growth rates) for Germany (Source: Author's calculation)

	Sample mean	Test statistic
GDP per capita	0.0134624	3.12534 (***0.004753***)
Labour productivity	0.017469	4.47521 (***0.0001722***)
Employment	0.0032225	1.28713 (0.2114)
Top 10% share	0.00452602	0.955094 (0.3495)

As already suggested, a significant growth of GDP per capita and labour productivity was not followed by a significant increase in employment that can be seen in Table 40. The top 10% share has an average growth of 0.45% annually which is not a significant growth, but it still has an increasing trend. GDP per capita recorded a growth of 1,34%, labour productivity 0,17% while employment a low annual growth of 0,32%.

4.1.3. The case of Finland

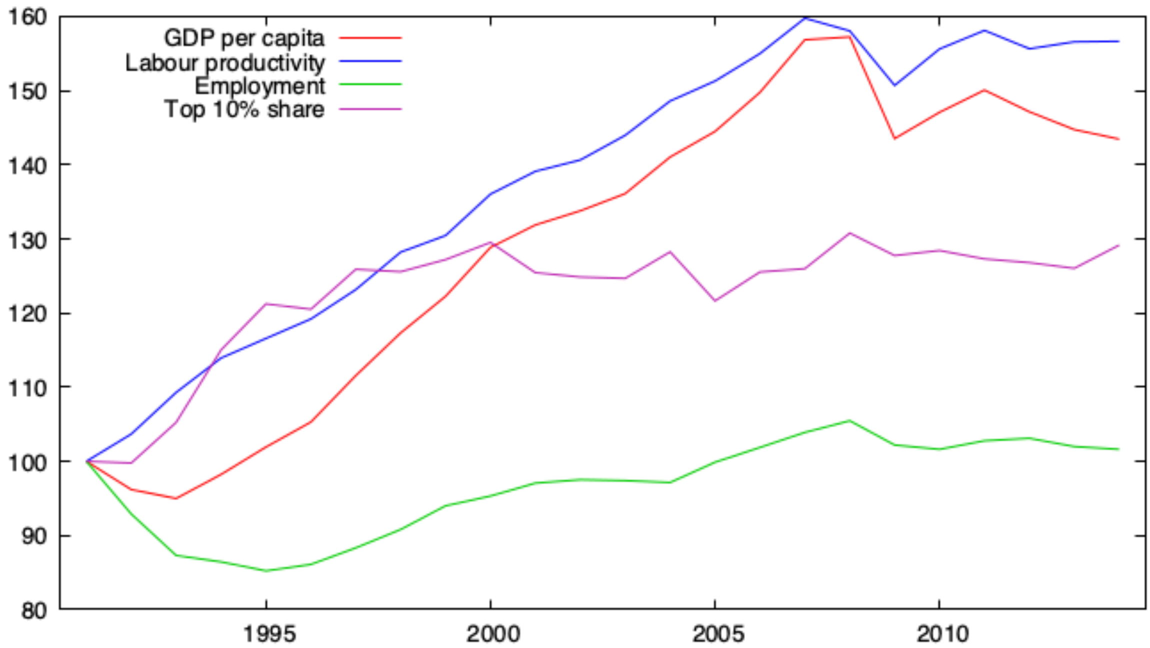

Figure 12. The Great Decoupling in Finland (1991-2014) (Source: Author's calculation)

Figure 12 represents the growth of GDP per capita, labour productivity, employment and top 10% share of income from 1991 to 2014. At first sight, the presented graph shows a trend of growth for all the variables without clearly visible divergences.

Table 41. Results of the 2 means test for Finland (Source: Author's calculation)

	GDP per capita	**Labour productivity**	**Employment**	**Top 10% share**
GDP per capita	-	0.335475 (0.7391)	1.12435 (0.2681)	0.304985 (0.7618)
Labour productivity	-	-	1.09476 (0.2807)	1.25055 (0.2174)
Employment	-	-	-	-0.989001 (0.328)
Top 10% share	-	-	-	-

Table 42. Results of the mean test (growth rates) for Finland (Source: Author's calculation)

	Sample mean	**Test statistic**
GDP per capita	0.0123054	1.60084 (0.1231)
Labour productivity	0.0190909	4.30274 (0.0002648)
Employment	0.000696238	0.1241 (0.9024)
Top 10% share	0.00923198	1.41668 (0.17)

In the case of Finland, as recorded in Table 42, no significant differences in means between the growth rates of the variables or individual growth was recorded. Based on the used data, it cannot be surely defined the presence of the phenomenon. Such results can be excused by the fact that Finland, out of the six countries, is the least strong and smallest economy. Based on projection by International Monetary Fund (IMF) outlook in 2018 for year 2019 and 2023, top ten countries in nominal terms and ppp are selected. In top 10, eight countries are common in both methods: United States, China, Japan, Germany, India, United Kingdom, Brazil and Canada. Four out of six countries are in the top ten. In nominal ranking, Sweden is at 23rd place and in PPP terms 12nd place while Finland in nominal ranking came 45th and in PPP terms 48th.

4.1.4. The case of the United Kingdom

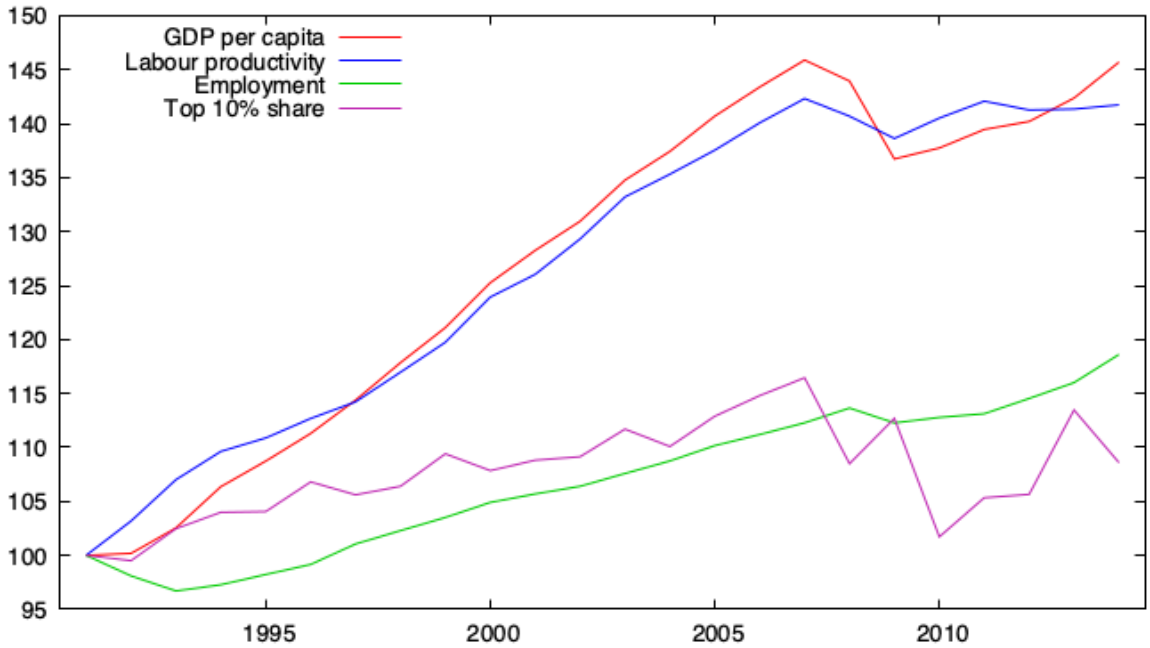

Figure 13. The Great Decoupling in the United Kingdom (1991-2014) (Source: Author's calculation)

Figure 25 is representing the trends of the Great Decoupling in the United Kingdom is displayed from the year 1991 until 2014. An unusual trend, in comparison with other analysed countries, is visible for the variable top 10% share.

Table 43. Results of the 2 means test for the United Kingdom (Source: Author's calculation)

	GDP per capita	Labour productivity	Employment	Top 10% share
GDP per capita	-	0.561961 (0.5774)	1.29249 (0.204)	1.36894 (0.1777)
Labour productivity	-	-	0.897507 (0.3751)	1.54552 (0.1291)
Employment	-	-	-	0.48565 (0.6296)
Top 10% share	-	-	-	-

Just like in the case of Finland, results for the United Kingdom (Table 43) do not strongly suggest that there were differences in means between growth rates of the variables for the country, speculating that there is no sign of divergence.

Table 44. Results of the mean test (growth rates) for the United Kingdom (Source: Author's calculation)

	Sample mean	**Test statistic**
GDP per capita	0.0150435	3.83808 (***0.0008403***)
Labour productivity	0.0157921	5.65453 (***9.34e-06***)
Employment	0.00742066	3.57766 (***0.001679***)
Top 10% share	0.00364273	0.495731 (0.6248)

Unlike differences in trends of growth rates, significant growth for GDP per capita, labour productivity and employment were recorded, 1,5%, 1,57% and 0,74% respectively. Top 10% share of income had a growth of 0,36% annually were shared in Table 44.

4.1.5. The case of Japan

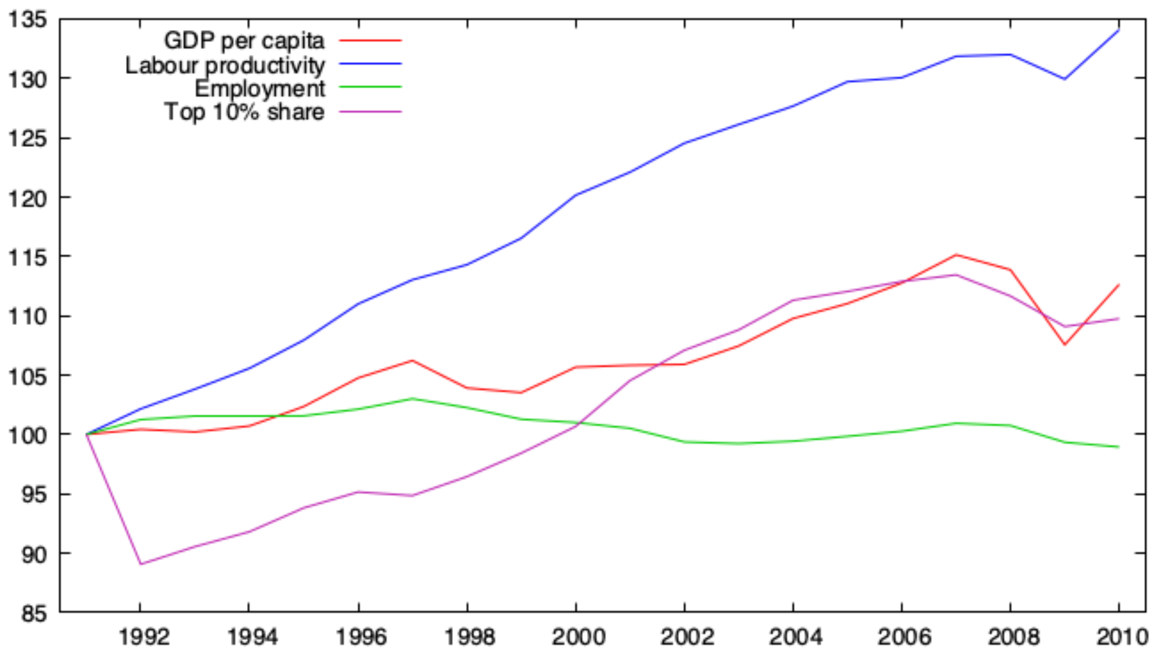

Figure 14. The Great Decoupling in Japan (1991-2010) (Source: Author's calculation)

The illustration of growth in Japan for the variables during the period 1991 until 2010, is no similar to graphs in other countries. After a slow start, as seen in Figure 26, the top 10% share had a sharp increase, reaching the level of growth of GDP per capita. The employment variable is visibly lagging behind other variables.

Table 45. Results of the 2 means test for Japan (Author's calculation)

	GDP per capita	**Labour productivity**	**Employment**	**Top 10% share**
GDP per capita	-	-1.27482 (0.2101)	1.55975 (0.1273)	0.474189 (0.6381)
Labour productivity	-	-	4.79652 (***2.641e-05***)	1.62955 (0.1115)
Employment	-	-	-	-0.504846 (0.6167)
Top 10% share	-	-	-	-

Table 46. Results of the mean test (growth rates) for Japan (Author's calculation)

	Sample mean	**Test statistic**
GDP per capita	0.00740322	1.54869 (0.138)
Labour productivity	0.0157344	6.55951 (***2.794e-06***)
Employment	-0.000557328	-0.349526 (0.7308)
Top 10% share	0.00328357	0.452633 (0.6559)

As the graph pointed, a significant growth of labour productivity of 1,57% is present, which is strongly diverged from the annual decrease in employment of 0,055% which was represented in Table 45. In Table 46, a 0,74% growth GDP per capita was recorded as a 0,32% growth in top 10% share.

4.1.6. The case of Sweden

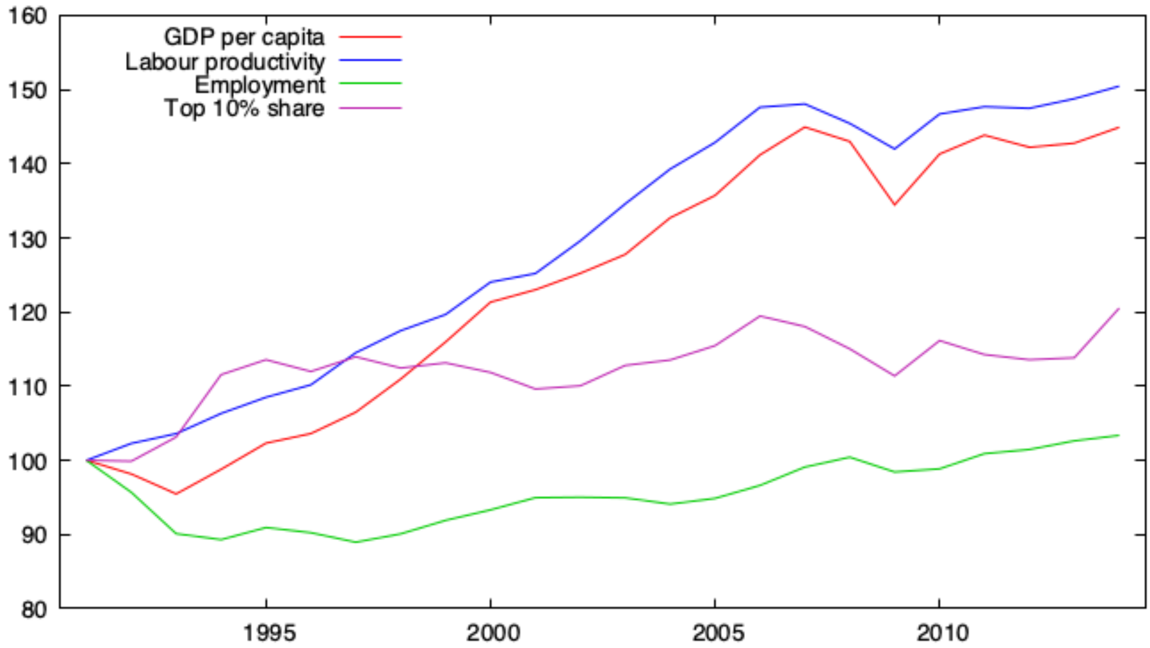

Figure 15. The Great Decoupling in Sweden (1991-2014) (Author's calculation)

The illustration in Figure 27represents the divergence of the variable in Sweden for the period of 1991 until 2014, which is similar to the trends analysed from the figure of Germany. It is noticeable that GDP per capita and labour productivity are growing in union, while other variables are lagging behind.

Table 47. Results of the 2 means test for Sweden (Author's calculation)

	GDP per capita	**Labour productivity**	**Employment**	**Top 10% share**
GDP per capita	-	0.254954 (0.8001)	1.88994 (0.06662)	0.660587 (0.5122)
Labour productivity	-	-	2.11925 (***0.04084***)	1.23046 (0.2248)
Employment	-	-	-	-1.11655 (0.2701)
Top 10% share	-	-	-	-

Table 48. Results of the mean test (growth rates) for Sweden (Author's calculation)

	Sample mean	**Test statistic**
GDP per capita	0.0146994	2.61061 (0.01563)
Labour productivity	0.0175285	5.16589 (***3.094e-05***)

Employment	0.00143882	0.329844 (0.7446)
Top 10% share	0.0094389	1.67618 (0.1072)

Results in Table 47 connoted that labour productivity, with a significant growth of 1,75%, and employment, with a growth of 0,14%, are growing diverged. Table 48 shows that GDP per capita had a growth of 1,46% and the top 10% share 0,93%.

4.2. An insight into the evidence

A two means test between every and each variable and their rate of growth was conducted. The null hypothesis is that the difference of means is 0. Figures of the modified model for the Great Decoupling for all countries are displayed to simplify the comparison in trends. Results of each countries are aggregated in the table below, displaying if there was evidence of divergence or not.

Table 49. The two means test - gathered data for all countries (Author's calculation)

	Labour productivity and GDP per capita	**Labour productivity and employment**	**Labour productivity and top 10% share**	**GDP per capita and employment**	**GDP per capita and top 10% share**	**Employment and top 10% share**
United States of America[1]	Not found	Not found	Found	Not found	Found	Found
Germany	Not found	Found	Found	Not found	Not found	Not found
Finland	Not found	Not found	Not found	Not found	Not found	Not found

[1] In the case of the United States of America, note that variables private employment and median household income were used instead of employment and top 10% share

United Kingdom	Not found	Not found	Not found	Not found	Not found	Not found
Japan	Not found	Found	Not found	Not found	Not found	Not found
Sweden	Not found	Found	Not found	Not found	Not found	Not found

Evidence of divergence between labour productivity and employment were found in Germany, Japan and Sweden. In Germany, it was found a time trend between labour productivity and the top 10% share. In the United States of America, the variable median household income was growing diverged from all the other variables in the model. A difficult challenge is to find variables which data can most reliably reflect the variables from the original model. The new elected "replacement" variables are the most accurate data that could be found, but still they do not offer the same content as private employment and median house income. It would be remarkable if institutions could gather data of the same category on a global scale, in that way comparisons between countries and their strategies would carry a more serious importance.

5. Panel Data Analysis

For the purpose of this dissertation, panel data is used. As Gujarati listed in his book *Basic of Economics* (2003), phenomena such as economies of scale and technological change can be better handled by panel data than by pure cross-section or pure time series data.

As panel data are multi-dimensional data, they do contain observations of multiple phenomena that are obtained over multiple time periods for the same individuals or companies. Multiple observations on each unit can provide superior estimates, it can make easier to recognize and comprehend social trends, measure cultural factors and social phenomena, changing behaviours, social relationships, individual growth or development as well as other occurrences of events (McManus, 2015). It “allows economists and other social scientists to analyse in depth more complex economic and related issues which could have been impossible to conduct with equal rigor using only time series or cross-sectional data alone” (Hsiao, 1985). Panel data regression methods enables economists and other researchers to use different sets of information, providing a large number of different data points and so increasing the researcher’s degree of freedom to further explore variables that are often omitted. Panel data give flexibility, and this is precisely the major advantage that panel data possess to conventional cross-sectional or time series data.

Panel data are becoming more popular and used in economic research. Some of the most famous panel data sets are (Gujarati, 2003):

1. The Panel Study of Income Dynamics (PSID) that is conducted by the Institute of Social Research at the University of Michigan. From 1968, every year the Institute collects data on some 5000 families about different socioeconomic and demographic variables.
2. The Bureau of the Census of the Department of Commerce conducts a survey that is similar to PSID and that is called the Survey of Income and Program Participation (SIPP). Respondents are interviewed about their economic condition four times in a year.

Hsiao (2007) states that there are at least three factors of great importance affecting the geometric growth of panel data studies. (i) data availability, (ii) greater capacity for modeling the complexity of human behaviour than a single cross-section or time series data, and (iii) challenging methodology.

In his paper, Hsiao (2007) writes about the very relevant advantages that panel data have over cross-sectional or time-series data:

1. The inference of model parameters is significantly more accurate. Panel data provide more degrees of freedom and in that way improving the efficiency of econometric estimates (Hsiao et al. 1995).
2. It simplifies and grants the researchers more dimensions that allows them to capture the tangled human behaviour in comparison with a single cross-section or time series data. Including:
    a. Enables more complex behavioural hypothesis to be tested and constructed
    b. Regulating the impact of omitted variables
    c. Exposing dynamic relationships, in his work, Hsiao (2007) cited "With panel data we can rely on the inter-individual differences to reduce the collinearity between current and lag variables to estimate unrestricted time-adjustment patterns (e.g., Pakes and Griliches 1984).
    d. Predictions for individual outcomes that are more definite by combining data rather than generating predictions of individual outcomes using the data on the individual in question. It makes is possible to have results and more detailed description of an individual's behaviour by supporting it with observations of gathered data of other (similar) individuals.
    e. Presenting micro foundations for aggregate data analysis. Panel data that incorporates more time series observations for a number of individuals is optimal for investigating the "homogeneity" versus "heterogeneity" issue.
3. Simplifying computation and statistical inference. Panel data has two dimensions: a cross-sectional dimension and a time series dimension. Sometimes the availability of panel data actually simplifies computation and inference.
    a. Analysis of nonstationary time series.
    b. Measurement errors.
    c. Dynamic Tobit models. When a variable is truncated or censored, the actual realized value is unobserved.

While in Hsiao's work we read also about the advantages of panel data, Baltagi (2005) listed in his book the main limitations of panel data that include:

1. Design and data collection problems. He mentions the existence of difficulties of data collection and data management (Kasprzyk et al. (1989)). One of the issues are also

problems of coverage, (incomplete account of the population of interest), nonresponse (due to lack of cooperation of the respondent or because of interviewer error), recall (respondent not remembering correctly), frequency of interviewing, interview spacing, reference period, the use of bounding and time-in-sample bias (see Bailar, 1989).

2. Invalid results due to faulty interviews, wrong identifies population, misinterpreted answers and other errors in measurements that may lead to wrong interpretations.
3. Selectivity problems
    a. Self-selectivity.
    b. Nonresponse (refusal or inability to participate)
    c. Attrition.
4. Short time-series dimension
5. Cross-section dependence. Taking into account for cross-section dependence that is important and that can affect final results.

The popularity and application of the methodology in the field of analysis of the panel series is growing. The improvement can be seen through the growing number of empirical studies based on panel series that are available in scientific literature, which can be also read in the book *Econometric analysis of panel data* written by Baltagi. In Europe, these studies began in the late 1980s when the results of the research of the German socio-economic panel (Huyer and Schneider, 1989) were published, then the Swedish studies on labor mobility (Bjorklund, 1989) and the Dutch studies on consumption households (Alessie, Kapteyn and Melenberg, 1989). The econometric methodology in the field of panel models has in time been applied in various fields of social sciences, for example, in political science (Beck and Katz, 1995), then sociology (England, Farkas, Kilbourne and Dou, 1988), finance (Brown, Kleidon and Marsh, 1983; Boehmer and Megginson, 1990), marketing (Erdem, 1996 and Keane, 1997), etc (Baltagi, 2008).

5.1. The Panel Data Regression

Panel data is also known as longitudinal or cross-sectional time-series data. Combing cross-sectional and time-series observations, we get a panel data with the following regression (1):

$$u_{it} \sim IID\ (0, \sigma^2{}_u);\ Cov(x_{it}, u_{it}) = 0 \qquad i = 1, 2, \ldots, N; t = 1, 2, \ldots, T$$

$$Y_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} + u_{it}. \tag{1}$$

Where i stands for the ith cross-sectional unit (represents the cross-section identifier) and t stands for the tth time period (represents the time identifier). The assumption is that there are a maximum of N cross-sectional units or observations and a maximum of T time periods (Gujarati, 2011).

In this model, we have to account for heterogeneity which may be often unobservable. Because of variability of the data (individuals, companies, countries and so on over time), in the model is used a two-way error component assumption (2) for the disturbances, u_{it} with:

$$u_{it} = \mu_i + \lambda_t + v_{it}. \tag{2}$$

Where μ_i represents the unobservable individual (cross section) heterogeneity, λ_t represents the unobservable time heterogeneity and v_{it} is the remaining random error term. The first two components, μ_i and λ_t, are also called within component and the last component, v_{it}, panel or between component (Vijayamohanan, 2016). Depending on the assumptions about the above-mentioned error components, there are two types of models, fixed effects and random effects.
If we assume that the μ_i and λ_t are fixed parameters to be estimated and the random error term, v_{it}, is identically and independently distributed with zero mean and constant variance σ_v^2, that is, $v_{it} \sim IID(0, \sigma_v^2)$, then the equation allows a two-way fixed effects error component model or fixed effects model. If we assume that the μ_i and λ_t are random just like the random error term, that is, μ_i, λ_t and v_{it} are all identically and independently distributed with zero mean and constant variance, or, $\mu_i \sim IID(0,\sigma_\mu^2)$, $\lambda_t \sim IID(0,\sigma_\lambda^2)$, and $v_{it} \sim IID(0,\sigma_v^2)$, with further assumptions that they are all independent of each other and of explanatory variables, then the equation allows a two-way random effects error component model or a random effects model.

It can be present a one-way error component (fixed or random effects model) with the appropriate assumptions about the error components, that is, whether μ_i or λ_t is assumed to be fixed or random (3). Here the error term u_{it} will become:

$$u_{it} = \mu_i + v_{it}$$

or

$$u_{it} = \lambda_t + v_{it}. \tag{3}$$

When we have panel data where each cross-sectional unit has the same number of time series observations, we have balanced panel. Unbalanced data panel is present when the number of observations is not the same among panel members. There is also a difference between short and long panel data. In a long panel the number of time periods *T* is greater than the number of cross-sectional or individual units *N*. If there is data where *N* is greater than *T*, we have a short panel Gujarati, D. (2011).

We consider mainly three types of panel data analytic models:

1) constant coefficients (pooled regression) models
2) fixed effects models
3) random effects models.

5.1.1. The Constant Coefficients (Pooled Regression) Model (OLS)

The most elementary model for panel data is pooled OLS. Mostly, this model is improbable to be suitable, but it provides a baseline for comparison with more complex models. An ordinary least squares (OLS) is run when there are not present indicative cross sectional or temporal effect. This regression model has an intercept α and slope coefficients βs constant across individuals or companies and time:

$$u_{it} \sim IID\ (0, {\sigma^2}_u), \qquad i = 1, 2, \dots, N; t = 1, 2, \dots, T.$$

$$Y_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} + u_{it}.$$

5.1.2. The Fixed Effects Model (FE)

Allison says "In a fixed effects model, the unobserved variables are allowed to have any associations whatsoever with the observed variables".
In the fixed effects model, the individual-specific effect is a random variable that is allowed to be correlated with the explanatory variables.

$$Y_{it} = \beta_1 X_{1it} + \beta_2 X_{2it} + u_{it}, \qquad i = 1, 2, \dots, N; t = 1, 2, \dots, T.$$

$u_{it} = \mu_i + \lambda_t + v_{it}$, $\quad$ or $u_{it} = \mu_i + v_{it}$,

or $u_{it} = \lambda_t + v_{it}$, $\quad$ $v_{it} \sim IID\ (0, \sigma^2{}_v)$.

We have two models: (i) Least Squares Dummy Variable model and (ii) Within-groups regression model.

5.1.2.1. Least Squares Dummy Variable model

If cross sectional or significant temporal effect is present, we cannot assume a constant intercept α for all the companies and years but rather take into account the one-way or two-way error components models. The term "fixed effects" is used because, although the intercept may differ across individuals (for the purpose of the dissertation research we will use the term countries), each country's intercept does not change over time; it is time invariant. Intercepts may differ and vary between countries. We can easily allow that by using dummy variable technique with focus on the differential intercept dummies. A dummy variable, or an indicator variable or design variable, is a variable that takes the form of the values 1 and 0 to indicate the absence or presence of some significant changes or effects in the model.

One should be careful and avoid falling into the dummy-variable trap and arising the situation of perfect collinearity. The trap can be avoided by using one of the countries observed as the comparison country or base country. For that one country, the dummy variable is not applied in order to avoid the trap while on remaining countries that are in the model, dummy variables are still applied. The intercepts of countries with dummy variables represent differential intercept coefficients that display how much their intercepts differ from the intercept of the one comparison country.

There are two assumptions:
(1) heterogeneous intercepts ($\mu_i \neq \mu_j$, $\lambda_t \neq \lambda_s$) and homogeneous slope ($\beta_i = \beta_j$; $\beta_t = \beta_s$) and
(2) heterogeneous intercepts and slopes ($\mu_i \neq \mu_j$, $\lambda_t \neq \lambda_s$); ($\beta_i \neq \beta_j$; $\beta_t \neq \beta_s$). (Judge et al., 1985).

It is considered that the fixed effects panel data models are with the following possible assumptions:

1. The slope coefficients constant but intercept varies over countries.
2. The slope coefficients constant but intercept varies over time.

3. The slope coefficients constant but intercept varies over countries and time.
4. All coefficients (intercept and slope) vary over countries.
5. All coefficients (the intercept as well as slope coefficients) vary over time.
6. All coefficients (the intercept as well as slope coefficients) vary over countries and time.

5.1.2.2. The slope coefficients constant but intercept varies over countries

This assumption considers a constant slope coefficient with no significant temporal effects but with significant changes among countries. This implies that countries will have separate intercepts and will have to calculate μ_i, the unobservable individual (cross section) heterogeneity. In the following model, since intercepts over countries are not fixed, a one-way error component is present:

$$u_{it} = \mu_i + v_{it}, v_{it} \sim \ IID\ (0, \sigma^2{}_v), \qquad i = 1, 2, \dots, N, t = 1, 2, \dots, T.$$

$$Y_{it} = \beta_1 X_{1it} + \beta_2 X_{2it} + u_{it}$$

or

$$v_{it} \sim \ IID\ (0, \sigma^2{}_v), \qquad i = 1, 2, \dots, N, t = 1, 2, \dots, T.$$

$$Y_{it} = \mu_i + \beta_1 X_{1it} + \beta_2 X_{2it} + v_{it}. \tag{4}$$

In order to allow separate intercepts to vary between countries, dummy variables have to be included for each unit i in the model, except for the comparison country. To make it simpler, we will take that the model has four countries (N=4) that are analysed over ten years (T=10) with regressors x_1 and x_2. The Least Squares Dummy Variable model (LSDV model) is also known as the covariance model and x_1 and x_2 are known as covariates.

After integrating the dummy variables and avoiding the dummy-variable trap, we form the model as a one-way error component model:

$$v_{it} \sim \ IID\ (0, \sigma^2{}_v), \qquad i = 1, 2, \dots, 4;\ t = 1, 2, \dots, 10.$$

$$Y_{it} = \Sigma \mu_i D_i + \beta_1 X_{1it} + \beta_2 X_{2it} + v_{it}.$$

or

$$Y_{it} = \mu + \mu_2 D_2 + \mu_3 D_3 + \mu_4 D_4 + \beta_1 X_{1it} + \beta_2 X_{2it} + v_{it}. \qquad (5)$$

5.1.2.3. The slope coefficients constant but intercept varies over time

The slope coefficients are constant but this time, unlike the first assumption above, the intercept does vary over time. There are no significant cross section differences (changes between countries) but there are significant temporal effects. This implies that the intercept terms vary over time and will have to calculate λ_t that represents the unobservable time heterogeneity. In the following model, since intercepts over time are not fixed, a one-way error component is present:

$$u_{it} = \lambda_t + v_{it}, v_{it} \sim \ IID\ (0, \sigma^2{}_v), \qquad i = 1, 2, \ldots, N, t = 1, 2, \ldots, T.$$

$$Y_{it} = \beta_1 X_{1it} + \beta_2 X_{2it} + u_{it},$$

or

$$v_{it} \sim \ IID\ (0, \sigma^2{}_v), \qquad i = 1, 2, \ldots, N, t = 1, 2, \ldots, T.$$

$$Y_{it} = \lambda_t + \beta_1 X_{1it} + \beta_2 X_{2it} + v_{it}. \qquad (6)$$

As in the previous model, dummy variables have to be included for each unit t in the model (T=10), except for the comparison or base country that is t=1.

Just as we used the dummy variables to account for cross section (country) effect, we can allow for time effect and introduce 9-time dummies for T=10 and write the model:

$$v_{it} \sim \ IID\ (0, \sigma^2{}_v), \qquad i = 1, 2, \ldots, 4, t = 1, 2, \ldots, 10.$$

$$Y_{it} = \Sigma \lambda_t Dum_t + \beta_1 X_{1it} + \beta_2 X_{2it} + v_{it}$$

or

$$Y_{it} = \lambda_2 Dum_2 + \ldots + \lambda_9 Dum_9 + \beta_1 X_{1it} + \beta_2 X_{2it} + v_{it}. \quad (7)$$

5.1.2.4. The slope coefficients constant but intercept varies over countries and time

In this assumption, the slope coefficient is constant with significant temporal effects and significant changes among countries. The following model has a two-way error component and is the combination of the first two assumptions, slope coefficients constant but intercept varies over countries and slope coefficients constant but intercept varies over time.

$$u_{it} = \mu_i + \lambda_t + v_{it}, v_{it} \sim \; IID\ (0, {\sigma^2}_v), \qquad i = 1, 2, \ldots, N, t = 1, 2, \ldots, T.$$

$$Y_{it} = \beta_1 X_{1it} + \beta_2 X_{2it} + u_{it}$$

or

$$v_{it} \sim \; IID\ (0, {\sigma^2}_v), \qquad i = 1, 2, \ldots, N, t = 1, 2, \ldots, T.$$

$$Y_{it} = \mu_i + \lambda_t + \beta_1 X_{1it} + \beta_2 X_{2it} + v_{it}. \quad (8)$$

With the inclusion of dummy variables for *N*=4 and *T*=10, and being careful to avoid the dummy trap, the model is the following:

$$v_{it} \sim \; IID\ (0, {\sigma^2}_v), \qquad i = 1,2,\ldots,4, t = 1,2,\ldots,10.$$

$$Y_{it} = \Sigma \mu_i D_i + \Sigma \lambda_t Dum_t + \beta_1 X_{1it} + \beta_2 X_{2it} + v_{it}$$

or

$$\begin{aligned} Y_{it} = \mu + \mu_2 D_2 + \mu_3 D_3 + \mu_4 D_4 + \beta_1 x_{1it} + \beta_2 x_{2it} + \ldots + \lambda_2 Dum_2 + \lambda_3 Dum_3 + \cdots \\ + \lambda_{10} Dum_{10} + \beta_1 x_{1it} + \beta_2 x_{2it} + v_{it} + \lambda + \lambda_2 Dum_2 + \lambda_3 Dum_3 + \cdots \\ + \lambda_{10} Dum_{10} + \beta_1 x_{1it} + \beta_2 x_{2it} + v_{it}\ . \end{aligned} \quad (9)$$

5.1.2.5. All coefficients (intercept and slope) vary over countries

In the first three assumptions of the fixed effects model, the slope coefficient was constant while the intercepts were not, going from one-way error component models to the one with two-way error component. Now, the slope coefficients and the intercepts alter over countries. The LSDV model with the assumption that the slope coefficients are constant, but intercept varies over countries, included dummy variables. This model is an extension of it. To account for slope differences, differential or slope dummies have to be included.

The differential or slope dummies can explain the differences in the γ's that express the differential slope coefficients. It is obtained by multiplying each of the countries dummies by each of the *x* variables.

$$Y_{it} = \mu + \mu_2 D_2 + \mu_3 D_3 + \mu_4 D_4 + \beta_1 x_{1it} + \beta_2 x_{2it} + \gamma_1 (D_2 x_{1it}) + \gamma_2 (D_2 x_{2it}) + \gamma_3 (D_3 x_{1it}) + \gamma_4 (D_3 x_{2it}) + \gamma_5 (D_4 x_{1it}) + \gamma_6 (D_4 x_{2it}) + v_{it}. \tag{10}$$

The βs and γs together represent the differential slope coefficients just as the μs represent differential intercepts in the model. If one or more of the γs coefficients are statistically significant, it will implicate that one or more slope coefficients are different from that of the base country.

5.1.2.6. All coefficients (the intercept as well as slope coefficients) vary over time

This model consists of slope coefficients and intercepts that vary over time. The model is not much different from the previous one where the slope coefficients and intercepts vary over countries. In this one, the μ_is, the unobservable cross section (country) heterogeneity, are replaced with the λ_t unobservable individual time heterogeneity. The extended LSDV model with time dummy variable is the following:

$$Y_{it} = \lambda_2 Dum_2 + \lambda_3 Dum_3 + \ldots + \lambda_{10} Dum_{10} + \beta_1 x_{1it} + \beta_2 x_{2it} + \gamma_1 (D_2 x_{1it} + \gamma_2 (D_2 x_{2it}) + \gamma_3 (D_3 x_{1it}) + \gamma_4 (D_3 x_{2it}) + \ldots + \gamma_{17} (Dum_3 x_{1it}) + \gamma_{18} (Dum_{10} x_{2it}) + v_{it}. \tag{11}$$

The λ represent differential intercepts, and the βs and γs together give differential slope coefficients.

5.1.2.7. All coefficients (the intercept as well as slope coefficients) vary over countries and time

The last assumption of the fixed effects model implicates that the intercepts and the slope coefficients change over time and over countries. This model is the combination of the two models each with its own assumption: all coefficients (intercept and slope) vary over countries and all coefficients (the intercept as well as slope coefficients) vary over time. The merger and the model is:

$$\begin{aligned} Y_{it} = \mu &+ \mu_2 D_2 + \mu_3 D_3 + \mu_4 D_4 + \beta_1 x_{1it} + \beta_2 x_{2it} + \gamma_1 (D_2 x_{1it}) \\ &+ \gamma_2 (D_2 x_{2it}) + \gamma_3 (D_3 x_{1it}) + \gamma_4 (D_3 x_{2it}) + \gamma_5 (D_4 x_{1it}) \\ &+ \gamma_6 (D_4 x_{2it}) + \lambda + \lambda_2 Dum_2 + \lambda_3 Dum_3 + \ldots + \lambda_{10} Dum_{10} \\ &+ \beta_1 x_{1it} + \beta_2 x_{2it} + \delta_1 (Dum_2 x_{1it}) + \delta_2 (Dum_2 x_{2it}) \\ &+ \delta_3 (Dum_3 x_{1it}) + \delta_4 (Dum_3 x_{2it}) + \ldots + \delta_{17} (Dum_3 x_{1it}) \\ &+ \delta_{18} (Dum_{10} x_{2it}) + v_{it}. \end{aligned} \tag{12}$$

5.1.2.8. Limitations of the fixed effects LSDV model

The LSDV model is quite easy to implement but one has to be aware of its limitations.

First, every additional dummy variable that is introduced, decreases the degrees of freedom making the error variance rise.

Second, hosting so many variables complicate to make a precise estimation of one or more parameters and corrupts the model with problems of multicollinearity.

Third, the LSDV approach may not be able to identify the impact of time-invariant variables (such as sex, education, colour, ethnicity).

Fourth, the error term follows the classical assumptions, $u_{it} \sim N(0,\sigma^2)$. As the *i* index specifies to cross-sectional (countries) observations and *t* to time series observations, the classical assumption for u_{it} may have to be adjusted. There are several possibilities (Gujarati, 2004).

1. One assumption can be that the error variance is the same for all cross-section units (countries) or that the error variance is heteroscedastic.
2. For each individual there can be an estimation that there is no autocorrelation over time.
3. During a given time, there is a possibility that the error term for one cross-sectional (country) observation is correlated with the error term for another observation. There is also the assumption that there is no such correlation.
4. There are many ways of combinations of the error term. Allowing for one or more of these possibilities there are mentioned above will make the analysis that much more complicated.

A discussion of the various possibilities can be found in Elements of Econometrics (Dielman, Sayrs, 1986).

5.1.2.9. Within-groups regression model

One of the biggest challenges about the fixed effects (LSDV) model, which can be seen from the above, is that it contains a high number of regressors. High number of regressors automatically creates a numerically unattractive model which may lead to problems such as multicollinearity. The degrees of freedom decrease as the number of regressors increase, which makes the error variance rise as well. A great disadvantage is that the FE model is unable to identify the impact of time-invariant variables (such as religion, sex, ethnicity, colour which are invariant over time).

Vijayamohanan (2017) suggests a simple way to estimate the fixed effects model without using dummy variables. He considered a simple one-way error components panel data model (with differential intercepts across individuals, which necessitate including dummy variables in estimation equation):

$$Cov(X_{it}, v_{is}) = 0;\ \forall t\ and\ s, \qquad i = 1, 2, \ldots, N,\ \ t = 1, 2, \ldots, T$$

$$Y_{it} = \alpha i + \beta_{it} + v_{it} v_{it} \sim\ IID\ (0, \sigma^2). \tag{13}$$

Averaging the regression equation over time gives

$$\bar{Y}_i = \alpha_i + \beta \bar{X}_i + \bar{v}_i,$$

$$where\ \bar{Y}_i = \Sigma t Y_{it}/T, \bar{X}_i = \Sigma t\ X_{it}/T, and\ \bar{v}_i = \Sigma t\ v_{it}/T$$

and subtracting it from the equation above

$$(Y_{it} - \bar{Y}_i) = \beta(X_{it} - \bar{X}_i) + (v_{it} - \bar{v}_i).$$

is called Q transformation (Baltagi, 2008), which wipes out the differential intercepts. Vijayamohanan (2017) wrote that the OLS estimator for β from this transformed model is called within-groups FE estimator, or simply within estimator, as this estimator is based only on the variation within each company; this is exactly identical to the LSDV estimator. The individual-specific intercepts are estimated unbiasedly as

$$\hat{\alpha}_i = \bar{Y}_i - \hat{\beta}\bar{X}_i, \qquad i = 1,\ldots,N. \tag{14}$$

5.1.3. The Random Effects Model (RE)

Allison (2009) states that "In a random effects model, the unobserved variables are assumed to be uncorrelated with (or, more strongly, statistically independent of) all the observed variables".
In the random effects model, the individual-specific effect is a random variable that is not correlated with the explanatory variables.
A simple one-way error components model is explained;

$$u_{it} = \mu_i + v_{it}, \qquad i = 1,2,\ldots,N, \quad t = 1,2,\ldots,T.$$

$$Y_{it} = \alpha + \beta x_{it} + u_{it}. \tag{15}$$

The assumption in a FE model is that the μ_is are fixed. The main problem that one encounters with the FE model is its specification with too many parameters, resulting in a significant loss of degrees of freedom as already mentioned. The problem in question can be solved if the μ_is are taken to be random; which results in random effects (RE) model with

$$v_{it} \sim IIN\,(0,\sigma^2{}_v),\ \mu_i \sim IID(0,\sigma^2{}_\mu),$$

$$Cov(v_{it},\mu_i) = 0 \quad Cov(v_{it},x_{it}) = 0 \quad Cov(x_{it},\mu_i) = 0. \tag{16}$$

Vijayamohanan (2017) demonstrates that the individual error components are not correlated with each other, and not autocorrelated across both cross-section and time series units.
The α and μ_i in the equation represent that the elected countries are drawn from the same population and have a common mean value for the intercept (α); the individual differences in the intercept values of each country is reflected in the error term μ_i.

The statistical properties of the composite error term is $u_{it} = \mu_i + v_{it}$:

$$E(u_{it}) = 0$$

$$and$$

$$Var(u_{it}) = \sigma^2{}_\mu + \sigma^2{}_v.$$

(which is the sum of within and between component variances).

In the case that $\sigma_\mu{}^2 = 0$, then $Var(u_{it}) = \sigma_v{}^2$; there is no difference between the pooled regression model and the RE model. Hence, the test on the null $\sigma_\mu{}^2 = 0$ can be interpreted as a poolability test in the context of pooled regression vs. RE model. Such a test is available in Breusch-Pagan test. The variance of the composite error term [$Var(u_{it}) = \sigma_\mu{}^2 + \sigma_v{}^2$] is constant and the composite error term is homoscedastic for all *i* and *t*; but serially correlated over time only between the errors of the same company (unless $\sigma_\mu{}^2 = 0$) Vijayamohanan (2017).

$$\begin{aligned} Cov\,(u_{it}, u_{js}) &= E[(\mu_i + v_{it})(\mu_j + v_{js})] = \sigma^2{}_\mu + \sigma^2{}_v, for\ i = j, t = s\ [= Var(u_{it})] \\ &= E(\mu^2{}_i) = \sigma^2{}_\mu, for\ i = j, t \neq s\ (same\ country, over\ time) \\ &= 0, otherwise. \end{aligned}$$

And the correlation coefficient of u_{it} and u_{js} is given by

$$\begin{aligned} \rho\,(u_{it}, u_{is}) &= 1, for\ i = j, t = s\ [= Var(u_{it})/\,Var(u_{it})] \\ &= \sigma^2{}_\mu \,/\, (\sigma^2{}_\mu + \sigma^2{}_v), for\ i = j, t \neq s\ \text{(same country, over time)} \\ &= 0, otherwise. \end{aligned}$$

The errors of each country are correlated over time. This correlation is called equi-correlation. The presence of such serial correlation makes the composite error term nonspherical, and the OLS estimation, inefficient.

In the presence of the (serially correlated) non-spherical error in our RE model, we need to modify our data using the information on the shape of the non-spherical error, and then apply OLS to the transformed data. This GLS estimator of the RE model is obtained by applying OLS to the data after the following transformation into quasi deviations:

$$(y_{it} - \bar{Y}_i) = (1 - \theta)\alpha + \beta(X_{it} - \theta\bar{X}_i) + \{(1 - \theta)\mu i + (v_{it} - \bar{\theta}_{vi})\}$$

where

$$\theta = 1 - \sqrt{\sigma^2{}_v} / (\sigma^2{}_v + T\sigma^2{}_\mu).$$

The term θ is interpreted as a measure of the relative sizes of the within and between component variances. We have the following results on the transformed quasi-deviation form model (Vijayamohanan, 2017):

1. $If\ \theta = 1$, the RE-estimator is identical with the FE-within estimator; this is possible when $\sigma^2{}_v = 0$, which means that every v_{it}t is zero, given $E(v_{it}) = 0$; in this case the FE regression will have an R2 of 1.
2. If $\theta = 0$, the RE-estimator is identical with the pooled OLS-estimator; this is because, $\sigma^2{}_\mu = 0$, which means that μ_i is always zero, given $E(\mu_i) = 0$.

Normally, θ will lie between 0 and 1.

If $Cov(x_{it}, \mu_i) \neq 0$, the RE-estimator will be biased. The degree of the bias will depend on the size of θ. If $\sigma^2{}_\mu$ is much larger than $\sigma^2{}_v$, then θ will be close to 1, and the bias of the RE-estimator will be low.

One major difficulty with RE estimator is that its small sample properties are unknown; it has only asymptotic properties.

5.2. OLS, FE or RE?

"The crucial distinction between fixed and random effects is whether the unobserved individual effect embodies elements that are correlated with the regressors in the model, not whether these effects are stochastic or not" (Green, 2008)

Judge, et al. (1988) propose the following simple rules:

1. If T is large and N small, there is little difference in the parameter estimates of FE and RE models. Hence computational convenience prefers FE model.

2. If N is large and T small, the two methods differ. If cross-sectional units in the sample are random drawings from a larger sample, RE model is appropriate; otherwise, FE model.
3. If the individual error component, μ_i, and one or more regressors are correlated, RE estimators are biased and FE estimators unbiased.
4. If N is large and T small, and if the assumptions of RE modeling hold, RE estimators are more efficient.

5.2.1. F-test

F- test is used when one estimates a model using fixed effects. It tests for the null hypothesis that all individual intercepts are equal to zero, i.e. $H_o : \alpha_i = 0$ in the regression model $y_{it} = \alpha_i + \beta x_{it} + \varepsilon_{it}$. More specifically, the result is an F-statistic that quantifies by how much the goodness-of-fit has changed (Park, 2011). F-test has the null hypothesis that the cross-sectional units all have a common intercept, meaning that all the α_is are equal, in which case the pooled model is adequate. If the p-value is small enough (at <0.05 level) one can reject the null hypothesis. Hence, there is a significant fixed effect and the FE model is thus preferred than a pooled OLS model.

5.2.2. The Breusch–Pagan test

When one has to estimate using random effects, the Breusch–Pagan and Hausman tests are presented and are the counterpart to the F-test mentioned above. The null hypothesis is that the variance of the unit-specific error equals 0; if the p-value is less than 5%, it indicates that the Breusch-Pagan test rejects the hypothesis that the effects are not random - in other words, the effects are random. If this hypothesis is not rejected, then again, we conclude that the simple pooled model is adequate.

5.2.3. Hausman test

A popular way to test which model is better to use, fixed or random, is the Hausman test.
Hausman test's null hypothesis is that the GLS estimates are consistent which means that the random effects are indeed random. If they are random then they should not be correlated with any of the other regressors. If they are correlated with other regressors, then fixed effects model should be used to obtain consistent parameter estimates of the slopes. The Hausman test is applied for different methods of estimating the panel data model with random effects: Swamy and Arora (1972), Amemiya (1971) and Nerlove (1971). Three types of critical values of the Hausman

statistics distribution exists: asymptotical and Bootstrap (based on simulation and bootstrapping) critical values as Monte Carlo (based on pure simulation) critical values for estimating the small sample properties of Hausman test (Sheytanova, 2014).

Gujarati (2004) underlined that the null hypothesis underlying the Hausman test is that the FE and RE estimators do not differ substantially. The test statistic developed by Hausman has an asymptotic distribution. If the null hypothesis is rejected, it can be concluded that the RE model is not the best option and that it is be better to use FE. As Gujarati (2011) wrote, despite the Hausman test, it is important to keep in mind the warning sounded by Johnston and DiNardo (1997) "...there is no simple rule to help the researcher navigate past the Scylla of fixed effects and the Charybdis of measurement error and dynamic selection. Although they are an improvement over cross-section data, panel data do not provide a cure-all for all of an econometrician's problems."

Table 50. The statistical tests in the context of panel data analysis in a nutshell (Vijayamohanan, 2016)

FE vs. OLS $H_0 = \mu_1 = \mu_2 = \ldots = \mu$ F or Wald Test	RE vs. OLS $H_0 = Var(\mu_i) = 0$ Breusch-Pagan Test	Your Model
H_0 not rejected $\Rightarrow$ No FE	H_0 not rejected $\Rightarrow$ No RE	Pooled OLS
H_0 rejected $\Rightarrow$ FE	H_0 not rejected $\Rightarrow$ No RE	FE Model
H_0 not rejected $\Rightarrow$ No FE	H_0 rejected $\Rightarrow$ RE	RE Model
H_0 rejected $\Rightarrow$ FE	H_0 rejected $\Rightarrow$ RE	Choose one based on Hausman test.

6. The Whys of Globalisation and Economics of AI-Driven Automation

In this chapter, the main focal point will be the inextricably linked effects of globalisation and AI-Driven Automation. Globalisation gifted communication and our everyday routines a new level of experience and familiarity, but the spreading growth of technology changed our interpretations and definitions of what is virtual and what is soon going to be virtual. It is essential to understand future trends in order to prepare for the possible consequences. Only by learning is possible to create is an indispensable mechanism of policy and strategies making that governments can use in the best interests for future generations of workers.

6.1. Globalisation

The word globalisation can be interpreted in many ways and has countless definitions that vary dependent of the different areas it affects. Just a part of globalisation will be covered, the one possibly connected with the phenomenon of the Great Decoupling. The IMF (2008) defined globalisation as "a historical process, the result of human innovation and technological progress. It refers to the increasing integration of economies around the world, particularly through the movement of goods, services, and capital across borders. The term sometimes also refers to the movement of people (labour) and knowledge (technology) across international borders. There are also broader cultural, political, and environmental dimensions of globalization." Globalisation, as a term, started to be used in the 1980's to put emphasises on rapid technological advances and international transactions. When the word globalisation is used in this chapter, it is used to mention the third globalisation (3.0), although the term globalisation 4.0 has been in the main focus of many economists.

Globalisation 4.0 as a term comes with the era of the Fourth Industrial Revolution, which is happening at this very moment.

Advanced technologies like nanotechnology, artificial intelligence, the internet of things, 3D printing, autonomous vehicles and big data are just a few of technologies that are being developed and that are going to shape global productivity. In order to understand better the fourth globalisation, one has to remember the benefits and consequences of the last ones, in a more Latin spirit - Historia magistra vitae est. The first globalization (1.0) was the pre-World War I globalization (Baldwin, 2019), which started with a sharp decrease in trade costs when innovations in transport and communications, including the steamships, railways and other forms of mechanical power made it affordable to consume goods made faraway. Baldwin states that there was no global governance, unless one takes into account the British Navy as the UN, the Bank of England as the IMF, and Britain's free trade stance as the WTO. There was little domestic policy to regulate international affairs.

Globalization 2.0 surged after the World War II when regulation was present. The market was responsible for efficiency while the government for justice. On an international scale, Globalization 2.0 witnessed the foundation of institute-based, rule-based international governance, specifically the UN, IMF, World Bank, GATT/WTO and many specialized agencies like the Food and Agricultural Organisation and International Labour Organisation (Baldwin, 2019).

Globalization 3.0, or the New Globalization meant that factories alongside other companies can cross borders, and the know-how of G7 firms along with them, "the monopoly that G7 factory workers had on G7 manufacturing technology was broken when their employers moved jobs and know-how abroad" (Baldwin, 2019). This resulted in a new structure where the world of manufacturing was composed of high-tech combined with low wages. This new structure created disorder in the labour market where lives of workers have difficulties and struggle to compete with high wages and high tech as well as with low wages and low tech.

Today, discussions about globalisation still rise controversy.
An emerging anti-globalisation phenomenon is evidenced by rising trade protectionism, the declining year-on-year global trade growth, the fragile and uneven global economic recovery, and partial marginalisation of multilateral trading systems. The results of anti-globalisation are reflected through a slowdown in trade and investment, disrupting world economic growth and recovery (The International Finance Forum and Central Banking Publications, 2018).

"The blue-collar anger over the last wave of globalisation that helped fuel the populism that led to Brexit and Donald Trump could soon be joined by a white-collar anger", argues Baldwin who is the author of the book The Globotics Upheaval. In 2018, the US president Donald Trump started the tariff war by reintroducing tariffs, unbalancing the relationship with his allies. The relationship with his Western allies became more fragile and ambiguous after the NATO and G7 summits. Another impact on globalisation was the referendum that was held in June 2016, to decide whether the United Kingdom should leave or remain in the European Union. The citizens in the United Kingdom voted to leave the European Union (Brexit). It seems that a new era of globalization has begun in 2018 (Gygli et al., 2019).

Globalisation is also often perceived as a threat to the world's cultural diversity. It can consume local economies, erase traditions and languages and transform the world ruled by the capitalist North and West. A practical definition comes from George Ritzer (2003) who wrote that "attitudes toward globalization depend, among other things, on whether one gains or loses from it". Globalisation promotes mostly the interests of the richest countries, which continue to dictate the pace of world trade at the expenses of developing countries. Comin and Mestieri (2018) stated that the average income per capita in 1820 of the seventeen advanced countries denoted by Maddison (2004) as "Western countries" was 1.9 times the average of non-Western countries. For the next 180 years, Western countries grew significantly faster and, by 2000, their income per capita was 7.2 times the average of non-Western countries. It is not uncommon that international companies with excessive economies of scale drive local companies out of business. One of the most dangerous consequences of such events is the direct effect on increasing income inequality and unfair competitive advantage. Trade and economic openness influence growth through competitiveness and labour productivity channels (Frankel and Roemer, 1999). Technologies are playing a fundamental role in allowing the globalisation of economic and social activities. The ways in which new technologies penetrate individual nations is heavily affecting their actual and potential economic development (Archibugi and Pietrobelli, 2003). In order to avoid strong negative consequences, one should pay more attention to regulations in the competitive markets and in enforcing the relationship between education and labour market. As the KOF Index of Globalisation was already covered in Chapter Two, this chapter will cover part of the negative effects on competition and those affecting the development of a healthy, educated and productive labour force. The focus is to justify and support the selected variables that will be used in the model (see Chapter Four).

6.1.1. Competitiveness

How we think about competitive strategy today has changed immensely over the past two decades. A revolutionary concept was coined in the early 1990s by Harvard Business School professor Clayton Christensen. The term disruptive innovation describes a process by which a product or service takes root initially in simple applications at the bottom of a market and then steadily moves up market, eventually displacing established competitors typically by being less expensive and more accessible (Clayton Christensen Institute for Disruptive Innovation). It seems that the competitor you have today may look a lot different in the future (e.g. Uber).

It was not long ago that professors W. Chan Kim and Renee Mauborgne launched another revolution in business strategy that they elaborated in their book, "Blue Ocean Strategy: How to Create Uncontested Market Space and Make Competition Irrelevant," in 2005. They encouraged companies to evacuate shark infested waters and find their own zero-sum competition in "uncontested market space". The book suggests to find the Blue Ocean where you do not have to fight your competitor, but to make you competitor irrelevant by finding and creating your own market. The four key questions to find it are: (i) Raise: What factors should be raised well above the industry's standard? (ii) Reduce: What factors were a result of competing against other industries and can be reduced? (iii) Eliminate: Which factors that the industry has long competed on should be eliminated? (iv) Create: Which factors should be created that the industry has never offered? They gave a different framework than the one in Michael E. Porter's work on competitive strategies (especially the five forces) that was used for a long time as cornerstone for business strategies. Instead of beating your competitor in the Red Ocean, find the Blue Ocean where there are none (e.g. Cirque du Soleil). But new oceans and unexplored dimensions were brought with globalisation, with the internet and global connectivity.

One of the trends with an increasing effect on the world economy is the rapid growth of international business that globalisation made easier to accomplish. Globalisation implies that a firm now competes in its market against other firms from all over the world. At first it does look like a fair competition but is this making it easier for smaller companies to survive the race or is it completely altering the nature of competition?

When someone mentions the word “international trade”, the first thing that comes to mind are import and export. It is self-evident that the analysis of competitiveness cannot be restrained only to the above-mentioned international trade.

Today companies win their market share via international trade with foreign direct investment flows, capital movements and increasing technology transfers that hold a crucial role in the market and that became a massive part of it. It has become clear that these forms that globalisation brought coexist and are interdependent. The French Industry Ministry conducted a study that showed that the most dynamic companies were those that were the most international.

Direct investment can either reduce flows of exports if it takes their place or increase them if it is complementary. In the case that there is subcontracting relocated to lower-cost regions, new flows of imports to the country of origin can take place. Though, there is always a possibility that some of these imports are re-exported in another form (finished products). International investment also results in numerous technology transfers (patents, licences, know-how, etc.), and the larger part of go through foreign affiliates (Hatzichronoglou, 1996).

The drivers of globalization are the forces that lead towards closer economic integration, and based on Bang and Markset (2011) are the following:

- Lower trade barriers
- Lower transportation costs
- Lower communication costs
- Information and communication technology (ICT) development
- Spread of technology

If a government or companies want to expand their market share abroad, it does not necessarily mean that it is competitive. It can be perceived as a necessity to relocate part of its production in countries with lower (labour) cost as a consequence of faster increasing costs in comparison with its competitors or because of environmental strict rules. Other companies invest abroad benefitting from their competitive advantage (know-how, technology, tradition) putting at high risk local companies and businesses. If it becomes cheaper for a company to operate in another country, current factories may end up in closure and local people jobless. And that is the greatest danger. Developed countries outsource their businesses to developing country mostly because of the low manufacturing cost and cheap labour available. That leads to workers in developed countries to lose their jobs due to this outsourcing. Such jobs are becoming insecure and workers fear for their permanent position. Because of relocation of jobs, their bargaining position of labour gets weaker. The OECD Directorate for Financial and Enterprise Affairs published a presentation by UK Competition and Markets Authority that found that the word "competition" in the annual reports in the United States of America have decreased significantly.

Figure 16. Frequency of words in annual reports of US companies, per 10,000 words (UK Competition and Markets Authority, 2019)

As technology is shifting the way we compete, the need for innovation in learning is essential. Education needs effective innovations of scale that can help produce high quality learning outcomes across the system. Innovative education is of great importance and should become a collective matter for all society (Serdyukov, 2017). In his paper, Jones (2015) wanted to know more about knowledge spill overs across countries, mentioning Eaton and Kortum (1999) who stated that only 60 percent of US growth in recent decades came from knowledge created in the United States. It was compared to the numbers for local knowledge in Japan of 35 percent and the United Kingdom of 13 percent - which are much lower. An interesting fact that Freeman (2010) mentions is that in the 1970s, China produced a very low number of PhD's in science and engineering, but by 2010, China was producing 26 percent more than those completed in the United States.

It is becoming increasingly important to investigate about the effect of the good public health system and education on the economic growth of countries around the globe (Alataş and Çakir, 2016).

It is indisputable that education and innovation are linked, and the question it arises is, is innovation the new word for competition?

Emergences of new innovations and altered forms of competition are changing the structure of economy. But countries progress has been uneven. While many companies have difficulties adopting new skills and technologies, companies that successfully implemented the capabilities are capturing disproportionate benefits. AI-automation technologies can create substantial performance gains and take the lead in their industries, even as their efforts contribute to economy-level increases in productivity. Some companies wield greater market power, raising the profit share of income at the expense of the labour share and customer (Blanchard and Giavazzi, 2003; Autor, Dorn, Katz, Patterson and Van Reenen, 2017; De Loecker and Eeckhout, 2017). Are the players with larger market share slowly suffocating competition? How is that affecting economic growth and income inequality?

When the fixed costs for the development of new digital services are being deployed, a growing market can be offered at an almost zero marginal costs (Ernst et al, 2018). It is solidified by the economies of scale that are undoubtedly larger than during the previous waves of technological change based on automation of mechanical tasks (Moretti, 2012). This grants super-star firms to dominate and occupy a privileged and highly profitable position. They are, in a concrete way, narrowing competitive pressure by erecting barriers to entry (Rosen, 1981).

The more an industry is exposed to international competition, the greater is the risk of the downward pressure on costs. In order to achieve productivity gains, companies generate strategies that can result in unfavourable impact on employment.

Autor et al. (2017) suggest that the fall in labour share is closely related to the increase in market concentration and firm size. One of the factors affecting it are also consumer behaviour and innovation. Imposing a Cobb-Douglas production function, Autor et al. (2017) documented an empirical association between rising industry concentration and declining labour shares within sector. Deregulation and other drivers increased the market power of firms, raising the profit share of income at the expense of the labour share (Blanchard and Giavazzi, 2003; Azmat, Manning, and Van Reenen, 2012; Barkai, 2016; Autor, Dorn, Katz, Patterson, and Van Reenen, 2017; De Loecker and Eeckhout, 2017). The role of market regulations is now at the forefront of the different explanations for the drop of labour share (Adrjan, 2018).

The Herfindahl-Hirschman index (HHI) is an accepted measure for market concentration. It is obtained by squaring the market share of each company competing in a market and then summing the resulting numbers. The range is from close to zero to 10,000 points. The U.S. Department of Justice is an institution that uses the HHI for classifying potential mergers issues.

The higher the change is that market is going closer to a monopoly, the higher the market's concentration. In the case that there was only one company in an industry, which would mean that their maker share result being 100%, then the Herfindahl-Hirschman Index (HHI) would equal 10,000 points, indicating a monopoly. If that company would not be the only one in the industry, but competing against over thousands of them, each would have nearly 0% market share, and the HHI would be close to zero, indicating nearly perfect competition.

The agencies consider a market in which the HHI of less than 1,500 points to be a competitive marketplace, an HHI of 1,500 to 2,500 points to be a moderately concentrated marketplace, and an HHI of 2,500 points or higher to be a highly concentrated marketplace. (U.S. Department of Justice). As a general rule, mergers that increase the HHI by more than 200 points in highly concentrated markets raise antitrust concerns, as they are assumed to boost market power under the section 5.3 of the Horizontal Merger Guidelines jointly issued by the department and the Federal Trade Commission (FTC).

In the following section graph representing the movement of Hirschman Herfindahl index for each country will be displayed. Based on the World Bank data (Worldbank, 2019), a country with trade (export or import) that is concentrated in a very few markets will have an index value close to 1 while a country with a perfectly diversified trade portfolio will have an index close to zero. The world median will be on view as benchmark.

The graphs represent the movement of the HH Market concentration Index during the period between 1988 and 2017 for Germany, Finland and Japan, for Sweden the analysed period is between 1992 and 2017 while the analysed period for the United Kingdom and the United States of America is between 1993 and 2017. It can be noticed that the countries that are part of the European Union, with the exception of the United Kingdom, have similar trends.

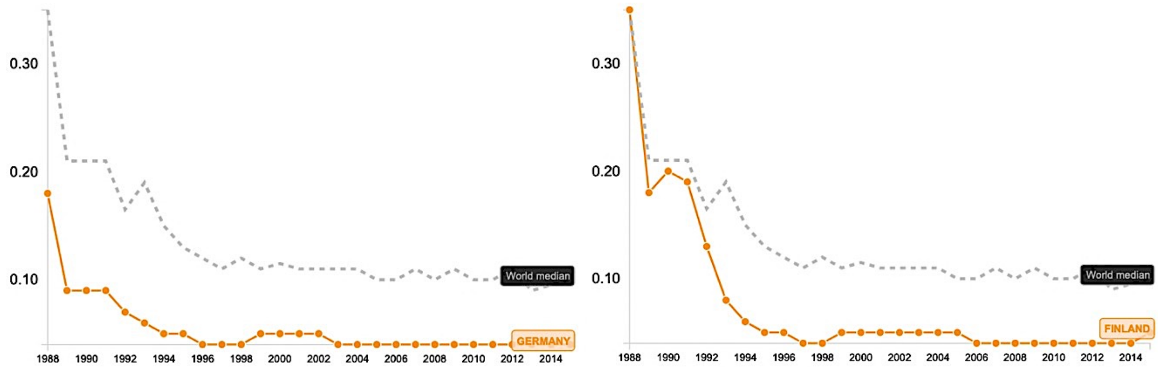

Figure 17. HH Market concentration Index for Germany and Finland (Worldbank, 2019)

Germany experienced a year-on-year average growth rate of -4.38% for the time period 1988 to 2015 while Finland an average growth rate of -5.34%.

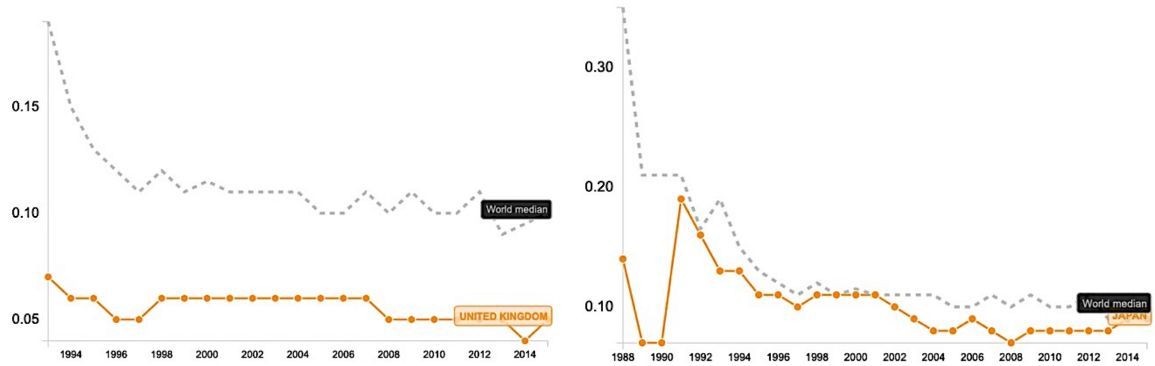

Figure 18. HH Market concentration Index for United Kingdom and Japan (Worldbank, 2019)

United Kingdom experienced a year-on-year average growth rate of -1.03% for the time period 1993 to 2015. For the time period 1988 to 2015, Japan experienced a year-on-year average growth rate of 2.14%.

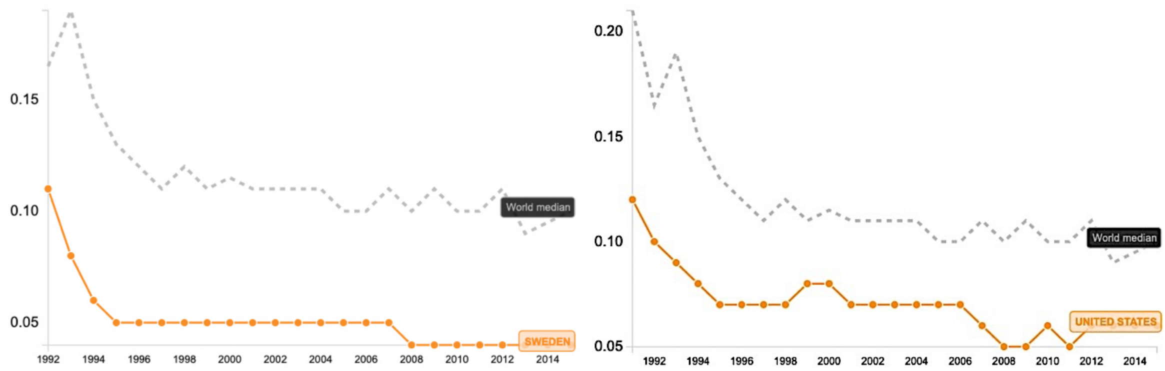

Figure 19. HH Market concentration Index for Sweden and United States of America (Worldbank, 2019)

Sweden experienced a year-on-year average growth rate of -3.87% for the time period 1992 to 2015, while the United States experienced a year-on-year average growth rate of -2.34% for the time period 1991 to 2015.

The following figures are showing the development of the HH Market concentration Index during the period 1994, 2000, 2009 and 2015 in order to better compare how the countries diversified trade portfolio.

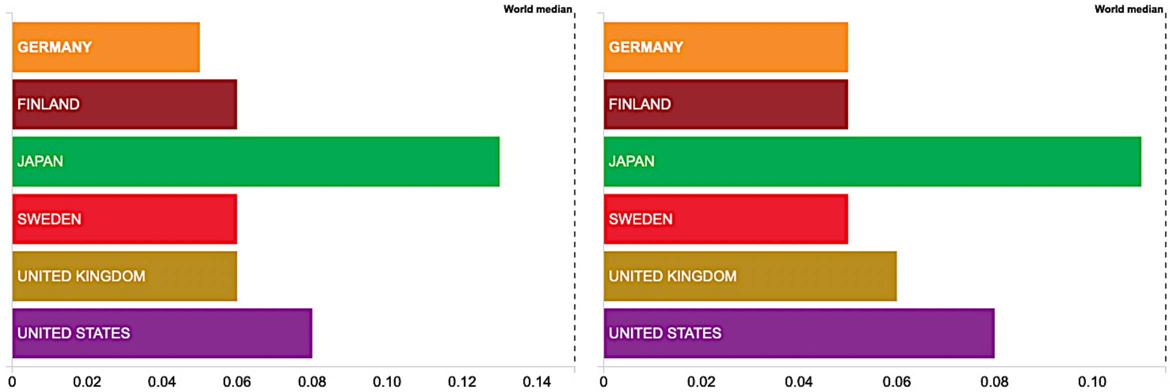

Figure 20. HH Market Concentration Index in 1994 and 2000 (Worldbank, 2019)

In 1994, Japan had the highest indicator value at 0.13 Index whereas Germany had the lowest indicator value at 0.05 Index. Among the selected countries, in 2000 Japan had the highest indicator value at 0.11 Index whereas Sweden had the lowest indicator value at 0.05 Index.

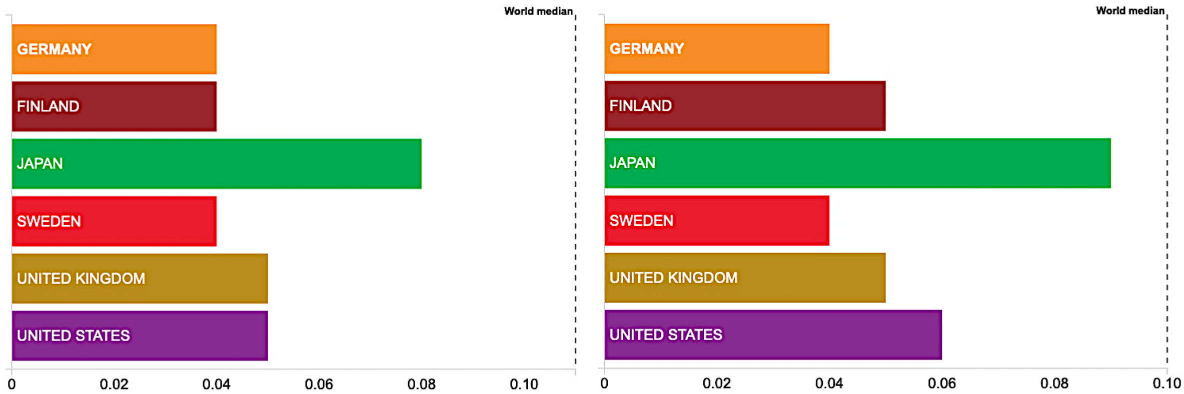

Figure 21. HH Market Concentration Index in 2009 and 2015 (Worldbank, 2019)

In 2009, the situation remains unchanged with Japan having the highest indicator value at 0.08 Index whereas Sweden the lowest indicator value at 0.04 Index.

The results for 2015 show that among the selected countries, Japan has the highest indicator value at 0.09 Index whereas Sweden has the lowest indicator value at 0.04 Index. Germany has the value 0.04 Index, Finland 0.05 Index, the United Kingdom 0.05 Index while the United States has the value 0.06 Index compared to the world median. It can be concluded that from the evaluated results, among the elected countries, Japan has the highest concentrated market while Sweden, Finland and Germany the least. All of the countries are well below the world median value.

6.1.2. The Human Capital Index

The impact of human capital on the economic growth gained a lot of attention. Higher educational investments influenced national economic growth. The weight of evidence suggests that a 1 percent increase in school enrolment rates has led to an increase in GDP per capita growth of between 1 and 3 percent (Wilson and Briscoe, 2004). The effect of human capital on economic growth has been debated since 1980 in terms of endogenous growth models developed by Romer, Lucas and Barro.

Summary of empirical literature studies analysing quantitative relationship and interaction between human capital and economic growth is shown in Table 51.

Table 51. Summary of empirical literature studies analysing quantitative relationship and interaction between human capital and economic growth (Alataş and Çakir, 2016)

Author(s)	Country	Period	Period Result(s)
Romer	112 Countries	1960-1985	↑ HC >>GRO ↑
Benhabib and Spiegel	78 Countries	1965-1985	↑ HC >>GRO ↑
Freire-Seren	72, 65 and 22 Countries	1960-1990	↑ HC >>GRO ↑
Ljunberg and Nilsson	Sweden	1870-2000	↑ HC >>GRO ↑
Aka and Dumont	USA	1929-1996	↑ HC >>GRO ↑

Ramos, Surinach and Artis	229 and 190 Regions in EU	1995-2000 2000-2005	↑ HC >>GRO ↑
Haldar and Mallik	India	1960-2006	↑ HC >>GRO ↑
Yaylalı and Lebe	Turkey	1938-2007	↑ HC >>GRO ↑
Koç	27 EU Countries	2012	↑ HC >>GRO ↑

The Human Capital Index is a new measure for capturing and tracking the state of human capital development around the world. It has three key features. First, the Index measures a broader set of indicators than the traditional definitions of human capital. Human capital is not a one–dimensional concept, but means different things to different stakeholders. In the business world, human capital is the economic value of an employee's set of skills. To the policy maker, human capital is the capacity of the population to drive economic growth. Traditionally, human capital has been viewed as a function of education and experience, the latter reflecting both training and learning by doing. But in recent years, health (including physical capacities, cognitive function and mental health) has come to be seen as a fundamental component of human capital. Additionally, the value of human capital is critically determined by the physical, social and economic context of a society, because that context determines how particular attributes a person possesses may be rewarded. The Index is thus based on four pillars: three core determinants of human capital (education, health and employment) plus those factors that allow these three core determinants to translate into greater returns. Second, the Index takes a long–term approach to human capital. In addition to providing a snapshot of the state of a country's human capital today through measures that reflect the results of a country's past practices, it includes indicators resulting from practices and policy decisions impacting the children of today and which will shape the future workforce. Long–term thinking around human capital often does not fit political cycles or business investment horizons; but lack of such long-term planning can perpetuate continued wasted potential in a country's population and losses for a nation's growth and productivity. The Index seeks to develop a stronger consciousness around the need for such planning. Third, the Index aims to take into account the individual life course. For example, the WHO states that is becoming increasingly important to investigate about the effect of the good public health system and education on the economic growth of countries around the globe (Alataş and Çakir, 2016; Imran et al., 2012).

Human capital is the crucial determinant needed for the long-term economic success than any other resource. Although high unemployment is present in many countries, the global economy has the problem of talent scarcity. If not recognising and addressing challenges related to human capital, negative consequences can be inflicted through instability in the long-term growth, prosperity and competitiveness of nations. The Human Capital Index examines the sources and roles to the development and deployment of a healthy, educated and productive labour force. The Index includes measures indicating quality of early childhood and captures the extent to which investments made in earlier years in health and education are being realised in the working age population through lifelong learning and training World Bank (2018). The Index takes into consideration the health and productivity of the older population. World Bank explained how is the Index measured in The Human Capital Project (2018).

It is structured by five indicators: the probability of survival to age five, a child's expected years of schooling, harmonized test scores as a measure of quality of learning, adult survival rate (fraction of 15-year olds that will survive to age 60), and the proportion of children who are not stunted.

The results indicated that globally, 56 percent of all children born today will grow up to be, at best, half as productive as they could be while 92 percent of all children will grow up to be, at best, 75 percent as productive as they could be. The Index includes 157 economies and is higher on average in rich countries than in poor countries and ranges from around 0.3 to around 0.9. As an example, if a country such as El Salvador, has an HCI of around 0.5 and if current education and health conditions in El Salvador remain the same, a child born today will be only half as productive as she could have been if she enjoyed complete education and full health.

Differences in human capital have large implications for the productivity of the next generation of workers (World Bank, 2019). In a concrete way, the Human Capital Index measures the consequences of neglecting investments in human capital in terms of the lost productivity of the next generation of workers.

In the next table is given a short overview of the Human Capital Index. Since all the chosen countries are developed countries, a short explanation for the HCI, expected years of school, Harmonized test scores and learning-adjusted years of school will be given for each country. Results for Survival to age, Adult survival rate and Not stunted rate will be left out of the profile.

Table 52. HCI by country (Human Capital Index, The World Bank, 2018)

Country	Germany	Finland	United Kingdom	Japan	Sweden	United States of America
HCI	0.79	0.81	0.78	0.84	0.8	0.76
Survival to Age	1	1	1	1	1	0.99
Expected Years of School	13.9	13.8	13.9	13.6	13.9	13.3
Harmonized Test Scores	528	548	517	563	525	523
Learning-adjusted Years of School	11.9	12.1	11.5	12.3	11.7	11.1
Adult Survival Rate	0.93	0.93	0.94	0.94	0.95	0.9
Not Stunted Rate	-	-	-	0.93	-	0.98

From the table above, it is shown that a child born in Germany today will be 79 percent as productive when she grows up as she could be if she enjoyed complete education and full health. A child who starts school at age 4 can expect to complete 13.9 years of school by her 18th birthday. On a scale where 625 represents advanced attainment and 300 represents minimum attainment, German students score 528 while expected years of school is only 11.7 years.

A child born in Finland today will be 81 percent as productive when she grows up as she could be if she enjoyed complete education and full health. If a child in Finland starts school at age 4, it can be expected to complete 13.8 years of school by her 18th birthday. Students in Finland score 548 on a scale where 625 represents advanced attainment and 300 represents minimum attainment while the expected years of school is only 12.1 years.

A child born in the United Kingdom today will be 78 percent as productive when she grows up as she could be if she enjoyed complete education and full health. A child who starts school at age 4 can expect to complete 13.9 years of school by her 18th birthday and scoring 517 on a scale where 625 represents advanced attainment and 300 represents minimum attainment. Factoring in what children actually learn in the United Kingdom, expected years of school is only 11.5 years.

Today, is a child is born in Japan, he or she will be 84 percent as productive when she grows up as she could be if she enjoyed complete education and full health. If starting school at age 4, it can be expected to complete 13.6 years of school by her 18th birthday. Japanese children score 563 on a scale where 625 represents advanced attainment and 300 represents minimum attainment. Expected years of school is only 12.3 years.

In Sweden, if today a child is born, he or she will be 80 percent as productive when she grows up as she could be if she enjoyed complete education and full health. A child who starts school in Sweden at age 4 can expect to complete 13.9 years of school by her 18th birthday. Students score 525 on a scale where 625 represents advanced attainment and 300 represents minimum attainment while expected years of school is only 11.7 years.

A child born in the United States today will be 76 percent as productive when she grows up as she could be if she enjoyed complete education and full health. If a child starts school at age 4 in the United States, it can be expected to complete13.3 years of school by her 18th birthday. On a scale where 625 represents advanced attainment and 300 represents minimum attainment, a student in the United States scores 523. Factoring in what children actually learn in the United States, expected years of school is only 11.1 years

The HCI for girls is higher than for boys in all countries with the exception of Japan because the lack of data prevents comparison of HCI by gender.

Difficulties to equate returns to the firm and the worker of investments in human capital are present due to rapid economic development. Biesebroek (2005) found only limited violations of equality between wage and productivity in the literature and suggested that it would be valuable to see more work along this line specifically focusing on developing countries.

Important factors for economic integration appear to be institutions, education, innovation and technological progress, which are in turn linked to education and institutions (Barro (1991), Aghion et al. (2008); Acemoglu et al. (2014). Aghion and Howitt (2009)).

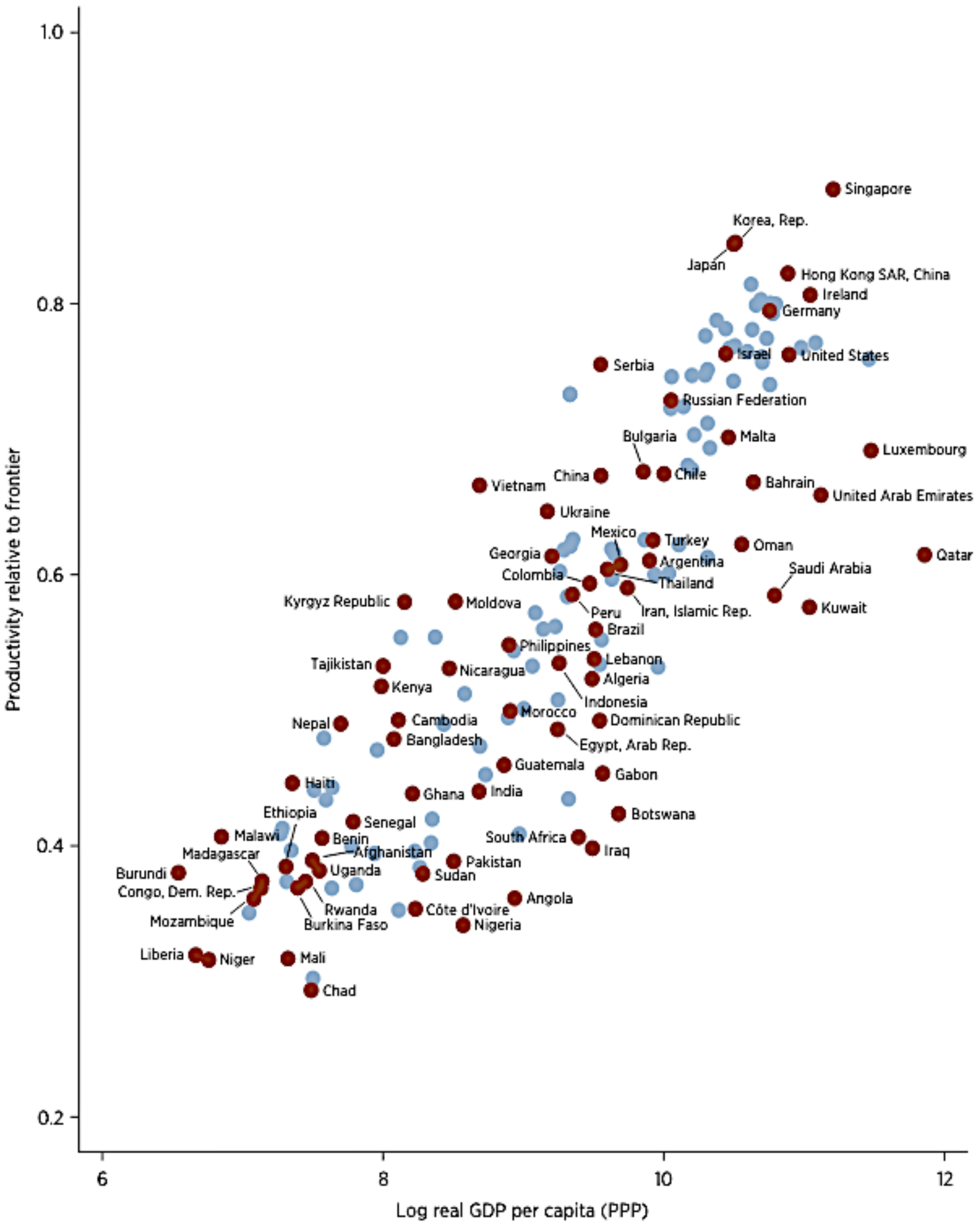

Figure 22 The Human Capital Index, 2018 (World Development Report, 2019)

As the Human Capital Index is a measurement tool created by the World Bank to influence countries to invest more in health and education, it is interesting to notice the ranking where the US scored 24th overall, tied with Serbia, where the GDP per capita is only about a quarter of the US level.

6.2. Economics of AI-Driven Automation

"Machines will be capable, within twenty years, of doing any work a man can do." Herbert Simon, often referred as father of artificial intelligence and Nobel Prize winner in economics, stated with confidence in 1956.

A successful AI journey begins with an understanding of the specific opportunities and limitations it brings. As recalled in the beginning, Turing's ideas about intelligent machines must be seriously taken. The concepts of intelligence, machine, working capacity, as well as many others in Computer Science are not completely or adequately defined (Falqueto et al., 2011). McKinsey (2017) has categorized key areas of AI development into five technology systems that are: robotics and autonomous vehicles, computer vision, language, virtual agents, and machine learning, which is based on algorithms that learn from data without relying on rules-based programming in order to draw conclusions or direct an action.

It is important for businesses to identify value realization and considerations for sustainable technology to support automation. It can help companies, organizations and institutions to identify the relevant use case and business function for AI adoption. Transform traditional processes in research and development, manufacturing, regulation, AI and automation can facilitate effective engagement and high-quality results. There are many opportunities where AI-driven automation can help create an effective chain in a global manufacturing and distribution environment.

Computer software has automated a great number of tasks performed by white-collar workers in retail, wholesale, and business services. Software and AI-powered technologies can now retrieve information, coordinate logistics, handle inventories, prepare taxes, provide financial services, translate complex documents, write business reports, prepare legal briefs, and diagnose disease.

Computerization of white-collar services in a great number of developed economies are significantly increased in recent years (Acemoglu and Restrepo, 2018b). Meanwhile, progress in machine learning is expanding the set of activities that can be operated more efficiently by computers than humans, such as image and speech recognition, natural language processing, and predictive analytics (Brynjolfsson, Mitchell, and Rock, 2018), which leads to a possible and unquestionably broader scope for task automation.

If we take, for example, that an increase in automation will lead to capital increases, the wage relative to the rental rate and the labour share will decrease and the equilibrium wage rate may follow. In the model in "The Race between man and machine" by Acemoglu and Restrepo (2017b) because the supply of labour is elastic, automation gravitates to reduce employment, on the other side the creation of new tasks increases employment. It is clear that although both types of technological changes reinforce economic growth, connotations regarding the factor distribution of income and employment are diverse. It is important to keep in mind that if human labour is indeed rendered superfluous by automation, then our chief economic problem will be one of distribution, not of scarcity (Autor, 2015). In the same year, Stephen Hawking stated that "If machines produce everything we need, the outcome will depend on how things are distributed. Everyone can enjoy a life of luxurious leisure if the machine-produced wealth is shared, or most people can end up miserably poor if the machine-owners successfully lobby against wealth redistribution." They both underlined what, in my modest opinion, is going to be a question for scientists and researcher of greatest importance.

A strategic rise of the digital mindset is happening and further embracement of transformative technologies is not going to decelerate. In a time where technological changes started dictating the pace our everyday living, transforming our work and using technology will be fundamental to advancing digital transformation.

6.2.1. AI and the Macroeconomy: Innovation and Productivity Growth

Over the past few years, artificial intelligence has matured considerably and is becoming the driver of digitalization and autonomous systems in all areas of life. Technology has been one of the main drivers of productivity growth. Changes in technology helped explaining a constant growth in productivity throughout the 1990s (Basu, Fernald and Shapiro, 2001).

Because of the exponential growth in technological advancements, AI hubs are being created as creative centres for growth and prosperity. In 2016, the United States was alone responsible for around 66 percent of external investment (Venture capital (VC), private equity (PE), and mergers and acquisitions (M&A) activity). China was second with 17 percent, but is growing stronger (McKinsey, 2017). On the European scene, strong AI ecosystems are being developed, significant start-up activity and VC investment in 2016 are recorded in Germany, France, and the Nordic region (Degtyareva, 2017). The main hubs (McKinsey, 2017) are those in Silicon Valley, top global hub for start-ups, New York, leading hub for financial and media industries, Beijing, leading in volume of academic research output in AI coming from Tsinghua, Beihang and Peking universities, Boston, where the cooperation between science and industry has long history, London, global finance centre, supporting both investment and fin-tech applications and Shenzhen, hub for electronics manufacturing firms such as Huawei and ZTE, Figure 34.

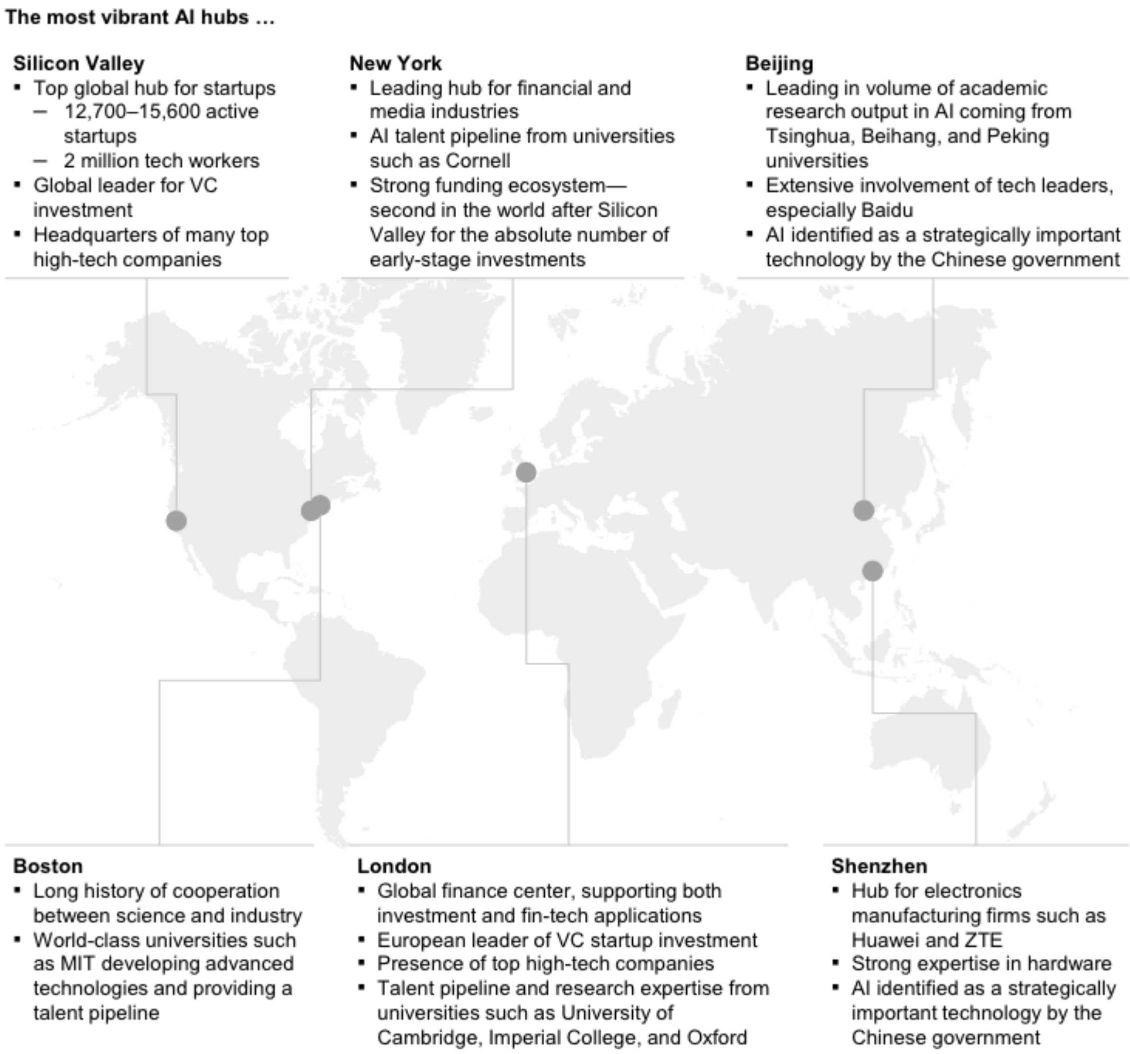

Figure 23. Leading AI hubs in the world (McKinsey Global Institute analysis, 2017)

From 2013 through 2016, external investment in AI technologies had an aggregate annual growth rate of almost 40 percent, as the McKinsey Global Institute report "Artificial intelligence: The next digital frontier?" (2017) states, while from 2010 to 2013 that percentage was 30. Businesses regarding AI technology are getting gigantic and large, and require fewer participants to complete the financing. This suggests that investors are growing more confident in the sector and its potential.

Companies such Amazon, Apple, Baidu, and Google are investing billions of dollars in artificial intelligence. Internal investment by large tech giants' corporations dominates: McKinsey (2017) estimated that $18 billion to $27 billion was invested in 2016 in internal investment while in external investment (from VCs, PE firms, M&A, grants, and seed funding) that number was around $8 billion to $12 billion. Machine learning attracted almost 60 percent of that investment while investments in Virtual agents around 1 percent.

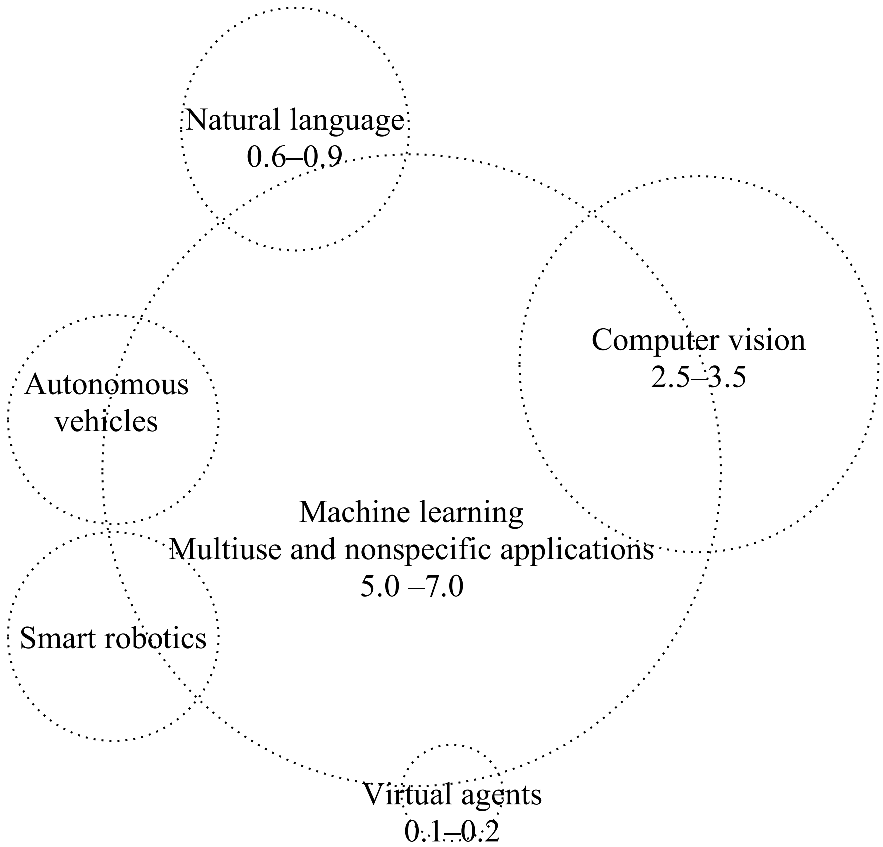

Figure 24. External investment in AI-focused companies by technology category, 2016 $ billion (McKinsey Global Institute analysis, 2017)

In the McKinsey Global Institute report, it is evaluated that tech giants spent \$20 billion to \$30 billion globally on AI in 2016, with 90 percent of this spent on R&D and deployment, and 10 percent on AI acquisitions. Other examples include Toyota. The company invested \$1 billion to establish a new research institute devoted to AI for robotics and driverless vehicles. Industrial giants such as ABB, Bosch, GE, and Siemens also are investing internally, mostly in machine learning and robotics in order to further develop their core businesses. IBM obliged to invest \$3 billion to make its Watson cognitive computing service a force in the internet of things. Baidu has invested \$1.5 billion in AI research over the last couples of years in addition to \$200 million it obliged to a new in-house venture capital fund, Baidu Venture. Tech giants such as Apple, Baidu, and Google, are developing and enhancing technologies internally, but they are focused to invest in AI that will create their best advantage. Amazon is working on robotics and speech recognition, Salesforce on virtual agents and machine learning. BMW, Tesla, and Toyota in robotics and machine learning for use in driverless cars.

Facebook, is opening an AI lab in Paris that will supplement similar facilities in New York and Silicon Valley while Google invested \$4.5 million in the Montreal Institute for Learning Algorithms. Intel contributed \$1.5 million to create a machine learning and cybersecurity research centre at Georgia Tech; and NVIDIA is collaborating with the National Taiwan University to establish an AI laboratory in Taipei.

The implementation of AI and the automation of activities can increase productivity growth and other benefits not only for businesses but also for entire economies. At a macroeconomic level, the estimation of automation alone could raise productivity growth on a global basis by 0.8 to 1.4 percent annually. AI and other technologies can be beneficial for societies by helping overcome challenges like climate change or curing disease.

“Macroeconomic impact of artificial intelligence”, a study done by PwC (2017), forecasted the distribution of the impacts of AI by 2030 by channels of impact, through productivity or through product enhancements. As it is shown in Table 53, all geographic regions of the global economy will have an increase in GDP as economic benefits from AI. North America and China will have considerable economic gains with AI increasing GDP by 26.1 percent and 14. 5 percent in 2030, equivalent to a total of \$10.7 trillion and accounting for almost 70 percent of the global economic impact.

Table 53. GDP impact of AI by geographical region and channel of impact by 2030 (PwC Analysis, 2017)

(%)	GDP impact associated with productivity	GDP impact associated with product enhancements	Total GDP impact
North America (US)	6.7	7.9	14.5
China	13.3	12.8	26.1
Developed Asia (Japan, South Korea)	3.9	6.5	10.4
Northern Europe (UK, Germany)	2.3	7.6	9.9
Southern Europe (Spain, Italy)	4.1	7.5	11.5
Latin America (Chile)	1.7	3.7	5.4
Africa, Oceania and other Asian markets	1.1	4.5	5.6

Companies are broadly investing in AI and automation, but countries are preparing too. It is their responsibility and duty to protect and prepare future generations of worker to live and work in the digital era. The Ministry of Economic Affairs and Employment published "Finland's Age of Artificial Intelligence" (2017) where they elaborated all the factors that their country should take into account for the coming changes. The Chinese government published its "Next Generation Artificial Intelligence Development Plan", with the objective to position China as a global leader in the development of AI and to become leading artificial intelligence innovation hub by 2030.

The European Commission established initiatives with the goal to harmonize practices and legislation (for example, MyData, Digital Single Market and Digitizing European Industry) and to support the development of AI and digital business. Member States hold responsibility for development, and each of them has differing strategies for the utilization of artificial intelligence.

Large Member States, such as France and Germany, have already invested in artificial intelligence with very different strategies.

Japan's plan's objective is to establish Japan as a Super Smart Society (i.e. Society 5.0). The Prime Minister is in charge of the programme, and its field specific programmes are under the leadership by selected corporate heads. For example, the Council for Science, Technology and Innovation (CSTI) will allocate $550 million via its ImPACT programme to 16 extensive consortiums, most of them are linked to the development of artificial intelligence. A total sum of $250 million will be designated annually from three ministries to the development of artificial intelligence.

McKinsey Global Institute also pointed out several key factors will influence the pace and extent of automation. These include:

1. technical feasibility of automation, a critical first step that will depend on sustained breakthrough innovation, but alone is not sufficient
2. cost of developing and deploying solutions
3. labour market dynamics, including supply and demand, and costs of human labour as an alternative to automation
4. business and economic benefits, not merely labour substitution benefits but also benefits from new capabilities that go beyond human capabilities
5. regulatory, user and social acceptance, which can affect the rate of adoption even when deployment makes business and economic sense.

The potential positive impact of AI- driven automation on productivity is notably extensive when taking into account current trends in productivity. Researches indicated that, despite the fact that technology boosts productivity, in the last decade, measured productivity growth has slowed in 30 of the 31 advanced economies. In the cast of United States, it slowed from an average annual growth rate of 2.5 percent in the decade after 1995 to only 1.0 percent growth in the decade after 2005. One of the main reasons behind it is the slowdown in investment in capital stock, but the slowdown in total factor productivity growth (the component influenced by technological change) has also been decisive. It influenced to slower growth in real wages and if continued will deteriorate improvements in living standards (Executive Office of the President, 2016).

There is also evidence that industrial robotic automation alone increased labour productivity growth by 0.36 percentage points across 17 countries between 1993 and 2007. (Graetz and

Michaels, 2018). Progress in machine learning is increasing the number of activities that can be performed more efficiently by computers than humans, such as image and speech recognition, natural language processing, and predictive analytics (Brynjolfsson, Mitchell, and Rock, 2018).
In „Robots and jobs", Acemoglu and Restrepo (2017a) suggested that greater penetration of robots into the economy affects wages and employment negatively because of a displacement effect, but also positively because of a productivity effect. In their working paper „Artificial intelligence, automation and work" (2018) suggested that automation will reduce the costs of production which will lead to the creation of productivity effect, capital accumulation and deepening of automation. Industrial robots are argued to have already deeply impacted the labour market and are expected to transform it in the decades to come (e.g., Brynjolfsson and McAfee, 2012; Ford, 2016). "Digital technologies are doing for human brainpower what the steam engine and related technologies did for human muscle power during the Industrial Revolution." Erik Brynjolfsson wrote in his book with McAfee (2014) The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies.

An interesting finding is that differential aging alone accounts for about 40% of the cross-country variation in investment in robotics. Demographic change not only motivates the adoption of automation technologies but also their development (working paper "Demographics and Automation", Acemoglu and Restrepo). The fact that it was technically possible to replace a worker with a robot did not mean it was economically attractive to do so and would depend on the relative cost and productivity of machines compared with humans, Hawksworth said. PwC expects this balance to shift in favour of robots as they become cheaper to produce over the coming decades. Graetz and Michaels (2015) stated that the cost of robots are decreasing, and that the marginal returns on increased robot densification seem to decrease fairly rapidly, which policy makers have to take into account.
AI adoption is occurring faster in more digitized sectors and across the value chain that is shown in Figure 40.

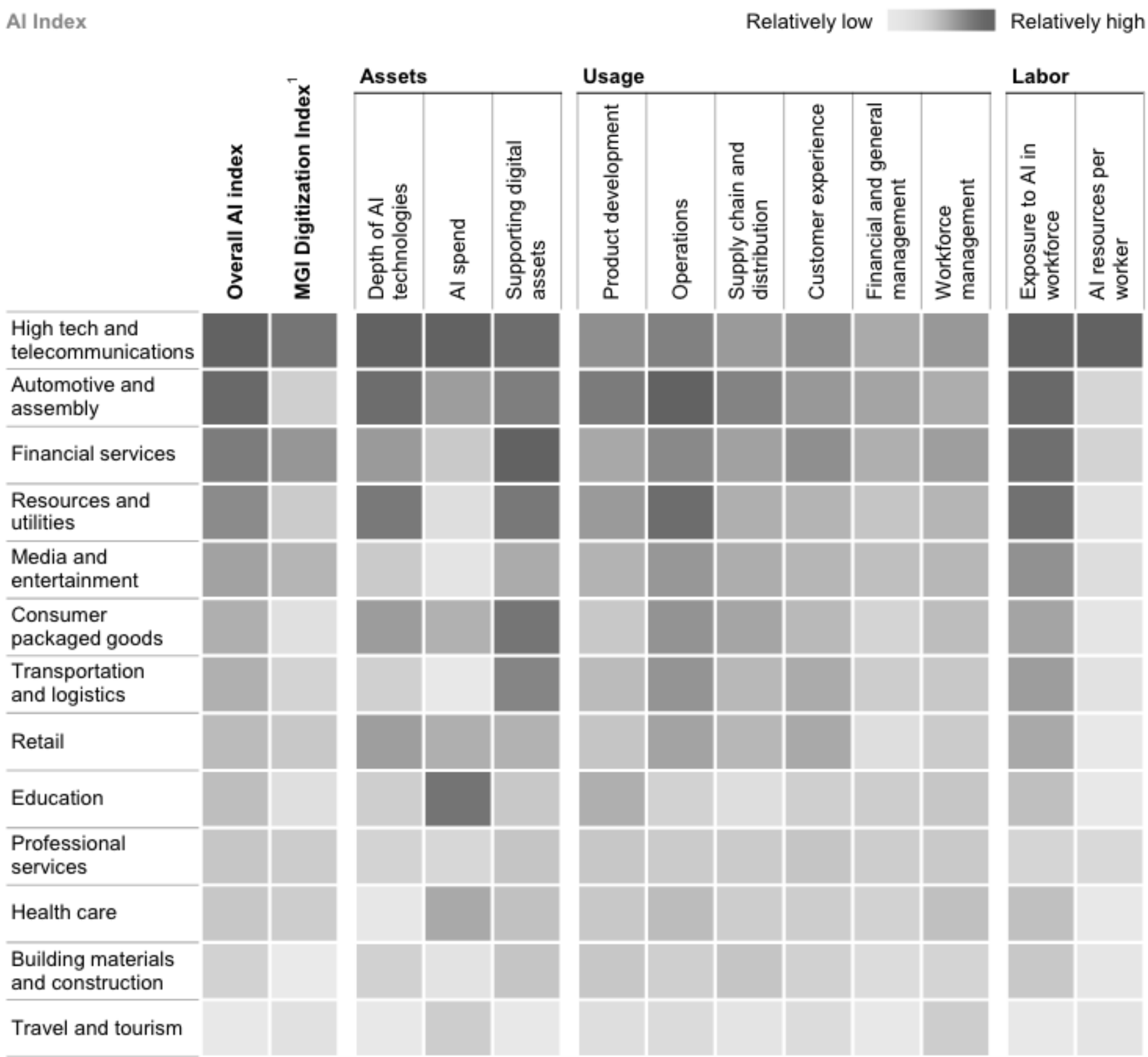

Figure 25. AI adoption/ AI index (McKinsey Global Institute AI adoption and use survey, 2017b)

In “The Innovation Premium to Low-Skill Jobs”, Aghion et al. (2018) found that more R&D intensive firms pay higher wages on average. They analysed that workers in low-skilled occupations are better off working in more R&D intensive firms than workers in high-skilled occupations. Developing a simple model, the authors delivered results where the complementarity between employees in “high-skilled occupation” and “low-skilled occupation” within the firm upturns proportionally with the firm’s degree of innovativeness, suggestion that workers in low-skilled occupations stay longer in more innovative firms.

It is needed a certain amount of time for the implementation of new technologies to become successful. The Center for Management in Denmark and Fremtidstanken – a forum for innovation thinkers – initiated a project in 2004 with the goal of developing an efficient and practical tool for managers that could lend guidance and deliver insight into managing the innovation process in an organisation in Denmark. In their report, “The Seven Circles of Innovation” Figure 37., is explained that for a successful implementation of an innovation, one needs to change the structure, the strategy, the culture etc. of the organisation and it requires coordination - like a Monet made of puzzles. The figure shows how innovation is only possible when the five development and learning circles of ideas, evaluation, prototyping, planning and implementation are connected and set into motion and synergy. Each of the circles has a role in the market, yet, as it is underlined in the report, building on the fundamentals and connecting and overlapping with each other, to create a continuous learning and development loop, enables growth.

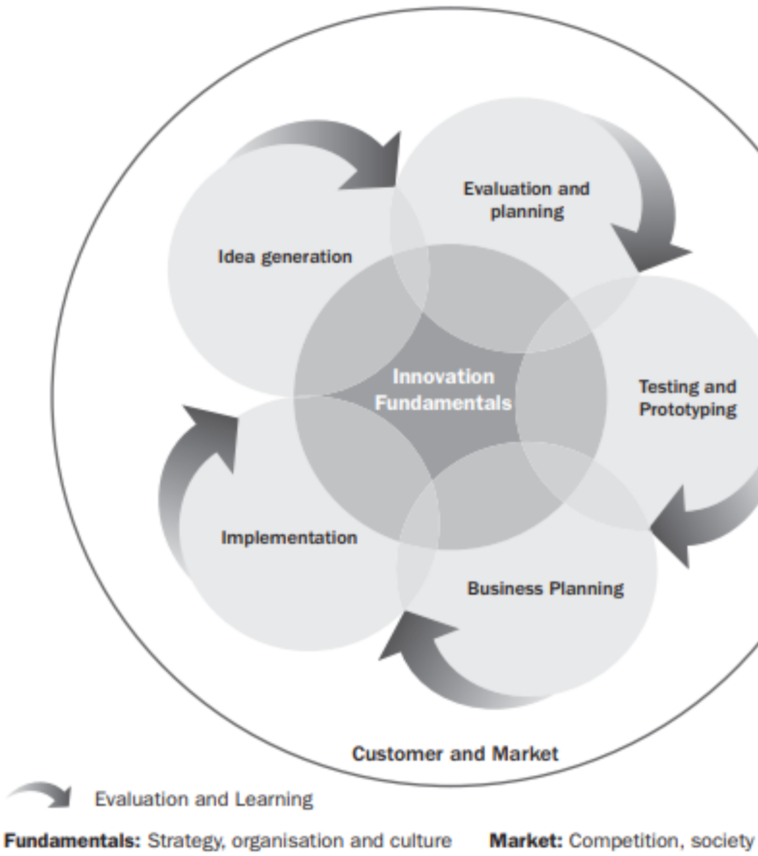

Figure 26. The Seven Circles of Innovation (The Center for Management in Denmark and Fremtidstanken, 2014)

Continuous learning includes:

- Focus on patients and regulators as partners, building partnerships that are strategic and relationship-driven
- Focus on external innovation and expanding a richly networked ecosystem

- Focus on mobilizing data and collaborating with non-traditional partners like start-ups and tech giants
- Focus on outsourcing for advanced technologies and manufacturing capabilities, and choosing vendors who share similar values and risk profiles

The main question they try to answer is how to achieve excellence in managing innovation. In the report is clear that a successful innovation should be correctly implemented. It requires an enduring managerial effort to consistently put focus on developing such a culture between workers and apply in their work mindset. Innovation projects are responsible for between 6 percent and 30 percent added revenue, with an average close to 20 percent which is important when taking into account that general revenue growth rates of between 5 percent and 10 percent. Companies who tend to be competitive and successful have to adapt to innovations and "live and breathe innovation". Efficient innovation management benefits also by generating savings, close to 10 percent on average. Public organisations have better results with higher savings, between 20 percent and 50 percent.

A significant result is that the team from the Center for Management in Denmark and Fremtidstanken delivered, in my opinion, is that innovation management delivers results regardless of the industry or the size of the company. Whenever those companies are small, large or companies in high-tech sectors, as the contribution to growth from innovation depends on the quality of the management effort in Denmark.

Chief Economist for Bloomberg Economics Tom Orlik (2019) stated that "The battle for control of the global economy in the 21st century will be won and lost over control of innovative technologies. Korea's number one spot and China's shift up the rankings is a reminder that the U.S. trade war might slow but won't stop Asia's technological rise."

The annual Bloomberg Innovation Index analyses many criteria using seven metrics, including research and development spending, manufacturing capability and concentration of high-tech public companies for the seventh year in a row, Table 54. South Korea is named most innovative country in the world. Bloomberg (2019) confirmed that Germany almost caught six-time champion South Korea on the strength of added-value from manufacturing and research intensity, that was built around industrial giants such as Volkswagen AG, Robert Bosch GmbH and Daimler AG. Germany in second place is rapidly building a reputation as Europe's tech start-up capital. Finland got third place and is in the top 10 in five of the seven categories: Productivity and Patent Activity:

5th place, Research Concentration: 8th place, and R&D Intensity and Tertiary Efficiency: 9th place, making name as a country with sustainable and steady growth. Sweden came in as the 7th most innovative country getting highest points in R&D Intensity, Research Concentration, Productivity and High-tech Density. The United States came in 8th, excelling in High-tech Density and Patent activity. In the category for concentration for high-tech company, a ranking not adjusted for the size of an economy and population, United States is the winner. Although, majorly thanks to Samsung, Korea is leading in the number of patents this year, Japan came in second place while United States and Germany in fourth and fifth. In the category research and development, Finland, Sweden and Japan came in third, fourth and fifth. In the overall ranking, all the countries analysed in this dissertation came in the top ten but the United Kingdom.

The UK fell from 17th in 2018. to 18th this year and lost out to China for the first time. China's score was due to it ranked No. 2 in patent activity on the strength of R&D from Huawei Technologies Co. and BOE Technology Group. The UK's highest scores were in the category Tertiary Efficiency, defined as total enrolment in tertiary education, where it was ranked 5th worldwide, in the category High-Tech Density where the score was 14th, and category Patent Activity where it came in 19th place.

Bloomberg 2019 Innovation Index

2019 Rank	2018 Rank	YoY Change	Economy	Total Score	R&D Intensity	Manufacturing Value-added	Productivity	High-tech Density	Tertiary Efficiency	Researcher Concentration	Patent Activity
1	1	0	S. Korea	**87.38**	2	2	18	4	7	7	20
2	4	+2	Germany	**87.30**	7	3	24	3	14	11	7
3	7	+4	Finland	**85.57**	9	16	5	13	9	8	5
4	5	+1	Switzerland	**85.49**	3	4	7	8	13	3	27
5	10	+5	Israel	**84.78**	1	33	8	5	36	2	4
6	3	-3	Singapore	**84.49**	13	5	11	17	1	13	14
7	2	-5	Sweden	**84.15**	4	15	9	6	20	5	25
8	11	+3	U.S.	**83.21**	10	25	6	1	43	28	1
9	6	-3	Japan	**81.96**	5	7	22	10	39	18	10
10	9	-1	France	**81.67**	12	41	13	2	11	20	15
11	8	-3	Denmark	**81.66**	8	21	15	12	19	1	28
12	12	0	Austria	**80.98**	6	11	12	24	8	9	18
13	14	+1	Belgium	**80.43**	11	26	10	9	41	16	9
14	13	-1	Ireland	**80.08**	32	1	1	16	15	14	38
15	16	+1	Netherlands	**79.54**	16	29	21	7	42	12	12
16	19	+3	China	**78.35**	14	13	47	11	6	39	2
17	15	-2	Norway	**77.79**	17	49	23	15	17	10	11
18	17	-1	U.K.	**75.87**	20	45	26	14	5	21	19
19	18	-1	Australia	**75.38**	19	56	17	20	18	15	6
20	22	+2	Canada	**73.65**	22	39	27	22	31	19	8

Figure 27. Bloomberg Innovation Index 2019 (Bloomberg, 2019)

Based on data from sources including the World Bank, IMF and OECD, Bloomberg's list listed the top ten most innovative countries: South Korea, Germany, Finland, Switzerland, Israel, Singapore, Sweden, United States, Japan, and France. The World's Most Innovative Economies can be seen on the map represented by Figure 42.

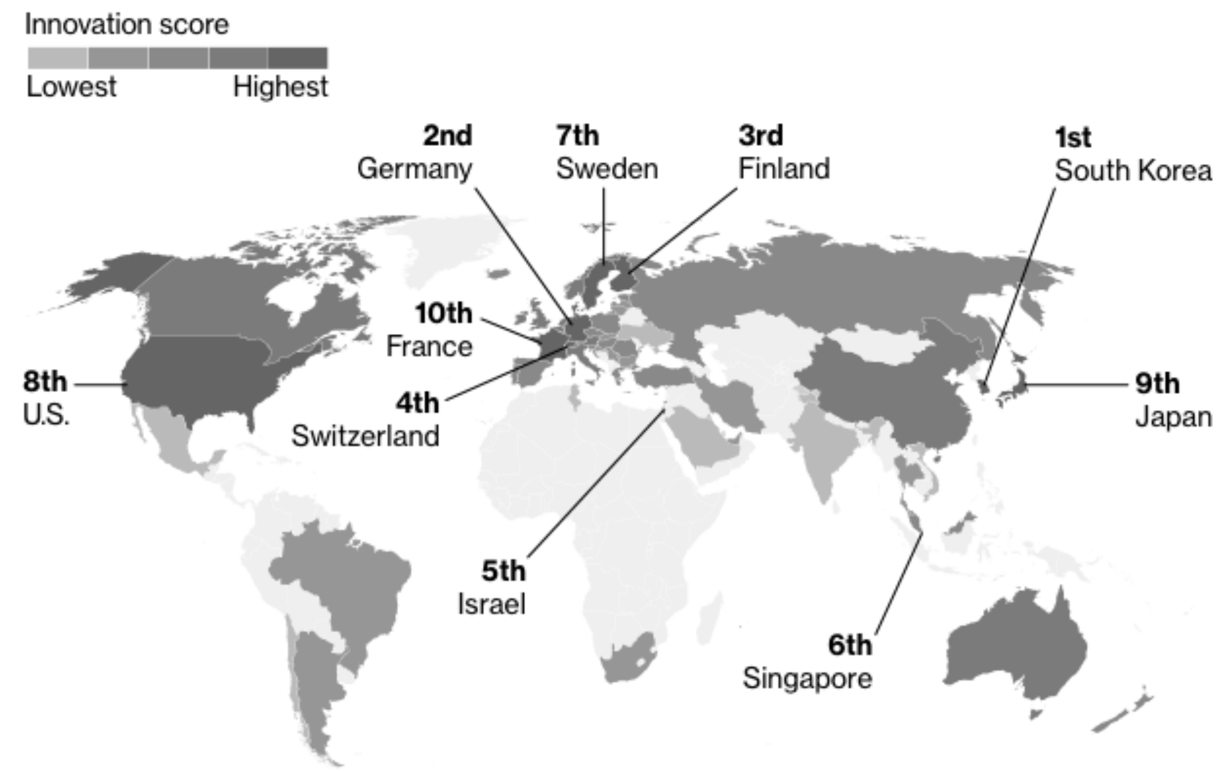

Figure 28. World's Most Innovative Economies (https://www.bloomberg.com/news/articles/2019-01-22/germany-nearly-catches-korea-as-innovation-champ-u-s-rebounds)

AI-driven automation helps to boost total factor productivity growth and create new potential to improve lives. The benefits of technological change and economic growth, however, are not necessarily shared equally. This can depend on both the nature and speed of the technological change as well as the ability of workers to negotiate for the benefits of their increased productivity. Understanding the determinants of technology adoption is key to explaining cross-country variation in total factor productivity (TFP). Robert Solow (1956), suggested that the long-run growth in income per capita in an economy with an aggregate neoclassical production function is driven by growth in total factor productivity (TFP). Comin (2006) recognised that a large portion of TFP growth is caused by endogenous innovation decisions, he positively linked innovation development with TFP growth rate. Beaudry et al (2005) suggests that the process of introducing new technologies could be costly and interact in nontrivial ways with demographic forces. These results also suggest that for countries close to the technological frontier with good institutions and broadly adequate support for research, development, and entrepreneurship, concerns about slow TFP growth may be less pressing as long as labour growth remains strong. In the paper Productivity or Employment: Is It a Choice? authors De Michelis, Estevão and Wilson (2013) suggest that countries which enact policies to reduce the cost of labour or increase immigration should not necessarily be alarmed to find TFP growth slowing.

6.2.2. AI and the Labour Market: Employment

Once a year, all the leaders from around the world gather in Davos at the World Economic Forum’s Annual Meeting to discuss the most urgent issues that are facing society. The meeting focused on the strategic implications of Globalization 4.0 and its future impact on cooperation on a global scale and the Fourth Industrial Revolution. They talked a lot about the future of work, where experts highlighted five of the most important insights (Mphuthing, 2019).

1. Jack Ma, Executive Chairman Alibaba Group Holding, suggested that it's smart to hire people smarter than you. "When I hire people, I hire the people who are smarter than I am. People who four, five years later could be my boss. I like people who I like, who are positive and who never give up."
2. IBM CEO Ginni Rometty says that as automation continues apace the skills gap and job insecurity fears are real. “When we talk of a skills crisis, I really do believe that 100 % of jobs will change,” realising that new collar workers are the future.
3. LinkedIn Co-Founder and Vice-President of Product Allen Blue underlines the importance of AI and machine learning to how all technology is built, when one considers phones, banking and many other products and activities. “It’s important, as we go forward, that we are designing and building that tech in the right way,”. He founds it fundamental to recruit women into technical roles since it will make machines learning more efficient.
4. France's Minister of Labour, Muriel Pénicaud, talked more about her re-skilling programme. The programme is designed in a way that includes giving employees 500 Euros a year to choose their own training programme. "Today access to capital is easier than access to skills," she said, "Many of our citizens think they are victims of globalization and technology. When you are not in the driving seat, change is always a threat. You need to be in the driving seat, you need to be able to choose your future."
5. John Flint, the CEO of HSBC, noted that survivors are assets and wants to create more supporting workplaces. He noted that survivors of mental health challenges are good for business, "Those who have recovered often possess a resilience and resourcefulness".

Automation, robots and artificial intelligence are having an arguably transformative effect on labour markets advanced economy (Acemoglu and Restrepo, 2017b).

In the Global Impact Report (2018) the team from Deloitte asked its readers to consider the following statistics:

- 65 percent of primary school children will work in jobs that do not exist today
- By 2030, one in five workers will not have even a basic education
- 750 million adults around the world are illiterate; two-thirds are women
- 2 billion jobs will be supplanted by automation by 2030

Economic growth over the last 50 years has been driven equally by growth in productivity and growth in labour supply. But no longer. Demographic effects, such as aging and falling birth rates, technology innovations are now set to dramatically slow the growth in labour supply. Adrjan (2018) suggests that one leading account is that technological change or declines in the price of capital relative to labour have led firms to substitute capital for labour, thus decreasing the overall share of income that accumulates to the latter factor of production (Acemoglu, 2003; Bentolila and Saint-Paul, 2003; Karabarbounis and Neiman, 2014).

Bringing the physical and digital worlds together will have a profound alteration and shift how humans live and work. It has now, become a question of identity.

Digital progress lowers prices, improves quality, and brings us into a world where abundance becomes the norm. But as technology races ahead, what it leaves behind can become a concern. Oliner et al. (2007) found that from 1995-2000, IT capital investments contributed 1.09 percentage points to annual US productivity growth, but its contribution subsequently dropped to 0.61 percentage points from 2000-2006.

Similarly, Jorgenson et al. (2011) found that IT capital was responsible for 1.02 percentage points of the annual output growth experienced from 1995-2000 in the US, and then only 0.49 percentage points of annual output growth from 2000-2007. Acemoglu and Restrepo (2016) argue that the decrease in productivity growth is more affected by a slower creation of new tasks or investment in developing technologies them automation.

Forward-thinking organizations already started selecting business-use cases that could deliver measurable value through AI-powered capabilities. The hype of AI's potential must be embraced in a balanced environment that will be able to develop the ability and skills to operate.

Carbonero F., Ekkehard, E. and Weber, E. (2018) found that robots have led to a drop in global employment of 1.3% between 2005 and 2014. The impact is weaker in developed countries, -0.54 percent but much more significant in emerging countries with about 14 percent. In their work they confirmed the result of De Backer et al. (2018), robots reduce the trend in offshoring. Robotization in developed countries have a negative effect on employment in emerging countries, providing the first evidence of cross-country effects via robot-driven re-shoring.

Graetz and Michaels (2018) suggested that industry-country that saw more rapid increases in robot density from 1993-2007, experienced larger gains in labour productivity. It needs to be mentioned once again: larger increases in robot density translated into increasingly small gains in productivity, suggesting that there are diminishing marginal gains from increased use of robots.
Countries with a stronger focus on high qualified workers have lower shares of workers at high risk. The reason is that high skilled workers rarely perform automatable tasks compared to low skilled workers. Automatability of jobs is lower in jobs with high educational job requirements or jobs which require cooperation with other employees or where people spend more time on influencing others. AI detects patterns and creates predictions, but it still fails to act or replicate social or general intelligence, creativity, or human judgment.

The Great Decoupling is not going to reverse course since progress in digital technologies are not about to stop.

Brynjolfsson and McAfee strongly believe that there has never been a better time to be a worker with special technological skills, but it certainly is no big advantage or great time to have ordinary skills (Bernstein and Raman, 2015). Frey and Osborne (2013), conducted a research where they stated that over the next two decades, 47 percent of US workers are at risk of automation. A report from McKinsey lowered that number to a 45 percent, while the World Bank estimated that 57 percent of jobs in the OECD could be automated over the next two decades (World Development Report, 2016). Technologies will alter the way we work and work itself around the world (Brynjolfsson and McAfee, 2012; Ford, 2016; McKinsey, 2017).

It is a challenge to predict exactly which jobs will be most immediately affected by AI - driven automation. There were reports and many of them had different results.

AI represents a collection of technologies that companies and economies can use to their advantage. Not all jobs will be evenly affected by AI and automation. Specific prediction that are based on the current trajectory of AI technology can list some jobs that can be done by machines and robots. One of them is driving-dominant professions where an automated vehicles (AV) can perform better taking into account capabilities of navigation, analysing dynamic surroundings and optimisation in general.

"Automation and Independent Work in a Digital Economy" is a policy brief on the future of works issued by OECD (2016), where it is argued that technological innovation is positively associated with employment in all groups of occupations (OECD, 2015) but artificial intelligence (AI) and digitalisation challenge high-routine jobs (Marcolin et al. 2016). In the brief is included Figure 5. Job polarisation in the European Union, Japan and the United States.

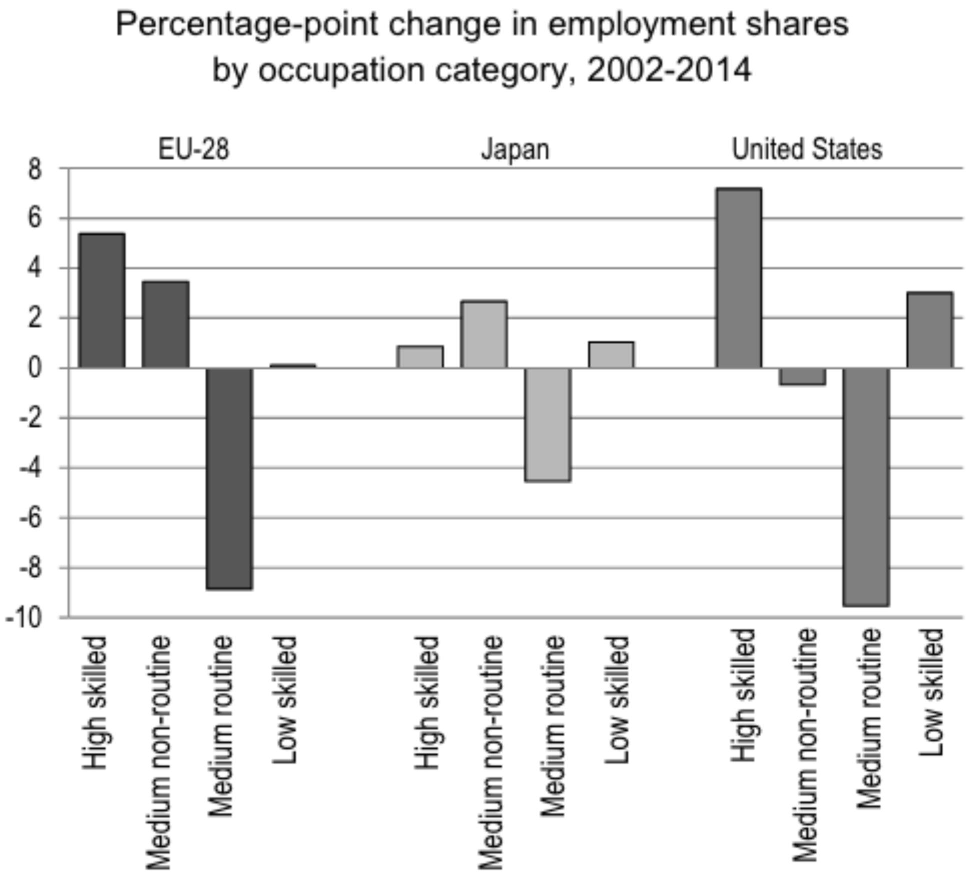

Figure 29. Job polarisation in the European Union, Japan and the United States (OECD, 2015)

It is visible that medium routine sections, in Japan, European Union and in the United States has the highest risk of automation.

Activities that are at higher risk to be more easily automatable are those including physical activities in highly predictable and structured environments, as well as data collection and data processing. These activities report for 51 percent of wages in the US economy. They are more present in sectors such as accommodation and food service, manufacturing, transportation and warehousing, and retail trade. The analysis includes 46 countries representing about 80 percent of the global workforce that has automation potential. The estimation resulted in about half of the activities that people are paid almost $15 trillion to do in the global economy have the potential to be automated by adapting currently demonstrated technology. A limited proportion of all occupations, about 5 percent, consist of 100 percent of activities that are fully automatable using currently demonstrated technologies. It is also found that about 30 percent of the activities in 60 percent of all occupations could be automated. Taking into account all the changes, workers will have to work aside with machines, that will also require additional skills. The rapid evolution in the nature of work will not leave anyone out - it will affect everyone from landscape gardeners, accountants—and CEOs; a high 25 percent of CEOs' time could be saved by machines analysing reports and data to inform decisions (McKinsey, 2017).

Automation leads to an increase in demand for capital and the rental rate, resulting in capital accumulation. In possible periods of fast automation, labour share declines and capital accumulation accelerates even if the elasticity of substitution between capital and labour is less than one. As Piketty argued (2014), rather than being the cause of the decline in the labour share, capital accumulation may be a response to automation and lessen its negative impact on the labour share (when the elasticity of substitution is less than one) Karabarbounis and Neiman (2013). Adrjan (2018) was in line when he stated that the elasticity of substitution between capital and labour may be greater than 1 at firms that employ a low-skilled workforce.

In "Low-Skill and High-Skill Automation", Acemoglu and Restrepo (2018a) state that automation squeezes out tasks previously performed by low-skill labour, and the creation of new tasks directly benefits high-skill labour, increase inequality. In the long-term implications of the creation of new tasks differ, the reason is that the new tasks are later standardized and used by low-skill labour. The authors warned that if this standardization effect is sufficiently powerful, there exists a BGP in which not only the factor distribution of income (between capital and labour) but also inequality between the two skill types stays constant.

In the “Race between man and machines” Acemoglu and Restrepo (2017b) show that automation always displaces the type of labour it directly affects, depressing its wage. The productivity effect is a counteracting effect that pushed up the price of all factors. The net impact of automation that directly affects the factor in question depends on the balance between the displacement and productivity effects. The effects are subjects to the gap between the effective cost of producing marginal tasks by labour and that by capital.
The same authors in “Artificial intelligence, automation and work” (2018) highlight other countervailing forces. The first one is the already mentioned productivity effect, capital accumulation and deepening of automation - all of them tend to increase labour demand.

The workforce of the future needs to navigate this wave of change, and businesses have a chance to lead all sectors of society through it.
Autor and Fournier (2019), did a research where they presented that in the suburban and rural U.S. populations during the last four decades the demand for certain labour-intensive, low-skill occupations is rapidly rising, while Acemoglu and Restrepo (2019) argued in “Demographics and Automation” about adoption and development of technologies that are receiving a powerful boost from demographic changes especially in a number rapidly-aging countries. All the mentioned changes are marking the future of new working generations and further research is needed. Lin (2011), Autor and Salomons (2019) identified one rapidly growing set of occupations, which they label ‘frontier jobs,’ that involve producing, installing, maintaining, and deploying new generations of technologies (Autor, 2019).

Technological change also generates additional jobs through demand for new technologies and through higher competitiveness fewer jobs have either very high or very low values of automatability when taking into account the variation of task- structures within occupations. AI may develop in the same way as the technologies before it, creating new products and new jobs such that the bulk of individuals will be employed as they are today (Budd, 2011). The sole invention of the personal computer in the US (since 1980), led to the creation of 18.5 million new jobs.
Another example is US’s transition out of agriculture. The decrease in farming jobs in the US was accomplished with high amounts spent on secondary education and new laws enforcing compulsory attendance. An interesting comparison to see the efficacy of the changes was that in 1910, only 18 percent of children aged 14 to 17 went to high school. 30 years later, in 1940, the

percentage jumped to 73 percent. Acemoglu and Restrepo (2016) documented that in the period between 1980 and 2010, new tasks and job titles helped to expand about half employment growth.

Di Pietro, Girsberger and Vuille (2007) have identified seven aspects of employment on which economic globalisation may have an impact:

- number of jobs
- structure of job
- composition of jobs
- R&D jobs
- job earnings
- migrations
- employment conditions

The World Bank (2019) suggests three way how to prepare and prevent negative consequences:

- Invest in human capital especially in disadvantaged groups and early childhood education to develop the new skills that are increasingly in demand in the labour market, such as high-order cognitive and socio behavioural skills.
- Enhance social protection to ensure universal coverage and protection that does not fully depend on having formal wage employment.
- Increase revenue mobilization by upgrading taxation systems, where needed, to provide fiscal space to finance human capital development and social protection.

The utilisation of new technologies is a slow process, due to economic, legal and societal hurdles, so that technological substitution often does not take place as expected.
These integrated developments are leading us in a new era of globalization. Whether it will improve the human condition will depend on whether corporate, local, national and international governance can adapt in time. Comin (2006) in his work listed the authors of the increasing number of theories linking the adoption of technologies to the role of institutions (Acemoglu et al., 2006), financial markets (Alfaro et al. (2006) and Aghion et al., 2006), endowments (Caselli and Coleman, 2006) and policies (Holmes and Schmitz, 2001).
Even if new technologies are introduced, workers can adjust to changing technological endowments by switching tasks, thus preventing technological unemployment.

The focus of policy makers should be on the relationship between education and automatability. How different types of automation technologies affect wages, unemployment, and inequality is an important area for research.

7. Discussion and results

In the panel data analysis (stacked time series), 6 cross-sectional units are analysed. The cross-sectional units (countries) with its corresponding abbreviations are:

1. Finland (FIN)
2. Germany (DEU)
3. Japan (JPN)
4. Sweden (SWE)
5. United Kingdom (GBR)
6. United States of America (USA)

Data for each country is available for the period 1975-2014. Thus, we have a balanced panel with 6 cross-sectional units and 39 time periods. In all, therefore, we have 234 observations.

7.1. GDP per capita, Total factor productivity, Capital intensity and Labour productivity

In the first model, we observe the following variables:

- Total factor productivity (TFP)
- KOF Index of globalisation (KOFGI)
- GDP per capita (GDPpc)
- Crisis that occurred in 2009
- Crisis that occurred in 1991, 1992 and 1993

In the model, the abbreviations that are used for Total factor productivity is *TFP* and are acting as regressors in the model. The dependent variable is GDP per capita with abbreviation *GDPpc*, that needed to be differentiated and one lag deducted to avoid autocorrelation and to interpret the influences of the variables on the rate of economic growth. *KOFGI* is the abbreviation for KOF Globalisation Index. If the error term u_t in the distributed lag serially correlated, statistical inference that rests on usual (heteroskedasticity-robust) standard errors can be strongly misleading. Heteroskedasticity- and autocorrelation-consistent (HAC) estimators of the variance-covariance matrix circumvent this issue (Heiss, 2016).

The variables for crises were added since they were significant. The abbreviation dt_35 represents the financial crises that occurred in 2009 while the financial crises that happened in 1991, 1992 and 1993 are grouped in the abbreviation crisis_1l.

7.1.1. The financial crises

A global recession is an extended period of economic decline worldwide. The International Monetary Fund (IMF) has a vast set of criteria that uses to identify global recessions, including an annual (PPP) decrease in per-capita gross domestic product (GDP) around the world. According to the definition issued by the International Monetary Fund, the drop in global output must coincide with a weakening of other macroeconomic indicators, like trade, capital flows, and employment (IMF, 2009).

In order to obtain more accurate results regarding the impact of globalisation and AI driven automation, financial crises had to be taken into account. In the figure below, a representation of derivation of GDP per capita is shown.

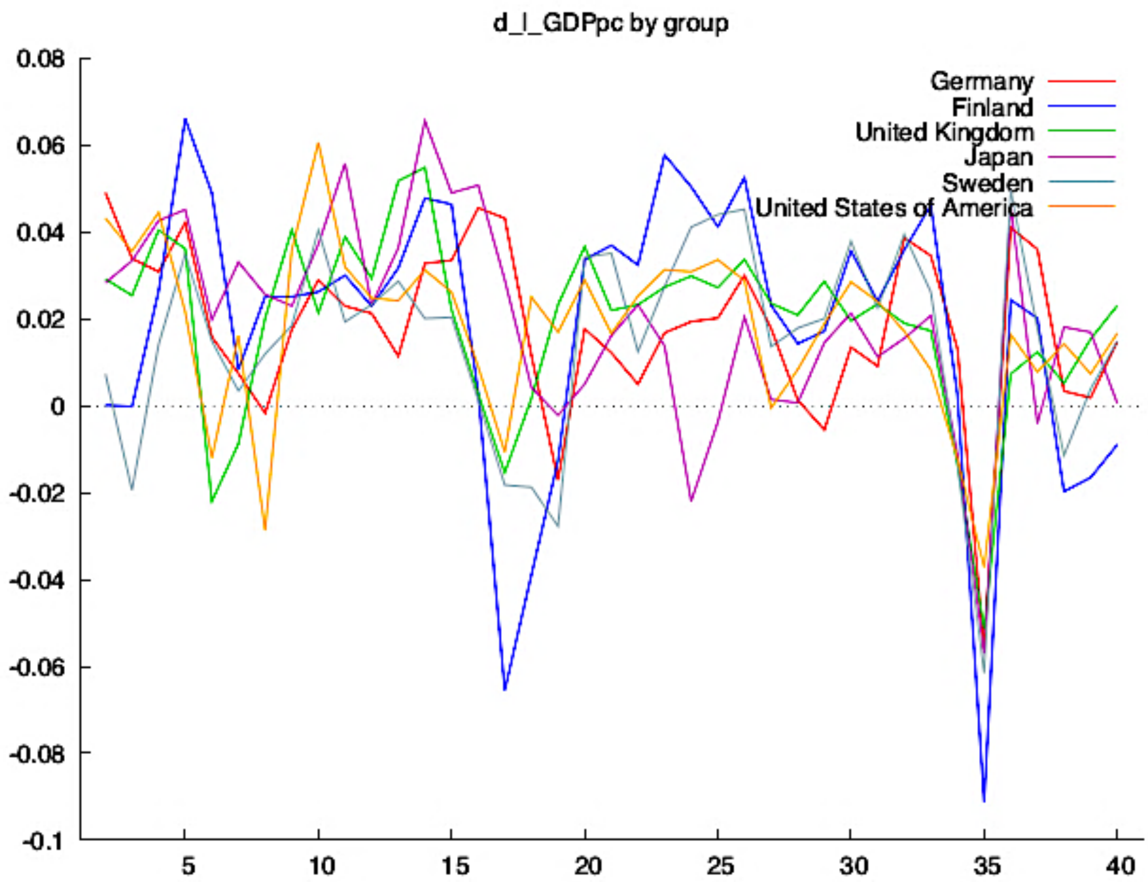

Figure 30. First derivation of GDPpc (Author's calculation)

The graph was created in the Gretl software and shows the following countries represented by numbers:

1. Germany (DEU) - red colour
2. Finland (FIN) - blue colour
3. United Kingdom (GBR) - green colour
4. Japan (JPN) - purple colour
5. Sweden (SWE) - grey colour
6. United States of America (USA) - yellow colour

From the graph, it can be seen that there were a lot of fluctuations in the 40 analysed years. Two of the financial crises that have had the greatest impact on the GDP per capita shown in the graph are the one from the period 1991, 1992 and 1993, and the second and latest financial crisis, from 2007 to 2009. The period 1991 to 1993 are represented by time dummy variables d_17, d_18 and d_19 grouped in the abbreviation crisis_l1.

According to the IMF's definition, since World War II there were only four global recessions in 1975, 1982, 1991 and 2009, all of which lasted only a year. Looking at global GDP by the more traditional method using exchange rates, the 1991 recession lasted until 1993 (Davis, 2009).
The financial crisis that happened in the 90's started in the USA during the presidency of president Ronald Reagan. By cutting taxes on the very wealthy, the policy brought an economic boom occurred but also an insufficient funding of expenditures. The policy resulted in large deficits and deeply affected 'Black Monday' and the Stock Market Crash of 1987.
The Federal Reserve Bank, to prevent additional deficits, tried to apply a restrictive monetary policy in order to restrain inflation and stabilize prices. The recession that began in July 1990 and ended in March 1991, was caused by the significant limit in economic growth as a result of that monetary policy.

When Iraq invaded Kuwait in August 1990, within a week of the invasion, crude oil prices had risen to well over $20 a barrel, an undesirable growth that affected everyone at the gas pump. Even though oil prices afterwards stabilized, the spike of oil prices that took place in 1990 added more insecurities to consumers and investors, despite the fact that the recession officially ended in March 1991.

The financial crisis from 2007 to 2009, is represented by time dummy variables d_33, d_34 and d_35. According to the IMF definition, the recession lasted only for one calendar year of 2009, which corresponds to d_35.

Below, two equations with the following variables will be shown:

1. crises_l1 and crises_l2
2. crises_l1 + d_17, d_18 and d_19; and crises_l2 + d_35

First equation (Author's calculation):

$$\hat{}d\_l\_GDPpc = \underset{(8.406)}{0.415} - \underset{(-7.867)}{0.0891} * l\_KOFGI + \underset{(5.452)}{0.0500} * l\_TPF - \underset{(-3.160)}{0.0269} * crisis\_l1 - \underset{(-5.318)}{0.0309} * crisis\_l2$$

n = 234, R-squared = 0.283

(t-ratio in parentheses)

From the high t-ration (>2), it can be seen that all variables are highly significant.

Second equation:

$$\hat{}d\_l\_GDPpc = \underset{(7.658)}{0.3974} - \underset{(-7.151)}{0.0852} * l\_KOFGI + \underset{(4.946)}{0.0448} * l\_TPF - \underset{(-3.185)}{0.0251} * crisis\_l1 -$$

$$\underset{(-1.129)}{0.0071} * crisis\_l2 - \underset{(-0.2797)}{0.0049} * dt\_17 - \underset{(-0.03220)}{0.00027} * dt\_18 - \underset{(-7.335)}{0.0704} * dt\_35$$

The reason for showing the equations is to present and follow the IMF's definition of global recession. The 1991 recession lasted until 1993, using market weights, all other recessions lasted one year.

As can be interpreted from the second equation, grouped time dummy variables under the abbreviation *crisis_l1* are significant to the model while individual time dummy variables *dt_17* and *dt_18* (*dt_19* is omitted due to correlation) are not. It is also shown that the variable *dt_35*, representing the year 2009, is highly significant to the model while the grouped variables *crisis_21* is not. Since the variable *dt_35* representing the year 2009 is highly significant and *crisis_21* is not, in the following models the used variables representing financial crises will be *crisis_l1* and *dt_35*.

Before proceeding, it is important to run the unit root test. The panel unit-root test is described by Levin, Lin and Chu (2002). The null hypothesis is that all of the individual time series exhibit a unit root, while the alternative is that none of the series has a unit root. In Table 54, the unit root results are displayed for N= 6, T = 40 and 234 observations, at a 5% significant level. Results show that the times series for all countries for l_TFP and l_KOFGI are stationary, while in its first derivation, GDPpc is stationary at a 5% significant level.

Table 54. Levin-Lin-Chu pooled ADF test for the variables TFP, KOFGI and GDPpc (Author's calculation)

Variable	**Levels**	**P-value**	**Log**	**P-value**	**1st Difference**	**P-value**
TFP	0.494075	$p < .05$	-0.089148	$p < .05$	-8.51852	$p < .05$
KOFGI	-2.51478	$p < .05$	-0.24092	$p < .05$	-12.6873	$p < .05$
GDPpc	0.675206	$p < .05$.	-0.094501	$p < .05$.	-6.37587	$p < .05$

7.1.2. Pooled OLS

As already mentioned, there are mainly three types of panel data analytic models: (1) constant coefficients (pooled regression) models, (2) fixed effects models, and (3) random effects models.

The first one that will be analysed will be the pooled regression. As seen in chapter 5 (Panel data), the equation is:

$$u_{it} \sim IID\,(0, \sigma^2{}_u), \qquad i = 1, 2, \dots, 6; t = 1, 2, \dots, 39.$$

$$Y_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} + u_{it}.$$

Equation 1. Model 1: Pooled OLS (Author's calculation)

^d_l_GDPpc = 0.133 + 0.00268*l_TPF - 0.0254*l_KOFGI - 0.0791*dt_35 - 0.0266*crisis_l1

(6.547) (0.4438) (−5.091) (−9.205) (−2.91412)

n = 234, R-squared = 0.400

Ordinary least squares was conducted to explain the relationship between the countries. Above in Equation 1, we can see the estimated coefficients.
The estimates of the marginal effects l_TPF, l_KOFGI, dt_35 and crisis_l1 and the intercept are given as coefficients along with the standard error and the corresponding t-ratio and p-value. Note that the t-ratio is estimated when the ratio of the coefficient value is divided with the corresponding standard error. The marginal effects of l_KOFGI, dt_35 and crisis_l1 are statistically significant. As it is visible, l_TPF is not statistically significant. The results show that an increase of 1% in Total factor productivity will result in an increase of 0.26% in the economic growth rate. The Globalisation Index, as well as the crises in the 2009 and the one from 1991-1993, had a significant negative impact on the rate of economic growth. An increase in Globalisation Index of 1% will have a negative effect and decrease 2.54% economic growth rate, while the crises of the year 2009 decreased it for 7.9% and those of 1991-1993 decreased the growth rate of GDPpc for 2.65%.
The R-square (R^2) for the regression model represents the measure of goodness of fit or the coefficient of determination, indicating that our model with four explanatory variables, l_TPF, l_KOFGI, dt_35 and crisis_l1, accounts for (or explain) about 40% of the variation in GDP per capita, leaving 60% unexplained.

The F-statistic tests the joint null hypothesis that all the coefficients in the model but the constant is zero. The p-value associated with this F-statistic is given as 0.000078. Hence, we reject the null hypothesis and conclude that the model as a whole is highly significant.
Running the Wald test for heteroskedasticity, the null hypothesis that the units have a common error variance cannot be rejected with the p-value = 0.314125. The model does not account for heteroskedasticity. The test for normality of residual, with p-value = 0.0683359 shows that the error is normally distributed.

7.1.3. Least squares dummy variable (LSDV) Model

Fixed effects model (FEM) consists of levels values of independent variables that are assumed to be fixed (or constant) while the dependent variable changes as a reaction to the levels of independent variables.

This section will include two models : (i) Least Squares Dummy Variable model and (ii) Within-groups regression model. The Least Squared Dummy Variable will include Slope coefficients constnat but intercept varies over countries and Slope coefficients constnat but intercept varies over time.

7.1.3.1. Slope coefficients constant but intercept varies over countries

The first assumption is that no significant temporal effects, but significant differences among countries. Meaning that a linear regression model in which the intercept terms vary over individual countries; the model can be presented as a one-way error component model:

$$u_{it} = \mu_i + v_{it}, v_{it} \sim IID\ (0, {\sigma^2}_v), \qquad i = 1, 2, \dots, 6, t = 1, 2, \dots, 39.$$

$$Y_{it} = \beta_1 X_{1it} + \beta_2 X_{2it} + u_{it}$$

Table 55. Model 2: Slope coefficients constant but intercept varies over countries (Author's calculation)

Model 2: Pooled OLS, using 234 observations
Included 6 cross-sectional units
Time-series length = 39
Dependent variable: d_l_GDPpc
Robust (HAC) standard errors

	coefficient	std. error	t-ratio	p-value	
const	0.414992	0.0513322	8.084	0.0005	***
l_TPF	0.0430546	0.00906190	4.751	0.0051	***
l_KOFGI	−0.0881389	0.0116224	−7.584	0.0006	***
dt_35	−0.0768644	0.00885698	−8.678	0.0003	***
crisis_11	−0.0266621	0.00862581	−3.091	0.0271	**
du_2	−0.0023976	0.000267892	−8.950	0.0003	***
du_3	0.00339960	0.000513081	6.626	0.0012	***
du_4	−0.0264190	0.00349161	−7.566	0.0006	***
du_5	0.000530674	0.000476268	1.114	0.3159	
du_6	−0.00864281	0.00109839	−7.869	0.0005	***

Model 2 in Table 55 summarizes the descriptive statistics and analysis results. We can see that the coefficients for l_TPF, l_KOFGI, dt_35 and crisis_l1 are statistically significant. A dummy variable or an indicator variable is a variable that takes on the values 1 and 0, where 1 means something is true. The least squares dummy variable (LSDV) model is also known as covariance model, since the explanatory variables are covariates. The dummy variables show that du_2, du_3, du_4 and du_6 are statistically significant and difference between countries are present. Countries that behaved differently in terms of GDPpc compared to Germany (du_1 = DEU) are Finland, United Kingdom, Japan and United States of America. Finland (du_2 = FIN) had a lower percentage of rate of economic growth compared to Germany of −0.23%, United Kingdom (du_3 = GBR) of 0.33%, Japan (du_4 = JPN) of significant −2.64% and United States of America (du_6 = USA) of −0.86%. It is shown that Sweden (du_5 = SWE) behaved similarly to Germany with a difference of 0.053% in difference in rate of economic growth. The null hypothesis that the units have a common error variance cannot be rejected with the p-value = 0.210428. Meaning, the model is not accounted for heteroskedasticity. On the other side, test for normality of residual shows that we can reject the null hypothesis that the error is normally distributed with p-value = 0.0409807. Test for differing group intercepts displayed that we can reject the null hypothesis that the groups have a common intercept with p-value = 0.0244534.

7.1.3.1.1. Slope coefficients constant but intercept varies over time

Unlike the first assumption, the second assumption is that no significant cross section differences, but significant temporal effects. A regression model in which the intercept terms vary over time; so the model can be displayed as a one-way error component model:

$$u_{it} = \lambda_t + v_{it}, v_{it} \sim IID\ (0, \sigma^2{}_v), \qquad i = 1, 2, \ldots, 6, t = 1, 2, \ldots, 39.$$

$$Y_{it} = \beta_1 X_{1it} + \beta_2 X_{2it} + u_{it},$$

Table 56. Model 3: Slope coefficients constant but intercept varies over time (Author's calculation)

Model 3: Pooled OLS, using 234 observations Included 6 cross-sectional units Time-series length = 39 Dependent variable: d_l_GDPpc Robust (HAC) standard errors

	coefficient	std. error	t-ratio	p-value	
const	−0.126921	0.0886414	−1.432	0.2116	
l_TPF	0.0664970	0.0134136	4.957	0.0043	***
l_KOFGI	0.0309262	0.0192080	1.610	0.1683	
dt_35	−0.0672010	0.0055304	−12.15	6.67e-05	***
crisis_l1	−0.000635	0.0092261	−0.068	0.9477	
dt_2	0.0410157	0.0113786	3.605	0.0155	**
dt_3	0.0327290	0.0148911	2.198	0.0793	*
dt_4	0.0467887	0.0121433	3.853	0.0120	**
dt_5	0.0534165	0.0169937	3.143	0.0256	**
dt_6	0.0236673	0.0208170	1.137	0.3071	
dt_7	0.0225019	0.0141940	1.585	0.1738	
dt_8	0.0210054	0.0171508	1.225	0.2752	
dt_9	0.0381127	0.00952597	4.001	0.0103	**
dt_10	0.0460681	0.00967776	4.760	0.0051	***
dt_11	0.0419646	0.0122786	3.418	0.0189	**
dt_12	0.0323861	0.00882107	3.671	0.0144	**
dt_13	0.0381883	0.0104978	3.638	0.0149	**
dt_14	0.0487991	0.0140701	3.468	0.0179	**
dt_15	0.0389807	0.0140718	2.770	0.0394	**
dt_16	0.0241499	0.0147651	1.636	0.1628	
dt_17	−0.00134906	0.0192328	−0.070.	0.9468	
dt_18	0.00156530	0.00880150	0.1778	0.8658	
dt_20	0.0274176	0.00795817	3.445	0.0183	**
dt_21	0.0239306	0.0102062	2.345	0.0660	*
dt_22	0.0199114	0.00990707	2.010	0.1007	
dt_23	0.0271084	0.0113369	2.391	0.0623	*
dt_24	0.0219704	0.0115828	1.897	0.1163	
dt_25	0.0230184	0.00848787	2.712	0.0422	**
dt_26	0.0291506	0.00809238	3.602	0.0155	**
dt_27	0.00662409	0.00649252	1.020	0.3544	
dt_28	0.00343175	0.00528833	0.6489	0.5450	

dt_29	0.00745958	0.00659105	1.132	0.3091	
dt_30	0.0166933	0.00741471	2.251	0.0741	*
dt_31	0.00913537	0.00516590	1.768	0.1372	
dt_32	0.0165680	0.00715807	2.315	0.0685	*
dt_33	0.0137076	0.00897851	1.527	0.1874	
dt_34	−0.0166621	0.00749894	−2.222	0.0769	*
dt_36	0.0211574	0.0105278	2.010	0.1007	
dt_37	0.00483676	0.00693200	0.6977	0.5164	
dt_38	−0.00820414	0.00688330	−1.192	0.2868	
dt_39	−0.00514553	0.00482264	−1.067	0.3348	

The 'base year' is 1975, and the constant intercept serves as the intercept for that year. As we can see, the coefficient TFP is statistically significant. This fixed effect model is also called least squares dummy variable (LSDV) model. It is also known as covariance model, since the explanatory variables are covariates. As it can be seen, in dt_2 to dt_5, dt_9 to dt_15, dt_20, dt_21, dt_23, dt_25, dt_26, dt_30, dt_32 and dt_34 there was a change related with d_GDP per capita. During the years 1976-1979, 1983-1989, 1994, 1995, 1997, 2000, 2001, 2004, 2006 and 2008 all the countries changed their behaviour.
Results from the Wald test for heteroskedasticity implicate that we cannot reject the null hypothesis: the units have a common error variance with p-value = 0.373154. The model accounts for heteroskedasticity. Additionaly, with p-value = 0.000356688, we can interpret that the error is not normally distributed.

7.1.3.2. The Fixed Effects Within-groups Regression Model

The main problem with the above fixed effects (LSDV) model is that it hosts too many regressors; this makes the model numerically not attractive and brings the problems of multicollinearity. As the number of regressors increases, the degrees of freedom fall, while the error variance rises, leading to Type 2 error in inference which is not rejecting a false null hypothesis. However, there is a simple way to estimate the fixed effects model without using dummy variables Newey and West (1987).

$$Cov(X_{it}, v_{is}) = 0; \ \forall t \ and \ s, \qquad i = 1, 2, \ldots, 6, \ \ t = 1, 2, \ldots, 39$$

$$Y_{it} = \alpha i + \beta_{it} + v_{it} v_{it} \sim \ IID \ (0, \sigma^2).$$

Equation 2. Model 4: The Fixed Effects Within-groups Regression Model (Author's calculation)

^d_l_GDPpc = 0.409 + 0.0431*l_TPF - 0.0881*l_KOFGI - 0.0769*dt_35 - 0.0267*crisis_l1
(0.0502) (0.00896) (0.0115) (0.00876) (0.00853)
n = 234, R-squared = 0.437
(standard errors in parentheses)

The estimates of the marginal effects l_TPF, l_KOFGI, dt_35 and crisis_l1 and the intercept are given as coefficients along with the standard error and the corresponding t-ratio and p-value in Table 57. The marginal effects of l_TFP, l_KOFGI, dt_35 and crisis_l1 are all statistically significant. The results show that an increase of 1% in Total factor productivity will result in an increase of 43.05% in the economic growth rate. The Globalisation Index, as well as the crises in the 2009 and the one from 1991-1993, had a significant negative impact on the rate of economic growth of 8,81%, 2,66% and 7,68%.

The R-square (R2) for the regression model represents the measure of goodness of fit or the coefficient of determination, accounts for (or explain) about 43,71% of the variation in GDP per capita, leaving 56,29% unexplained.

Distribution free Wald test for heteroskedasticity with the p-value = 0.210428, cannot reject that the units have a common error variance.

Test for normality of residual with p-value = 0.0409807 shows that we can reject the null hypothesis that the error is normally distributed.

7.1.4. Random Effect Model

In a FE model, the μ_is are assumed to be fixed. However, the main problem with the FE model is its specification with too many parameters, resulting in heavy loss of degrees of freedom. Individual error components are not correlated with each other, and not autocorrelated across both cross-section and time series units.

A simple one-way error components model is explained;

$$u_{it} = \mu_i + v_{it}, \qquad i = 1,2,\ldots,6, \quad t = 1,2,\ldots,39.$$

$$Y_{it} = \alpha + \beta x_{it} + u_{it}.$$

The marginal effects of l_KOFGI, dt_35 and crisis_l1 are all statistically significant while the one for l_TPF is not. The results show that an increase of 1% in Total factor productivity will result in an increase of 0.26% in the economic growth rate. The Globalisation Index, as well as the crises in the 2009 and the one from 1991-1993, had a significant negative impact on the rate of economic growth of 2,54%, 2,65% and 7,9%.

Equation 3. Model 5: Random Effect Model (Author's calculation)

```
^d_l_GDPpc = 0.338 + 0.0325*l_TPF - 0.0720*l_KOFGI - 0.0774*dt_35 - 0.0266*crisis_l1
             (0.0584)(0.0171)       (0.0.0137)        (0.0130)       (0.00318)

n = 234, loglikelihood = 594
(standard errors in parentheses)
```

Equation 3, shows that the marginal effects of l_KOFGI, l_TPF, dt_35 and crisis_l1 are all statistically significant. The results show that an increase of 1% in Total factor productivity will result in an increase of 3,25% in the economic growth rate. The Globalisation Index, as well as the crises in the 2009 and the one from 1991-1993, had a significant negative impact on the rate of economic growth of 7,20%, 2,66% and 7,74%.

According to Wooldridge (2010), pooled OLS is used when you select a different sample for each year/month/period of the panel data. Fixed effects or random effects are used when analysing the same sample of individuals/countries/states/cities/etc.

Breusch-Pagan test shows that the p-value is 0.477194 which is greater than 5% (v=0), resulting in the interpretation that there are no significant differences between countries.
When running the Hausman test we have to assume:

H_0: random effects would be consistent and efficient,
versus
H_1: random effects would be inconsistent.

The p-value is 0.0935527, which is greater than 5% and we cannot reject the H_0 that the random effects would be consistent. Hence, we select the RE model. The tests hints that the countries effects in the data set are not correlated with the explanatory variables. They can be taken as random; the RE estimators will be consistent.

Although the Hausman test suggests that the RE model is a better model to use, based on Judge, et al. (1988) and the simple rule that "if T is large and N small, there is little difference in the parameter estimates of FE and RE models. Hence computational convenience prefers FE model." it can be concluded that both models are good for the estimation. Results from both models imply that the selected variables are significant to the model.

Test for normality of residual, with p-value = 0.155651 confirms that the error is normally distributed.

8. Conclusion

The dissertation has been articulated in eight chapters. Chapter One briefly presented to the readers the challenges, approach and how to read the dissertation. Mapping our digital future can sometimes look as an intro in a SF movie. It is important to predict, follow the trends and develop tools to predict them. Evaluating emerging technologies is of a great value in order to recognize their full potential but also to be aware of their disruptive effects.

Chapter Two tackled the macroeconomic implications that the phenomenon of the Great Decoupling may bring. Being aware of the possibilities surrounding us can leads as to create a series of well-defined but aspirational ambitions. Such approach can create the confidence and secure needed skills to embrace digital, while preparing productive grounds to move beyond the digital frontier.

Chapter Three offered a statistical background backed by the finding of the 2019 index of economic freedom. Chapter Four offered evidence of the presence of the Great Decoupling in four major economies and Chapter Seven implemented a modified model via panel data analysis. Results gathered in the two chapters will be elaborated shortly.

Chapter Five displayed a theory on panel data analysis while Chapter Six provided arguments and literature review to build the modified model implemented and discussed in Chapter Seven.
As already mentioned, this dissertation also investigated the presence and identified potential factors influencing the phenomenon of the Great Decoupling. A research was conducted by modifying the original model of the Great Decoupling created by Brynjolfsson and McAfee where they focused on the divergence of Labour productivity and GDP per capita with Private employment and Median household income.

In particular, three main issues have been explored. First and most important, evidence of existence of the Great Decoupling demonstrated in Chapter Four. The model of the divergence with the variables of GDP per capita, labour productivity, median household income and private employment was applied to the four major world economies of the United States of America, the United Kingdom, Japan and Europe: Germany, Finland and Sweden. The variable private employment and median household income were possible to implement in the model only for the country the United States of America due to data unavailability for the remaining countries. For the other countries, instead of the original variables in the model, variables employment and index of the top 10% share of income inequality were used. The model was analysed in order to test if the phenomenon of the Great Decoupling is present in the selected countries. Each and every variable was compared to the growth rate in order to test if the difference of their means was different from 0, meaning that they were growing decoupled. In the case of the United States of America, median household income became decoupled from all the variables; in the case of Germany, employment and top 10% share became diverged from labour productivity; in the case of Japan and Sweden, labour productivity and employment became diverged while in the case of Finland and the United Kingdom - no results suggesting presence of the divergence were found.

Second, a short summary with data on average growth rates and difference in population (if the variables were stagnating or significantly growing/falling) was displayed. All the countries, except Finland, had witnessed a significant growth in labour productivity. Besides labour productivity, Germany witnessed a significant growth of GDP per capita, while the United States of America and the United Kingdom witnessed a significant growth in all the variables besides median household income/the top 10% share.

To sum up, in the main research part of this dissertation, it was analysed the relationship between the variables of GDP per capita, labour productivity, employment and top 10% share of income for the countries of Germany, Finland, the United Kingdom, Japan, Sweden and the United States of America. A trend between the rate of growth of the mentioned variables was found, confirming the high possibility of the presence of the Great Decoupling in the countries of Germany, Japan, Sweden and the United States of America. Data of the variable's private employment and median household income that were included in the original model were not available, so further research to implement the best possible replacement for mentioned variables is needed.

Finally, data for all countries were collected and a panel data model was presented in Chapter Seven. The panel data model is a model based on the opinion of the author of the dissertation that is supported by an indicative literature review. The idea is that there exists a positive impact on economic growth of technological advancement through AI-driven automation that can be represented with the variable Total factor productivity. The negative impact of globalisation on economic growth can be represented through the KOF Globalisation Index.

In the model panel data analysis, financial crisis of 2009 and the one of 1991,1992 and 1993 were included in order to prevent possible disturbances in the econometric model. With the elected variables of GDPpc, TFP and KOF GI, results implied that longer-term global trends such as technological change like AI-driven automation have a positive impact on economic growth while globalisation a negative. It is clear that technological advancement and globalisation alone cannot fully account for decoupling of wages from productivity and further research is needed. Still, it provides policy makers good grounds and more data to take into account when structuring strategies. Including public policy settings, further research may play a significant role in shaping the effects of global trends on labour shares and wage inequality. Results from the random effects model, suggested running the Hausman test, are presented in the table below.

The results demonstrate that an increase of 1% in total factor productivity will result in an increase of 3,24% on the economic growth rate. The KOF Globalisation index will have a negative impact of a decrease of 7,1% on the economic growth rate.
A carefully planned strategic model should be followed in order to adopt these technologies to gain internal and competitive confidence. Firms can grow rapidly and improve their productivity mostly because of digital transformation and education that the globalised world can now provide much easier and faster. On the other side, it can help blur the boundaries of competition, especially with local or smaller firms with much narrower economies of scale. AI driven automation can help boost productivity and innovation, which benefit would be collected by society. The other part of the coin is that if innovation is growing at a slower pace than automation, and if job creation does not follow productivity just as wages do not follow labour productivity, the only remedy is the government to intervene.

The education and learning systems of today have helped to empower the expansion of the middle class across a number of developed and developing economies. But they lack the features to achieve the scale and speed needed in the new world of work. In the hub of the fourth industrial revolution, which is defined by expeditious and unexpected change across economies and labour markets, a new common vision for talent is needed to safeguard current and future social mobility.

What have mainly motivated me in this analysis has been the recognition that the literature limits itself to consider mainly unemployment as a result of AI-driven automation consequences. I found it quite controversial that while entering the era of the fourth industrial revolution and fourth globalisation, institutions and governments are doing very little to safeguard and maintain high quality of life to workers around the world. The lack of the features to achieve the scale and speed needed in the new world of work is ruinous. The main reason of the human development is the ability to gain a decent standard of living. As the creators of such technological changes, it is not right to fear it, only to embrace it and learn how to cope with the effects that it may convey.

In the time when talent is scarce, educational institutions, businesses, education innovators and policy-makers should intensely collaborate to provide skills and knowledge to shape future generations of workers. Collaborating with law enforcing new proposals, one can introduce greater efficiency and concede re- and upskilling programmes. One of the most popular proposals, that was not mention in this dissertation, is to increase minimum wages to workers, many of whom are not able to acquire new digital skills, but nevertheless are entitled to live a dignified life.

Moreover, I dismissed the principle that higher productivity leads to higher profits: it is shown that median household income is not growing in union with other variables and that the rich get richer and the poor get poorer. Such statement is backed by the paradox that globalisation is shrinking gaps between countries, but increasing differences within countries.
Technology is changing the skills that employers seek. Workers need to be good at complex problem-solving, teamwork and adaptability. Technology is changing how people work and the terms on which they work. Even in advanced economies, short-term work, often found through online platforms, is posing similar challenges to those faced by the world's informal workers. At the beginning of chapter 12 of The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies (Brynjolfsson and McAfee, 2014) Pablo Picasso is quoted what he thinks about computers with "But they are useless. They can only give you answers.". We should not forget that human power is fuelling all the innovation and technological advancements. A pensively question asked by Comin and Mestieri (2018) is that "if technology has arrived everywhere, why has income diverged?" I think we should all start with asking the right questions.

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Appendix

Appendix

Appendix 1. Data used in Chapter 4 - United States of America

Data used in Chapter 4 - United States of America

obs	LP	GDPpc	MEDIANHOUSE	PRIVT
1984	37.95837	31535.36	50511	78385250
1985	38.68204	32559.84	51455	80996916.66
1986	39.57575	33378.72	53309	82660250
1987	39.86431	34197.35	53945	84958416.66
1988	40.33556	35284.12	54390	87835916.6
1989	40.69401	36221.12	55329	90120000
1990	41.40836	36550.05	54621	91116583.33
1991	41.90023	36163.17	53025	89891000
1992	43.39838	37079.89	52615	90010916.6666
1993	43.57846	37714.73	52334	91943500
1994	43.87330	38823.71	52942	95115166.666
1995	44.15350	39476.65	54600	97982333.3
1996	45.04831	40487.40	55394	100300250
1997	45.84536	41777.03	56533	103281500
1998	46.88815	43087.96	58612	106237166.6
1999	48.26330	44562.22	60062	108925083.
2000	49.50391	45866.84	59938	111240416.66
2001	50.64865	45844.47	58609	110974083.33
2002	52.27871	46230.65	57947	109142750
2003	54.25407	47114.27	57875	108764750
2004	55.60976	48477.21	57674	110156583.3
2005	56.68629	49657.53	58291	112235833.33
2006	57.14001	50517.59	58746	114476416.66
2007	57.84353	50939.58	59534	115775166.66
2008	58.13047	50321.10	57412	114738750
2009	59.66641	48485.10	57010	108753083.33
2010	61.08847	49288.50	55520	107863916.66
2011	60.87653	49674.81	54673	109845916.666
2012	61.25202	50390.97	54569	112254083.333
2013	61.54319	50764.77	56479	114526416.66
2014	61.83327	51620.79	55613	117065916.66

Appendix 2. Data used in Chapter 4 - Germany

Data used in Chapter 4 - Germany

obs	LP	GDPpc	Top10	E
1991	42.82017	33308.76	0.3091	37695000
1992	43.90552	33698.48	0.3044	37094000

1993	44.71898	33128.02	0.2978	36329000
1994	45.93223	33720.25	0.2934	36208000
1995	46.81578	34135.47	0.2927	36351000
1996	47.73114	34306.27	0.3018	36086000
1997	48.99393	34888.22	0.3089	35858000
1998	49.56578	35571.78	0.3162	35911000
1999	50.24242	36298.27	0.3146	36447000
2000	51.51284	37405.34	0.3157	36739000
2001	52.89640	38079.75	0.3162	36833000
2002	53.54565	38130.84	0.3169	36629000
2003	53.97943	37920.65	0.3095	36305000
2004	54.51726	38435.78	0.3216	35859000
2005	55.34375	38788.88	0.3411	36299000
2006	56.40872	40318.86	0.3449	36965000
2007	57.26425	41737.17	0.3611	37834000
2008	57.37161	42287.54	0.3651	38282000
2009	55.90073	39983.94	0.3514	38267000
2010	57.28340	41658.92	0.3504	38668000
2011	58.46122	43189.35	0.3499	39594000
2012	58.82401	43335.62	0.3516	39874000
2013	59.29450	43417.27	0.3546	40304000
2014	59.53213	44067.87	0.3478	40595000

Appendix 3. Data used in Chapter 4 - Finland

Data used in Chapter 4 - Finland

obs	LP	GDPpc	Top10	E
1991	31.20866	25609.36	0.2209	2416000
1992	32.35758	24632.47	0.2204	2244000
1993	34.10886	24323.20	0.2325	2109000
1994	35.55644	25156.93	0.2541	2088000
1995	36.37983	26104.07	0.2678	2059000
1996	37.20295	26964.97	0.2662	2080000
1997	38.43716	28568.65	0.2781	2134000
1998	40.01747	30046.60	0.2774	2194000
1999	40.71310	31311.73	0.2810	2271000
2000	42.45725	33001.32	0.2861	2303000
2001	43.41635	33774.96	0.2771	2345000
2002	43.89669	34262.02	0.2758	2356000
2003	44.93217	34856.94	0.2754	2353000
2004	46.37705	36121.23	0.2833	2347000
2005	47.21773	37001.36	0.2687	2413000
2006	48.37105	38353.93	0.2773	2461000
2007	49.85911	40169.12	0.2783	2510000
2008	49.32851	40269.51	0.2889	2548000
2009	47.03191	36757.60	0.2822	2469000
2010	48.56672	37665.61	0.2837	2455000

2011	49.34476	38432.57	0.2812	2483000
2012	48.57364	37683.12	0.2801	2491000
2013	48.86589	37066.44	0.2784	2464000
2014	48.88855	36737.24	0.2853	2455000

Data used in Chapter 4 - United Kingdom

Appendix 4.Data used in Chapter 4 - United Kingdom

obs	LP	GDPpc	Top10	E
1991	38.19622	25076.05	0.3108261	26399000
1992	39.41039	25120.06	0.3092733	25896000
1993	40.87292	25711.89	0.3185012	25527000
1994	41.87343	26672.09	0.3232357	25679000
1995	42.35083	27265.76	0.3234225	25930000
1996	43.04149	27908.56	0.3319764	26177000
1997	43.63041	28682.30	0.3282625	26678000
1998	44.67908	29552.79	0.3307061	27004000
1999	45.73637	30368.37	0.3400633	27325000
2000	47.33782	31409.99	0.3352352	27694000
2001	48.14138	32159.81	0.3382323	2.79E+07
2002	49.39382	32839.00	0.3392343	28088000
2003	50.88171	33793.86	0.3471778	28401000
2004	51.68587	34462.46	0.3421690	28708000
2005	52.53691	35280.62	0.3508947	29082000
2006	53.50393	35957.65	0.3568302	29356000
2007	54.36269	36584.13	0.3619557	29641000
2008	53.73766	36095.88	0.3372249	30001000
2009	52.95115	34287.33	0.3502650	29638000
2010	53.67165	34540.34	0.3161587	29772000
2011	54.27006	34971.65	0.3273992	29863000
2012	53.95843	35156.45	0.3283902	30236000
2013	53.98963	35701.34	0.3526807	30624000
2014	54.14236	36536.42	0.3375344	31312000

Appendix 5. Data used in Chapter 4 - Japan

Data used in Chapter 4 - Japan

obs	LP	GDPpc	Top10	E
1991	29.36314	31178.31	0.37871	64177000
1992	29.99854	31311.74	0.33732	64982000
1993	30.48585	31243.93	0.34294	65137000
1994	30.99891	31401.34	0.34768	65135000
1995	31.69798	31913.09	0.35529	65184000
1996	32.59349	32664.30	0.36035	65547000
1997	33.18919	33118.19	0.35921	66108000

1998	33.56105	32398.31	0.36526	65628000
1999	34.21732	32278.42	0.37276	65001000
2000	35.28137	32945.76	0.38126	64825000
2001	35.85183	32994.73	0.39590	64512000
2002	36.56607	33018.14	0.40557	63774000
2003	37.03254	33501.72	0.41208	63685000
2004	37.48498	34225.20	0.42154	63815000
2005	38.08865	34614.90	0.42433	64078000
2006	38.19007	35157.20	0.42752	64354000
2007	38.71690	35895.88	0.42962	64778000
2008	38.75921	35503.04	0.42286	64660000
2009	38.15232	33534.74	0.41313	63757000
2010	39.37394	35120.50	0.41566	63501000

Appendix 6. Data used in Chapter 4 - Sweden

Data used in Chapter 4 - Sweden

obs	LP	GDPpc	Top10	E
1991	36.61913	29252.22	0.2329	4577000
1992	37.45452	28709.23	0.2326	4379000
1993	37.93703	27924.05	0.2402	4124000
1994	38.93490	28896.16	0.2598	4087000
1995	39.73183	29929.55	0.2645	4162000
1996	40.34759	30305.90	0.2608	4130000
1997	41.93400	31150.82	0.2654	4071000
1998	43.02428	32459.81	0.2619	4123000
1999	43.82404	33921.14	0.2635	4206000
2000	45.42113	35492.61	0.2605	4271000
2001	45.84709	35981.03	0.2553	4346000
2002	47.45973	36631.41	0.2563	4349000
2003	49.28477	37375.22	0.2627	4345000
2004	51.00576	38819.20	0.2644	4307000
2005	52.31915	39701.62	0.2689	4342000
2006	54.05909	41301.77	0.2782	4422000
2007	54.22019	42399.83	0.2749	4535000
2008	53.25884	41829.95	0.2679	4596000
2009	51.99717	39332.53	0.2594	4505000
2010	53.72225	41337.71	0.2705	4524000
2011	54.08455	42080.07	0.2661	4618000
2012	54.00358	41602.99	0.2645	4644000
2013	54.47935	41765.80	0.2651	4697000
2014	55.10000	42391.74	0.2807	4731000

Data used in Chapter 7 - Panel data
Germany -1
Finland - 2
United Kingdom -3
Japan - 4
Sweden - 5
United States of America -6

obs	TPF	GDPpc	KOFGI	crisis_11
1:01	0.655499	21555.67	70.66312	0
1:02	0.672487	22640.60	71.37577	0
1:03	0.686532	23422.20	71.73219	0
1:04	0.696325	24157.00	71.95174	0
1:05	0.709623	25198.71	72.23208	0
1:06	0.708525	25601.28	72.82729	0
1:07	0.708925	25792.60	73.53391	0
1:08	0.703839	25749.53	73.71836	0
1:09	0.712711	26206.59	73.71664	0
1:10	0.724249	26977.89	74.12496	0
1:11	0.734337	27604.77	75.06990	0
1:12	0.741875	28199.15	74.62901	0
1:13	0.745767	28523.85	74.51155	0
1:14	0.761996	29474.34	73.95717	0
1:15	0.785154	30479.35	73.36816	0
1:16	0.825859	31900.86	73.10539	0
1:17	0.881098	33308.76	77.98914	1
1:18	0.890606	33698.48	78.41698	1
1:19	0.888897	33128.02	78.94907	1
1:20	0.900215	33720.25	78.76859	0
1:21	0.905732	34135.47	79.14034	0
1:22	0.910158	34306.27	79.96677	0
1:23	0.922056	34888.22	81.33370	0
1:24	0.925175	35571.78	82.14195	0
1:25	0.929814	36298.27	83.20403	0
1:26	0.945531	37405.34	85.29345	0
1:27	0.960627	38079.75	85.42323	0
1:28	0.962840	38130.84	85.26031	0
1:29	0.959971	37920.65	86.07380	0
1:30	0.964688	38435.78	86.41580	0
1:31	0.970649	38788.88	86.90884	0
1:32	0.988961	40318.86	87.63346	0
1:33	1.003294	41737.17	87.94353	0
1:34	1.000997	42287.54	87.49532	0
1:35	0.957914	39983.94	86.94757	0
1:36	0.980940	41658.92	86.90385	0
1:37	1.000000	43189.35	87.17752	0
1:38	0.998524	43335.62	87.28943	0

1:39	0.996432	43417.27	87.29549	0
1:40	0.996098	44067.87	87.64118	0
2:01	0.680663	18172.90	62.49193	0
2:02	0.672155	18176.29	64.13085	0
2:03	0.670418	18173.12	65.26023	0
2:04	0.680983	18660.44	66.68483	0
2:05	0.711858	19935.63	67.60114	0
2:06	0.726156	20936.58	68.43842	0
2:07	0.714143	21112.93	69.21716	0
2:08	0.720390	21650.95	71.32700	0
2:09	0.731225	22202.20	71.28938	0
2:10	0.740268	22793.57	72.52970	0
2:11	0.751349	23489.00	73.77016	0
2:12	0.765167	24035.82	73.32269	0
2:13	0.773532	24810.79	73.95452	0
2:14	0.790437	26026.29	73.26494	0
2:15	0.809216	27262.94	71.77967	0
2:16	0.812702	27343.00	72.40894	0
2:17	0.794238	25609.36	75.40546	1
2:18	0.799784	24632.47	76.47256	1
2:19	0.821393	24323.20	78.28352	1
2:20	0.851002	25156.93	79.17310	0
2:21	0.870815	26104.07	80.15504	0
2:22	0.886980	26964.97	81.29131	0
2:23	0.916326	28568.65	82.40945	0
2:24	0.946042	30046.60	82.86203	0
2:25	0.959734	31311.73	83.28514	0
2:26	0.991398	33001.32	85.14074	0
2:27	0.999964	33774.96	85.51041	0
2:28	1.000012	34262.02	84.36755	0
2:29	1.008142	34856.94	84.86940	0
2:30	1.028462	36121.23	85.92605	0
2:31	1.035427	37001.36	85.04880	0
2:32	1.051661	38353.93	85.86097	0
2:33	1.074422	40169.12	86.65645	0
2:34	1.053066	40269.51	86.60248	0
2:35	0.975748	36757.60	85.73354	0
2:36	0.993639	37665.61	85.68681	0
2:37	1.000000	38432.57	85.85258	0
2:38	0.972636	37683.12	86.40895	0
2:39	0.959125	37066.44	86.23156	0
2:40	0.949377	36737.24	87.26231	0
3:01	0.693385	17365.77	75.52814	0
3:02	0.707695	17881.15	77.08041	0
3:03	0.716666	18341.62	77.91413	0
3:04	0.735487	19099.44	77.64705	0
3:05	0.755294	19802.94	78.85307	0
3:06	0.737777	19372.86	79.18645	0

3:07	0.744635	19205.56	79.46039	0
3:08	0.763302	19597.49	79.44299	0
3:09	0.786440	20408.66	79.68318	0
3:10	0.784259	20850.01	80.02811	0
3:11	0.800483	21677.86	80.07294	0
3:12	0.817167	22323.44	79.55374	0
3:13	0.838456	23510.60	80.48054	0
3:14	0.852344	24837.40	80.01694	0
3:15	0.847761	25393.27	79.80152	0
3:16	0.845003	25463.98	79.49132	0
3:17	0.845823	25076.05	81.06062	1
3:18	0.862149	25120.06	81.37091	1
3:19	0.881043	25711.89	82.65397	1
3:20	0.896229	26672.09	83.15804	0
3:21	0.897346	27265.76	83.45798	0
3:22	0.901906	27908.56	83.70223	0
3:23	0.914817	28682.30	84.15825	0
3:24	0.921608	29552.79	84.79929	0
3:25	0.932441	30368.37	85.74998	0
3:26	0.952748	31409.99	87.11434	0
3:27	0.964529	32159.81	87.25967	0
3:28	0.979960	32839.00	87.62608	0
3:29	1.000524	33793.86	88.17232	0
3:30	1.013700	34462.46	88.06116	0
3:31	1.019181	35280.62	88.23472	0
3:32	1.030040	35957.65	88.53670	0
3:33	1.037497	36584.13	88.33405	0
3:34	1.024240	36095.88	88.16934	0
3:35	0.985427	34287.33	88.37783	0
3:36	0.989654	34540.34	88.62344	0
3:37	1.000000	34971.65	89.03916	0
3:38	0.993761	35156.45	88.96631	0
3:39	0.998388	35701.34	89.05595	0
3:40	1.004105	36536.42	88.89165	0
4:01	1.104684	17140.15	52.34463	0
4:02	1.085414	17632.37	52.63084	0
4:03	1.072620	18231.49	52.85223	0
4:04	1.069019	19026.60	54.98359	0
4:05	1.061225	19906.20	55.25029	0
4:06	1.035791	20304.83	55.52971	0
4:07	1.033899	20988.25	55.59410	0
4:08	1.024909	21533.38	56.31682	0
4:09	1.017302	22034.62	56.69673	0
4:10	1.023935	22870.30	57.03997	0
4:11	1.055143	24183.01	57.29608	0
4:12	1.046381	24751.56	57.44418	0
4:13	1.049456	25668.06	57.55436	0
4:14	1.070995	27409.36	57.29471	0

4:15	1.073651	28786.89	57.30111	0
4:16	1.076973	30287.06	57.50676	0
4:17	1.056844	31178.31	58.51845	1
4:18	1.028446	31311.74	61.93513	1
4:19	1.016340	31243.93	62.66632	1
4:20	1.001763	31401.34	62.73247	0
4:21	1.000915	31913.09	60.04831	0
4:22	1.000699	32664.30	64.14880	0
4:23	1.000931	33118.19	65.83618	0
4:24	0.980243	32398.31	66.96382	0
4:25	0.983072	32278.42	67.70625	0
4:26	0.990718	32945.76	68.67602	0
4:27	0.987565	32994.73	69.19849	0
4:28	0.990107	33018.14	69.84057	0
4:29	0.994405	33501.72	71.00499	0
4:30	1.006836	34225.20	71.31133	0
4:31	1.007635	34614.90	71.73321	0
4:32	1.007040	35157.20	73.17987	0
4:33	1.015524	35895.88	74.25347	0
4:34	1.003782	35503.04	73.96870	0
4:35	0.970637	33534.74	73.92101	0
4:36	1.006453	35120.50	74.51298	0
4:37	1.000000	34979.34	74.68266	0
4:38	1.006143	35620.40	75.47157	0
4:39	1.016858	36230.03	76.25968	0
4:40	1.008022	36250.46	76.55815	0
5:01	0.804604	23440.78	73.36380	0
5:02	0.790579	23614.05	73.78283	0
5:03	0.765888	23160.05	74.02181	0
5:04	0.763496	23490.15	74.48294	0
5:05	0.764823	24326.50	75.75990	0
5:06	0.760693	24692.17	75.85026	0
5:07	0.756747	24777.96	76.91701	0
5:08	0.753917	25076.33	78.36032	0
5:09	0.755224	25544.56	79.06348	0
5:10	0.771949	26600.35	79.07017	0
5:11	0.770634	27119.99	79.93385	0
5:12	0.777403	27759.96	79.03146	0
5:13	0.784321	28568.92	79.26688	0
5:14	0.779916	29149.48	78.62459	0
5:15	0.780985	29750.52	77.89768	0
5:16	0.772416	29789.88	78.24055	0
5:17	0.767926	29252.22	80.03970	1
5:18	0.769151	28709.23	80.11501	1
5:19	0.766332	27924.05	81.48188	1
5:20	0.789582	28896.16	82.97886	0
5:21	0.809588	29929.55	84.15828	0
5:22	0.816938	30305.90	84.28761	0

5:23	0.840445	31150.82	85.56142	0
5:24	0.863057	32459.81	86.44719	0
5:25	0.883437	33921.14	86.83870	0
5:26	0.912792	35492.61	88.23154	0
5:27	0.915367	35981.03	88.60786	0
5:28	0.933950	36631.41	88.27484	0
5:29	0.955438	37375.22	88.55748	0
5:30	0.982648	38819.20	88.54179	0
5:31	0.997720	39701.62	89.03078	0
5:32	1.024029	41301.77	89.14939	0
5:33	1.027838	42399.83	89.53835	0
5:34	1.002615	41829.95	89.41383	0
5:35	0.958959	39332.53	89.15870	0
5:36	0.993513	41337.71	89.18533	0
5:37	1.000000	42080.07	88.85290	0
5:38	0.989524	41602.99	88.53414	0
5:39	0.992430	41765.80	88.52567	0
5:40	0.998230	42391.74	90.24283	0
6:01	0.731888	25381.51	61.72231	0
6:02	0.746794	26503.18	62.01573	0
6:03	0.752271	27464.03	62.37934	0
6:04	0.758068	28714.75	62.77582	0
6:05	0.755871	29343.61	63.28677	0
6:06	0.744884	28994.32	63.58474	0
6:07	0.754283	29467.21	63.82067	0
6:08	0.739750	28633.88	64.00951	0
6:09	0.757323	29680.29	63.76483	0
6:10	0.777068	31535.36	64.34921	0
6:11	0.787037	32559.84	67.03207	0
6:12	0.797394	33378.72	67.30884	0
6:13	0.800448	34197.35	67.06393	0
6:14	0.808351	35284.12	67.22215	0
6:15	0.813557	36221.12	70.50080	0
6:16	0.819473	36550.05	70.58545	0
6:17	0.818952	36163.17	71.90378	1
6:18	0.840329	37079.89	72.20895	1
6:19	0.842713	37714.73	73.24877	1
6:20	0.850312	38823.71	74.00031	0
6:21	0.850730	39476.65	75.01329	0
6:22	0.864973	40487.40	75.48729	0
6:23	0.875547	41777.03	76.87421	0
6:24	0.888878	43087.96	77.58346	0
6:25	0.905222	44562.22	77.94350	0
6:26	0.920583	45866.84	78.19106	0
6:27	0.925201	45844.47	78.64304	0
6:28	0.938835	46230.65	78.41679	0
6:29	0.956795	47114.27	78.73851	0
6:30	0.974149	48477.21	79.17563	0

6:31	0.984566	49657.53	79.48368	0
6:32	0.986382	50517.59	80.99397	0
6:33	0.987370	50939.58	81.34473	0
6:34	0.980900	50321.10	80.79767	0
6:35	0.980702	48485.10	80.03148	0
6:36	0.999061	49288.50	80.17655	0
6:37	1.000000	49674.81	80.89596	0
6:38	1.005146	50390.97	80.72646	0
6:39	1.006470	50764.77	81.07088	0
6:40	1.014108	51620.79	81.59064	0

Appendix 8. GDP deflator for all countries

GDP deflator for all countries

Country Name	Germany	Finland	United Kingdom	Japan	Sweden	United States
Indicator Name	GDP deflator (base year varies by country)	GDP deflator (base year varies by country)	GDP deflator (base year varies by country)	GDP deflator (base year varies by country)	GDP deflator (base year varies by country)	GDP deflator (base year varies by country)
1975	47.089998	23.0303601	15.388708	72.373992	19.462150	31.056468
1976	48.646885	26.053021	17.714657	78.169619	21.781837	32.765626
1977	50.155288	28.506867	20.146342	83.4453706	24.075371	34.801472
1978	51.933715	30.631823	22.455059	87.286993	26.374344	37.249350
1979	54.155513	33.175790	25.615518	89.688809	28.469313	40.339777
1980	57.107632	36.372471	30.661696	94.566072	31.804923	43.983684
1981	59.492012	40.611074	34.203295	97.333863	34.593370	48.145499
1982	62.217376	44.293573	36.735195	99.032308	37.390107	51.120035
1983	63.964402	47.926110	38.617065	99.968817	41.1119425	53.122290
1984	65.2367481	51.979673	40.5566631	101.44173	44.2512	55.038793
1985	66.622850	54.696371	42.772244	102.72005	47.085316	56.779365
1986	68.621231	57.314599	44.630820	104.3761	50.062391	57.922842
1987	69.499352	59.765177	47.100105	104.211309	52.425811	59.354980
1988	70.674211	64.354227	49.976624	104.86293	55.870819	61.448689
1989	72.708969	68.558913	53.947357	107.07437	60.2983958	63.857687
1990	75.178633	72.125405	58.19855	109.86399	66.010957	66.248093
1991	77.497954	73.249663	61.924833	113.08064	71.4547421	68.488442
1992	81.595119	73.930279	64.000503	114.96529	72.1802515	70.049231
1993	84.969508	75.263758	65.726247	115.61872	73.7770744	71.708894
1994	86.8083984	76.650509	66.610826	115.92570	75.6643262	73.240150
1995	88.5233203	79.8670988	73.8559164	115.307290	78.5403585	74.7758729
1996	89.0740033	79.7873587	76.8709178	114.734804	79.3644698	76.1450422
1997	89.3077491	81.4777208	77.420474	115.312873	80.6109220	77.4580805
1998	89.850849	84.012841	78.2555657	115.260844	81.2487326	78.3298870
1999	90.136555	84.808697	78.8723535	113.751512	82.0119526	79.4608166
2000	89.731132	86.191497	80.5412567	112.177549	83.2952641	81.2371428
2001	90.876998	89.064629	81.1995401	110.9385294	85.3864757	83.0190189

2002	92.104339	89.928803	82.9726831	109.320728	86.7526932	84.3321830
2003	93.215915	90.120938	84.9672621	107.553032	88.2727453	85.898312
2004	94.235443	90.668642	87.0639416	106.369157	88.6507133	88.2108767
2005	94.820357	91.506073	89.2859332	105.265647	89.3622614	90.9585947
2006	95.108654	92.341024	91.9042178	104.335754	90.9856568	93.7111879
2007	96.72301	94.894290	94.2412599	103.574645	93.6058795	96.2285317
2008	97.534321	97.814077	96.9214285	102.558686	96.7165675	98.1003035
2009	99.247993	99.650453	98.4914252	101.931773	99.0192792	98.8481711
2010	100	100	100	100	100	100
2011	101.07047	102.58402	101.919329	98.3256742	101.183110	102.088903
2012	102.62725	105.61390	103.512158	97.5768701	102.257465	104.046814
2013	104.64428	108.30887	105.443236	97.2517664	103.335936	105.872748
2014	106.48484	110.14242	107.247733	98.9491153	105.171787	107.875746
2015	108.59228	111.982	107.71472	101.071966	107.343102	109.029306
2016	110.073	112.1385	109.934197	101.342415	109.114260	110.221569
2017	111.75939	113.1939	112.357277	101.119376	111.576233	112.316636
2018	113.84217	115.3916	114.490012	101.024964	114.028470	114.849715

Constant coefficients (pooled regression) models

Appendix 9. Constant coefficients (pooled regression) models (Author's calculation)

Model 1: Pooled OLS, using 234 observations

Included 6 cross-sectional units

Time-series length = 39

Dependent variable: d_l_GDPpc

Robust (HAC) standard errors

	coefficient	std. error	t-ratio	p-value
const	0.132673	0.0202648	6.547	0.0012 ***
l_TPF	0.00268221	0.00604321	0.4438	0.6757
l_KOFGI	−0.0254217	0.00499314	−5.091	0.0038 ***
dt_35	−0.0790749	0.00859058	−9.205	0.0003 ***
crisis_l1	−0.0265738	0.00911978	−2.914	0.0332 **

Mean dependent var	0.018009	S.D. dependent var	0.023210
Sum squared resid	0.075270	S.E. of regression	0.018130
R-squared	0.400308	Adjusted R-squared	0.389833
F(4, 5)	89.03014	P-value(F)	0.000078

Log-likelihood	608.8811	Akaike criterion	−1207.762
Schwarz criterion	−1190.486	Hannan-Quinn	−1200.796
rho	0.411115	Durbin-Watson	1.149263

Distribution free Wald test for heteroskedasticity -

Null hypothesis: the units have a common error variance

Asymptotic test statistic: Chi-square(6) = 7.07326

with p-value = 0.314125

Test for normality of residual -

Null hypothesis: error is normally distributed

Test statistic: Chi-square(2) = 5.36664

with p-value = 0.0683359

Appendix 10. Model 2: Slope coefficients constant but intercept varies over countries (Author's calculation)

Model 2: Pooled OLS, using 234 observations

Included 6 cross-sectional units

Time-series length = 39

Dependent variable: d_l_GDPpc

Robust (HAC) standard errors

	coefficient	std. error	t-ratio	p-value
const	0.414992	0.0513322	8.084	0.0005 ***
l_TPF	0.0430546	0.00906190	4.751	0.0051 ***
l_KOFGI	−0.0881389	0.0116224	−7.584	0.0006 ***
dt_35	−0.0768644	0.00885698	−8.678	0.0003 ***
crisis_11	−0.0266621	0.00862581	−3.091	0.0271 **
du_2	−0.0023976	0.000267892	−8.950	0.0003 ***
du_3	0.00339960	0.000513081	6.626	0.0012 ***
du_4	−0.0264190	0.00349161	−7.566	0.0006 ***
du_5	0.000530674	0.000476268	1.114	0.3159
du_6	−0.00864281	0.00109839	−7.869	0.0005 ***

Mean dependent var	0.018009	S.D. dependent var	0.023210
Sum squared resid	0.070648	S.E. of regression	0.017759
R-squared	0.437139	Adjusted R-squared	0.414524
Log-likelihood	616.2970	Akaike criterion	−1212.594
Schwarz criterion	−1178.041	Hannan-Quinn	−1198.662
rho	0.387449	Durbin-Watson	1.189019

Excluding the constant, p-value was highest for variable 26 (du_5)

Distribution free Wald test for heteroskedasticity -

Null hypothesis: the units have a common error variance

Asymptotic test statistic: Chi-square(6) = 8.39712

with p-value = 0.210428

Test for normality of residual -

Null hypothesis: error is normally distributed

Test statistic: Chi-square(2) = 6.38931

with p-value = 0.0409807

Appendix 11. Test on Model: Slope coefficients constant but intercept varies over time (Author's calculation)

Model 3: Pooled OLS, using 234 observations

Included 6 cross-sectional units

Time-series length = 39

Dependent variable: d_l_GDPpc

Robust (HAC) standard errors

	coefficient	std. error	t-ratio	p-value	
const	−0.126921	0.0886414	−1.432	0.2116	
l_TPF	0.0664970	0.0134136	4.957	0.0043	***
l_KOFGI	0.0309262	0.0192080	1.610	0.1683	
dt_35	−0.0672010	0.0055304	−12.15	6.67e-05	***

crisis_l1	−0.000635	0.0092261	−0.068	0.9477	
dt_2	0.0410157	0.0113786	3.605	0.0155	**
dt_3	0.0327290	0.0148911	2.198	0.0793	*
dt_4	0.0467887	0.0121433	3.853	0.0120	**
dt_5	0.0534165	0.0169937	3.143	0.0256	**
dt_6	0.0236673	0.0208170	1.137	0.3071	
dt_7	0.0225019	0.0141940	1.585	0.1738	
dt_8	0.0210054	0.0171508	1.225	0.2752	
dt_9	0.0381127	0.00952597	4.001	0.0103	**
dt_10	0.0460681	0.00967776	4.760	0.0051	***
dt_11	0.0419646	0.0122786	3.418	0.0189	**
dt_12	0.0323861	0.00882107	3.671	0.0144	**
dt_13	0.0381883	0.0104978	3.638	0.0149	**
dt_14	0.0487991	0.0140701	3.468	0.0179	**
dt_15	0.0389807	0.0140718	2.770	0.0394	**
dt_16	0.0241499	0.0147651	1.636	0.1628	
dt_17	−0.00134906	0.0192328	−0.070.	0.9468	
dt_18	0.00156530	0.00880150	0.1778	0.8658	
dt_20	0.0274176	0.00795817	3.445	0.0183	**
dt_21	0.0239306	0.0102062	2.345	0.0660	*
dt_22	0.0199114	0.00990707	2.010	0.1007	
dt_23	0.0271084	0.0113369	2.391	0.0623	*
dt_24	0.0219704	0.0115828	1.897	0.1163	
dt_25	0.0230184	0.00848787	2.712	0.0422	**
dt_26	0.0291506	0.00809238	3.602	0.0155	**
dt_27	0.00662409	0.00649252	1.020	0.3544	
dt_28	0.00343175	0.00528833	0.6489	0.5450	
dt_29	0.00745958	0.00659105	1.132	0.3091	
dt_30	0.0166933	0.00741471	2.251	0.0741	*
dt_31	0.00913537	0.00516590	1.768	0.1372	
dt_32	0.0165680	0.00715807	2.315	0.0685	*
dt_33	0.0137076	0.00897851	1.527	0.1874	
dt_34	−0.0166621	0.00749894	−2.222	0.0769	*

dt_36	0.0211574	0.0105278	2.010	0.1007
dt_37	0.00483676	0.00693200	0.6977	0.5164
dt_38	−0.00820414	0.00688330	−1.192	0.2868
dt_39	−0.00514553	0.00482264	−1.067	0.3348

Distribution free Wald test for heteroskedasticity -

Null hypothesis: the units have a common error variance

Asymptotic test statistic: Chi-square(6) = 6.46508

with p-value = 0.373154

Test for normality of residual -

Null hypothesis: error is normally distributed

Test statistic: Chi-square(2) = 15.8773

with p-value = 0.000356688

Test on Model 3:

Null hypothesis: the regression parameters are zero for the variables

crisis_l1, dt_35

Test statistic: F(2, 5) = 306.958, p-value 5.86606e-06

Omitting variables improved 0 of 3 information criteria.

Model: Fixed-effects, using 234 observations

Included 6 cross-sectional units

Time-series length = 39

Dependent variable: d_l_GDPpc

Omitted due to exact collinearity: const

	coefficient	std. error	t-ratio	p-value
const	0.494432	0.107158	4.614	6.62e-06 ***
l_KOFGI	−0.108586	0.0243457	−4.460	1.29e-05 ***
l_TPF	0.0460380	0.0182747	2.519	0.0125 **

Mean dependent var	0.018009	S.D. dependent var	0.023210
Sum squared resid	0.114551	S.E. of regression	0.022514
LSDV R-squared	0.087351	Within R-squared	0.084322
LSDV F(7, 226)	3.090112	P-value(F)	0.003947
Log-likelihood	559.7488	Akaike criterion	−1103.498
Schwarz criterion	−1075.855	Hannan-Quinn	−1092.352
rho	0.328945	Durbin-Watson	1.318896

Joint test on named regressors -

Test statistic: F(2, 226) = 10.4058

with p-value = P(F(2, 226) > 10.4058) = 4.75254e-05

Test for differing group intercepts -

Null hypothesis: The groups have a common intercept

Test statistic: F(5, 226) = 2.63461

with p-value = P(F(5, 226) > 2.63461) = 0.0244534

Appendix 12. Model 4: The Fixed Effects Within-groups Regression Model (Author's calculation)

Model 4: Fixed-effects, using 234 observations

Included 6 cross-sectional units

Time-series length = 39

Dependent variable: d_l_GDPpc

Robust (HAC) standard errors

	coefficient	std. error	t-ratio	p-value
const	0.409404	0.0501644	8.161	0.0004 ***
l_TPF	0.0430546	0.00896243	4.804	0.0049 ***
l_KOFGI	−0.0881389	0.0114949	−7.668	0.0006 ***
crisis_l1	−0.0266621	0.00853112	−3.125	0.0261 **
dt_35	−0.0768644	0.00875976	−8.775	0.0003 ***

Mean dependent var	0.018009	S.D. dependent var	0.023210
Sum squared resid	0.070648	S.E. of regression	0.017759
LSDV R-squared	0.437139	Within R-squared	0.435271
Log-likelihood	616.2970	Akaike criterion	−1212.594
Schwarz criterion	−1178.041	Hannan-Quinn	−1198.662
rho	0.387449	Durbin-Watson	1.189019

Joint test on named regressors -

Test statistic: F (4, 5) = 264.475

with p-value = P (F (4, 5) > 264.475) = 5.2942e-06

Robust test for differing group intercepts -

Null hypothesis: The groups have a common intercept

Test statistic: Welch F (5, 106.2) = 0.785924

with p-value = P (F (5, 106.2) > 0.785924) = 0.562053

Distribution free Wald test for heteroskedasticity -

Null hypothesis: the units have a common error variance

Asymptotic test statistic: Chi-square(6) = 8.39712

with p-value = 0.210428

Test for normality of residual -

Null hypothesis: error is normally distributed

Test statistic: Chi-square(2) = 6.38931

with p-value = 0.0409807

Random effects

Appendix 13. Model 5: Random Effect Model (Author's calculation)

Model 5: Random-effects (GLS), using 234 observations

Using Nerlove's transformation

Included 6 cross-sectional units

Time-series length = 39

Dependent variable: d_l_GDPpc

Robust (HAC) standard errors

	coefficient	std. error	z	p-value
const	0.338137	0.0506623	6.674	2.48e-11 ***
l_TPF	0.0324650	0.0174579	1.860	0.0629 *
l_KOFGI	−0.0719924	0.0118985	−6.051	1.44e-09 ***
crisis_l1	−0.0266459	0.00368718	−7.227	4.95e-13 ***
dt_35	−0.0774163	0.00547093	−14.15	1.86e-45 ***

Mean dependent var	0.018009	S.D. dependent var	0.023210
Sum squared resid	0.085647	S.E. of regression	0.019297
Log-likelihood	593.7704	Akaike criterion	−1177.541
Schwarz criterion	−1160.264	Hannan-Quinn	−1170.575

'Between' variance = 0.000120576

'Within' variance = 0.000301913

theta used for quasi-demeaning = 0.754379

corr (y,yhat)^2 = 0.342527

Joint test on named regressors -

Asymptotic test statistic: Chi-square (4) = 833.289

with p-value = 4.72545e-179

Breusch-Pagan test -

Null hypothesis: Variance of the unit-specific error = 0

Asymptotic test statistic: Chi-square (1) = 0.505269

with p-value = 0.477194

Hausman test -

Null hypothesis: GLS estimates are consistent

Asymptotic test statistic: Chi-square (2) = 4.73846

with p-value = 0.0935527

Test for normality of residual -
Null hypothesis: error is normally distributed
Test statistic: Chi-square(2) = 3.72028
with p-value = 0.155651