The impact of technological change and international trade on inequalities

Stefano Rossini

Department of Management Engineering

Politecnico di Milano

Supervisor

Miriam Manchin

October 2020

Abstract

This Thesis aims at analysing the effects of technological changes and international trade on wage and employment inequalities between skilled and unskilled workers in developed countries.

To highlight this state of affairs I have drawn on the statistics and analyses of a cross section of economists and analysts specifically related to three global markets—The OECD countries, the United States, and China.

What is evolving at present, is that advanced countries are moving towards a scenario in which there is a significant gap in terms of wages and the rate of employment between skilled and unskilled workers. This scenario, if not properly managed, could lead to serious social problems.

List of figures

List of tables

List of Content

1. INTRODUCTION

My Thesis addresses a topic which has been much written about in recent years and which has been analysed by renowned economists and data scientists from different countries around the world. I am specifically speaking about the disproportionate inequalities in wages between skilled, and unskilled workers caused by improving international trade and technological changes. Although this serious issue transcends both female and male workers, for this study, I have chosen to address the plight of male unskilled workers versus the progress of male skilled workers.

Many factors play into the predicament that unskilled workers find themselves in today. Economists may differ in opinion on the prevailing circumstances. I have selected three global economies as the bedrocks for my study, namely OECD countries, the United States and China.

Wage inequalities based on workers' skills have increased in several countries since the beginning of the 1980s (e.g. Stephen Machin and John van Reenen 1998; David H. Autor, Lawrence F. Katz, and Melissa S. Kearney 2008). Economists mainly identified the so called "Skill Biased Technological Change" and International Trade, as the main drivers for expanding this skilled wage gap. Whether Skill Biased Technological Change affected this gap more than International Trade, has been one of the major issues in economic studies in the last decades (e.g. Daron Acemoglu 2003, Afonso 2012).

According to the theoretical Heckscher – Ohlin model, both of these drivers significantly widen the wage differential between skilled and unskilled workers in developed countries (e.g. Krugman, Obstfeld and Melitz in "International Economics theory and policy"). Specifically, a reduction in the relative price of imported goods leads to a decline in the return on that factor which is intensively used in the production of those goods. Conversely, a rise in the relative price of exported goods leads to an increase in the return on the specific intensively used factor. Therefore, while trading, developed countries specialising on skill-intensive goods (technologically advanced goods), expanding the relative demand and relative wage for skilled workers (e.g. engineers, software developers, ecc...) at the expense of unskilled workers (e.g. restaurant waiting staff, assembly line workers ecc...).

In this paper I first illustrate a number of trends, which summarize several major variations in OECD labor markets (attention focused on the US). These trends aim at presenting the issues at the core of my report. Secondly, I present the theoretical predictions provided by Krugman, Obstfeld and Melitz through the Heckscher – Ohlin model regarding wage and employment inequalities between skilled and unskilled workers in developed countries. I proceed to compare these predictions with empirical findings obtained by top economists in their empirical studies and researches. Specifically, I illustrate those results obtained by their econometric models and summarize their “considerations”, in order to understand whether the theoretical predictions resulted to be verified. Finally, conclusions will be illustrated in the final section.

To conclude this introduction, I am highlighting the fact that what you will discover in the following sections originates from empirical researches based on realistic cases developed by different economists, which will be referenced accurately and honestly.

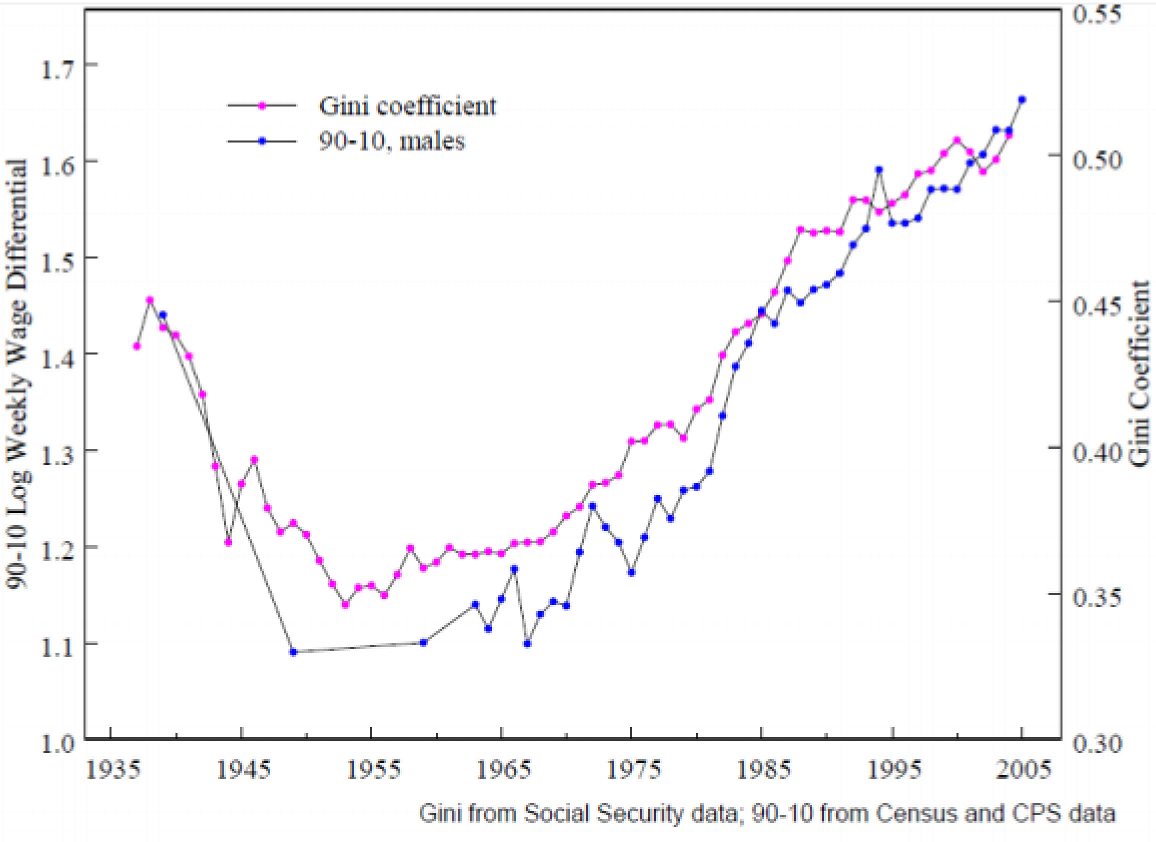
2. TRENDS

2.1 Wage inequality trends

In this section we will observe several trends which are useful to illustrate the core issues as the basis of our discussion.

The following graph is taken from Goldin and Katz (2008) and it was commented on by John Van Reenen in his article "Wage inequality, Technology and Trade: 21st Century Evidence".

In this graph, the economist shows how US male wage inequality evolved from 1935 to 2005. Our interests in this figure rely on the blue line, which represents the wage difference between the 90th and 10th percentiles. These numbers identify the two extreme ends of the skill levels required by different jobs. Therefore, at the 90th percentile we recognise those jobs which need highly qualified, educated, trained and skilled people (e.g. C.E.O., C.F.O., bankers, lawyers ...) while at the 10th percentile we recognise those job positions which do not require a deep experience to develop specific skills (e.g. restaurant waiting staff, cleaners ...). These percentiles recognise the so called high skilled workers (90th percentile) and low skilled workers (10th percentile). In the

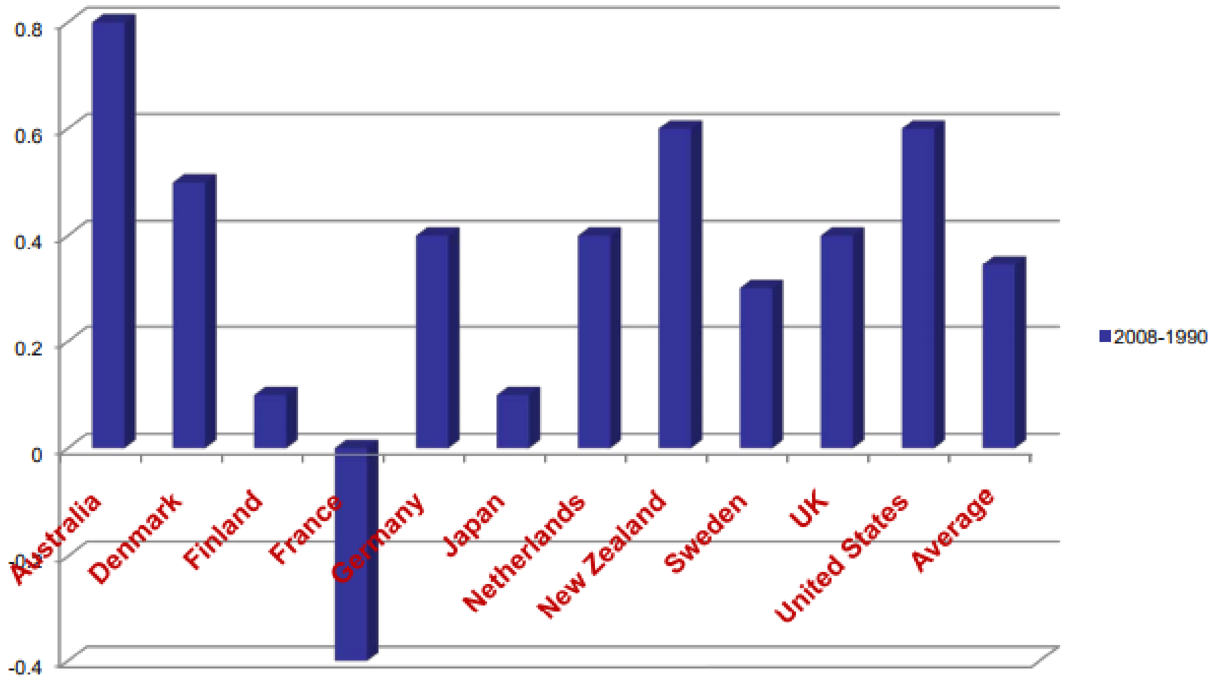


Source: Goldin and Katz (2008)

Figure 1: US male wage inequality 1937 - 2005

middle of this range there are intermediate job positions, which require better skills as we move towards the 90th percentile. In these types of analysis, percentiles lower than 10 and higher than 90 are not considered in order to avoid outlier situations.

In his article, John Van Reenen indicates that the blue line is following a “U-shape”, suggesting that the wage difference between the 90th (skilled workers) and the 10th percentile (unskilled workers) has not always followed the same trend. As John Van Reenen explains, there was a drop in inequality from 1935 to the mid-1950s. After that period, wage inequality was almost stable until the 1970s, when inequality took off and has continued to rise ever since. Inequality rose faster from the late 1970s to the late 1980s.



Source: Machin and Van Reenen (2010), OECD
Note: Netherlands has a break in series in 1993

Figure 2: Change in male wage inequality OECD countries in the 1990s and 2000s

Although the United States have one of the highest wage inequalities among advanced countries, this phenomenon is also very prominent in almost all developed countries throughout the world. Indeed, as John Van Reenen writes, the same broad pattern is observed in the UK. Moreover, the economist shows in Figure 2 (taken form Machin and Van Reenen 2010) that the UK and the US are not out of line with the experience in other OECD countries. As a matter of fact, wage inequality rose across almost all countries and, in Australia, Denmark, Germany and New Zealand inequality rose more than in the UK. Therefore, as also indicated by Atkinson et. al. (2010), increasing wage inequality between skilled and unskilled workers is a globally widespread phenomenon.

2.2 How manufacturing employment has changed over time

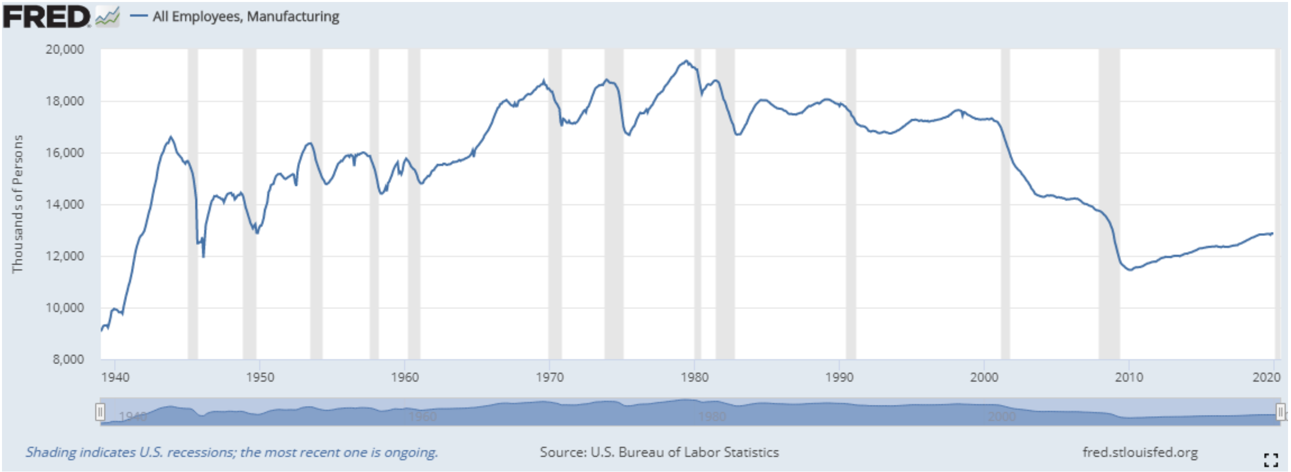


Figure 3: US manufacturing employment trend from 1940 to 2020 (pre COVID - 19)

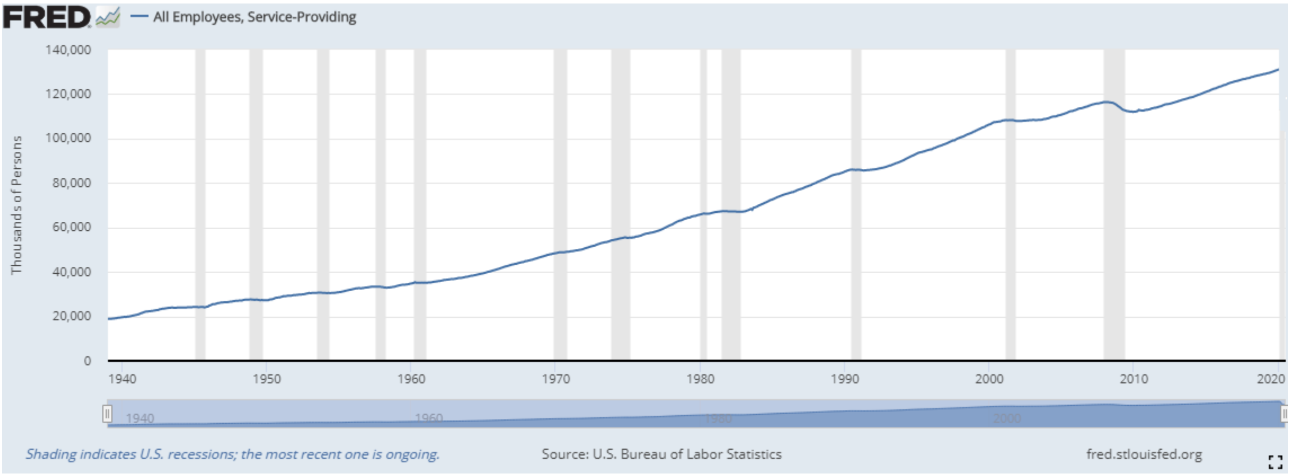


Figure 4: US Service-providing employment trend from 1940 to 2020 (pre COVID - 19)

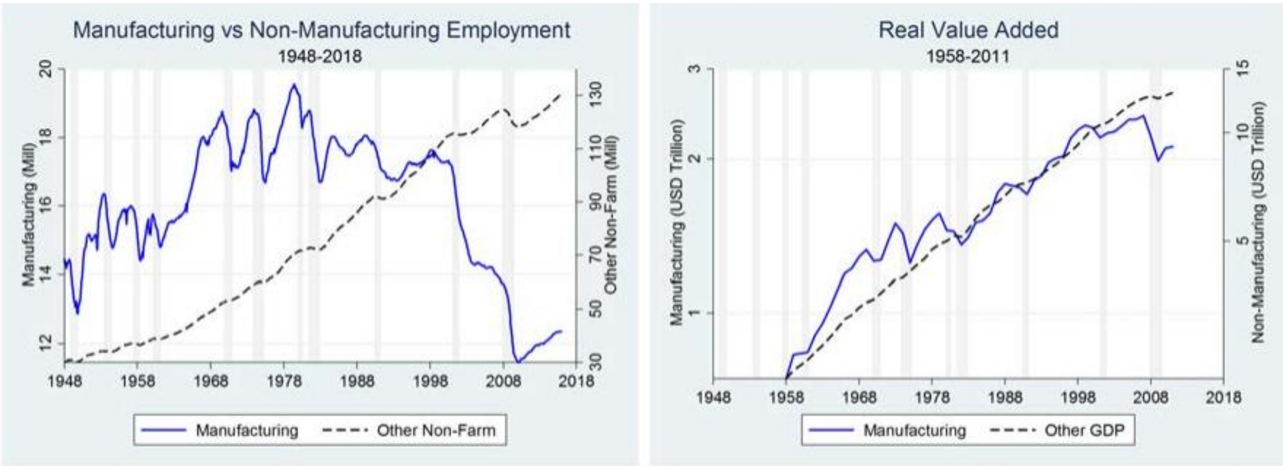
The manufacturing industry has radically changed throughout the history, shifting away from the old assembly lines where a lot of unskilled workers were dedicated to very simple and repetitive activities. As a matter of fact, as a consequence of technological progress, now people must manage those machines used for numerous simultaneous automated activities, which replaced a large number of unskilled workers.

Figure 3 shows how American manufacturing employment has changed over time. As we can see, manufacturing employment experienced a strong decrease at the end of the World War II but then, however, it increased again until the 1970s. Through the 1970s we can recognise a fluctuation level, which is irrelevant in our analysis, while from the mid-1970s a decreasing trend is clearly recognisable ever since, even if a very weak growth has been experienced in the last decade.

If we analyse the employment evolution regarding service-providing sectors instead, the situation is totally different. As a matter of fact, differently from manufacturing employment, this trend has always registered a positive and monotonic growth, except for short periods of time reflecting different recessions which impacted the American Economy. Furthermore, looking at these recession periods from both manufacturing and service-providing perspectives, it is evident that manufacturing employment suffered much more than the service-providing employment sector.

Another significant pattern could be found by comparing manufacturing employment evolution to figure 1, from Goldin and Katz 2008, illustrating how US male wage inequality evolved from 1935 to 2005. As I previously referenced, John Van Reenen illustrated that a decrease in inequality occurred from 1935 to the mid-1950s. After that period, wage inequality remained stable until the 1970s when inequality took off and has continued to rise ever since, with a faster growth from the late 1970s to the late 1980s. This trend seems to be closely connected to manufacturing employment evolution. From the 1950s to the 1970s, when wage inequality proved to be stable, manufacturing employment grew. Conversely, since the 1970s, when wage inequality has started its growth, manufacturing employment has always decreased.

A comparison between how US male wage inequality evolved, and the evolution of service-providing employment does not show a similar path. In fact, service providing employment evolution has continuously grown since the 1940s.



Source: Monthly employment data are from U.S. Bureau of Labor Statistics. Annual manufacturing real value added data are from NBER-CES Manufacturing Industry Database. Annual real GDP data are from U.S. Bureau of Economic Analysis. Non-manufacturing value added is real GDP less manufacturing real value added, both in 2009 dollars. Gray bars indicate duration of recessions as determined by the NBER Business Cycle Dating Committee. Axes of right panel are in logs.

Figure 5: US manufacturing vs non-manufacturing employment and real value added

Very significant observations were made by Teresa C. Fort, Justin R. Pierce and Peter K. Schott in their research “New perspectives on the decline of US manufacturing employment”. Graphs above compare manufacturing vs Non-manufacturing employment evolution on the left, whereas on the right, they show the value-added evolution provided by both manufacturing and other GDP industries.

In their work, Teresa C. Fort, Justin R. Pierce and Peter K. Schott recognised two main notable trends. The first one is similar to the one that we have previously illustrated, and it refers to the divergence between manufacturing employment from non-manufacturing one, while the second one has not been defined yet.

By looking at the graph on the right, the authors recognised that despite the remarkable decline in the US manufacturing employment, there has been a monotonic rise in the real value added provided by manufacturing activities. Moreover, this rise registered a rate close to the non-manufacturing GDP activities one, over the same period of time. It is important to note, however, that non-manufacturing activities have always increased their employment over time, as opposed to the manufacturing industry.

What the authors explain is that the combination of declining employment and rising output, corresponds to an indication that, in the long-run, labour productivity has increased in manufacturing sectors due to technological development. In addition, Teresa C. Fort, Justin R. Pierce and Peter K. Schott, suggest that if expenditures dedicated to manufactured goods have a fixed percentage on consumers total spending, an improvement in labour productivity would lead to a reduction in the need for workers to satisfy the demand for those goods.

2.3 How the U.S. tech industry and the tech workforce have changed in the last decade

The following graphs were taken from “The definitive guide to the U.S. tech industry and tech workforce”, an annual statistical analysis which studies how American tech industry has changed through years under different perspectives.

Differently from the manufacturing sectors, the tech industry requires people with a developed knowledge of technologies, programming, software etc. Employees in this industry should have followed technological based university courses and they should also be always updated about technological changes. Therefore, the majority part of workers in the tech industry are skilled workers.

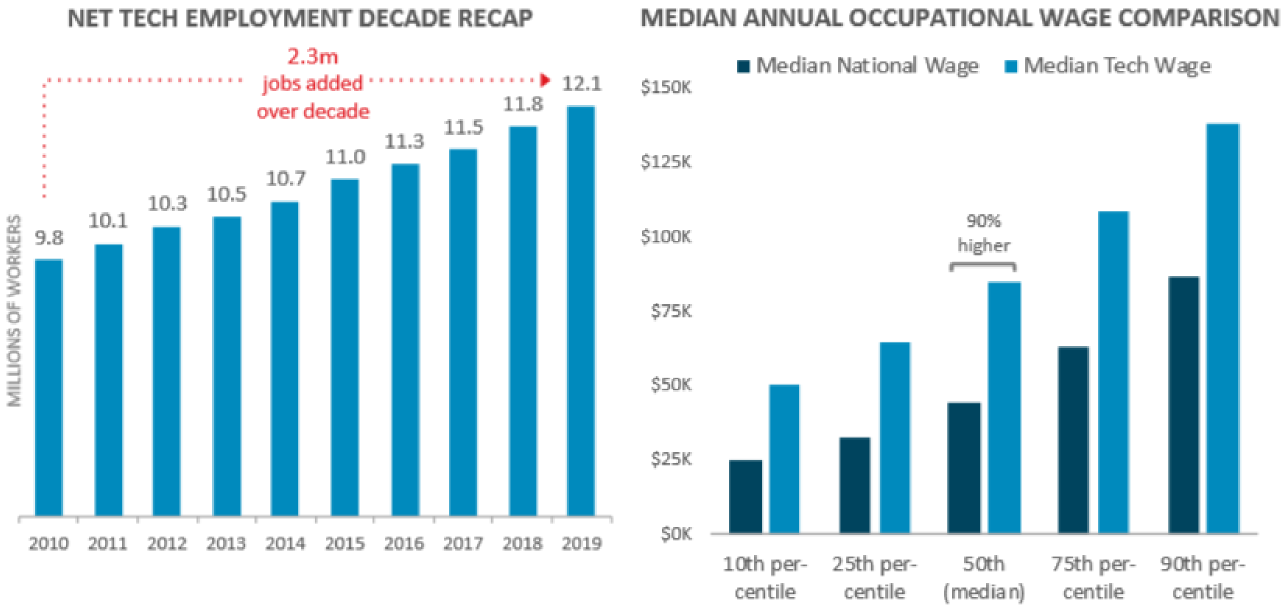


Figure 6: US net tech employment growth and a comparison between average wage paid diversified by percentiles in net tech sector and other sectors

Source: "The definitive guide to the U.S. tech industry and tech workforce"

The first graph represents the employment evolution of the American tech industry from 2010 to 2019. Keeping in mind how manufacturing employment evolved through recent years, we can now recognise a totally different trend. Specifically, this trend is benefitting from a much stronger growth than the manufacturing one. Indeed, as the statistical analysis explains, people employed in the net tech industry were 12.1 million in 2019 which correspond to an absolute increase of 2.3 million or a relative increase of 23% on the level registered in 2010. Specially, 2018 recorded the largest growth reaching 334.000 net new jobs, followed by 2015, year during which 315.000 net new jobs were created.

Another relevant statistic provided by this analysis is illustrated in the comparison between median tech wages and median national wages divided in percentile groups. The median wage, as defined in this guide, refers to the 50th percentile. At this percentile level, the tech wage is estimated to be 84.284$, which nearly doubles the 44.432$ provided by the median wage of the U.S. labour force.

It is therefore evident that the high-tech industry is experiencing a rapid growth which leads to a very high employment growth rate and significant wage differences with other types of industries.

2.4 Patterns of exports between Developed and Developing countries

In order to illustrate this trend, I based my research on Chapter 5 of "International Economics Theory and Policy" by Krugman, Obstfeld, and Melitz.

Figure 7: Changes in Chinese export pattern to the US from 1983 to 2012, divided in skill intensity groups

Source: International Economics Theory and Policy, Krugman, Obstfeld and Melitz

In this book the authors analyse how export, divided into four different skill-intensity groups, evolve in case of a country grows and shifts to a relatively skill abundant country. Krugman, Obstfeld and Melitz analysed the Chinese case from 1983 to 2012 and explained that, during this period, China saw a substantial increase in skill abundance. The accompanying graph, taken from their book, shows how Chinese exports to the U.S., divided in skill intensity groups, changed over the time considered. In their analysis, the authors clearly highlight that the "specialization" of Chinese exports shifted from least skill-intensity sectors towards high skill-intensity ones.

2.5 Trend recap

These trends provide us with different information about the current scenario in which workers, in developed economies, are living. As John Van Reenen explains, the wage and employment inequality between skilled and unskilled workers in developed countries, has continuously grown for decades. Although the US has one of the highest wage inequalities, this problem is also very significant in almost all advanced countries throughout the world.

Teresa C. Fort, Justin R. Pierce and Peter K. Schott recognised that despite the remarkable decline in the US manufacturing employment, there has been a monotonic rise in the real value added. The authors explain that the combination of declining employment and rising output, corresponds to an indication that, in the long-run, labour productivity has drastically increased in manufacturing sectors due to technological development, substituting a large number of unskilled workers which were dedicated to a group of very simple and repetitive activities.

The situation is radically different in the high-tech sector, where high-skilled workers are required to operate and develop technology. This sector benefited from a 23% employment growth in the last nine years and, compared to other industry median wages, it pays much higher salaries. It is therefore evident that the American high-tech industry is experiencing a continuous and remarkable growth, as opposed to the American manufacturing sector.

The changing pattern of Chinese exports should be compared to the previously illustrated trends regarding the fall of manufacturing employment and the growth of the tech industry in the US. By doing this, we can recognise that, as Krugman, Obstfeld and Melitz explain, international trade is changing in China, moving towards high skill-intensity sectors for exporting, following a pattern similar to a developed country such as the US.

Therefore, our interests rely on understanding whether the previously mentioned wage and employment inequalities between skilled-unskilled workers in developed countries have been caused by technological changes and international trade.

3. THEORETICAL REVIEW

In order to understand the theoretical reasons at the basis of the previously illustrated wage and employment inequalities between skilled and unskilled workers in developed countries we can exploit the Heckscher-Ohlin Model.

In this section we will present this model, based on Krugman, Obstfeld and Melitz, from a theoretical perspective. By analysing empirical researches in the empirical section, we will understand whether its theoretical predictions materialised. Specifically, we will empirically understand which are the effects of international trade and the so called "skill biased technological change" on wage and employment inequalities between skilled and unskilled workers in developed countries.

3.1 The Heckscher-Ohlin Model and its expectations

Before starting with the discussion of the H.O. Model I would like to underline the fact that everything I wrote in this section was taken from the book "International Economics Theory and Policy" by Krugman, Obstfeld and Melitz. This book enabled me to understand the empirical research discussed in the next section.

There are different assumptions at the basis of the 2 by 2 model used by Krugman, Obstfeld and Melitz to introduce the discussion. The first assumption they make is that there are two countries, two goods to produce and two factors of production. Countries are called "Home" and "Foreign" while goods are described as "cloth" (measured in yard) and "food" (measured in calories). In their explanation the authors assume that factors of production are mobile in the long run, thus labour could be used in both industries where capital could be used both for buying a power loom and for buying a tractor. The supply of capital and labour is fixed for each Economy.

In this model producers do not have to consider a fixed amount of input requirements for producing one unit of product but, instead, they can rely on a trade-off. Therefore, to produce one calorie of food, a farmer can use more or less capital or labour. One important item to remember here is the fact that the more labour/capital a farmer uses for producing one calorie of food for example, the less is its marginal contribution to the

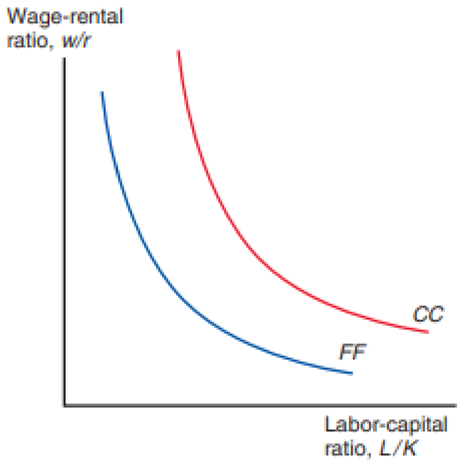


Figure 8: Input choices depending upon factor prices

production. This choice is driven by the relative costs of the factors of production. Relative factor demand curves illustrated above show that, if wages w are high while rental rates r are low, the producer will exploit relatively little labour and a lot of capital (e.g. German industrial production). The FF curve illustrates this relationship for the production of food while, conversely, the CC curve illustrates this relationship for the production of cloth. An important aspect that Krugman, Obstfeld and Melitz highlight in this graph is that the CC curve is shifted out relative to FF. They highlight that for any given level of factor price, cloth production always requires more labour to capital than food production does. The authors write that this is due to the fact that cloth production is labour-intensive while food production is capital intensive.

Figure 9: Link between good and factor prices

To explain the next concept Krugman, Obstfeld and Melitz assumed that an economy produces both cloth and food. They explained that if wages increase, the price of goods, which require labour for production, also increases. As the authors explain this increase in price depends however on the involvement of the factor price in production. Therefore, an increase in wages will have a stronger impact on cloth price than on food price because, as the authors explain, cloth production is labour intensive and thus, labour involvement is relatively higher than capital involved. This relationship is illustrated in figure 9.

Krugman, Obstfeld and Melitz now integrate figure 8 and figure 9 in figure 10. They set on the left side figure 9, turned counterclockwise 90 degrees, while on the right side they set figure 8. In order to explain the following concept the authors start from specific values in the previous graph. They initially presume a starting relative price of cloth to food quals to to (Pc/Pf)1. At this level the ratio between wages and capital is set to (w/r)1. Based on this ratio Krugman, Obstfeld and Melitz equalize the relative amount of labour to the amount of capital used in both productions to (Lc/Kc)1 and (Lf/Kf)1.

The authors now presume a relative price increase of cloth over food (Pc/Pf). Specifically, they suppose a relative price increase of cloth over food to the level indicated by (Pc/Pf)2. Under these new conditions, Krugman, Obstfeld and Melitz explain that the ratio between wage to rental rate would rise to a new level indicated by (w/r)2. Labour becomes relatively more expensive to capital, therefore, as the authors show in their graph, both sectors tend to avoid the use of labour and prefer to use more capital for producing goods. This is illustrated by the decreased levels of labour to capital employed in production of cloth and food (Lc/Kc)2 and (Lf/Kf)2.

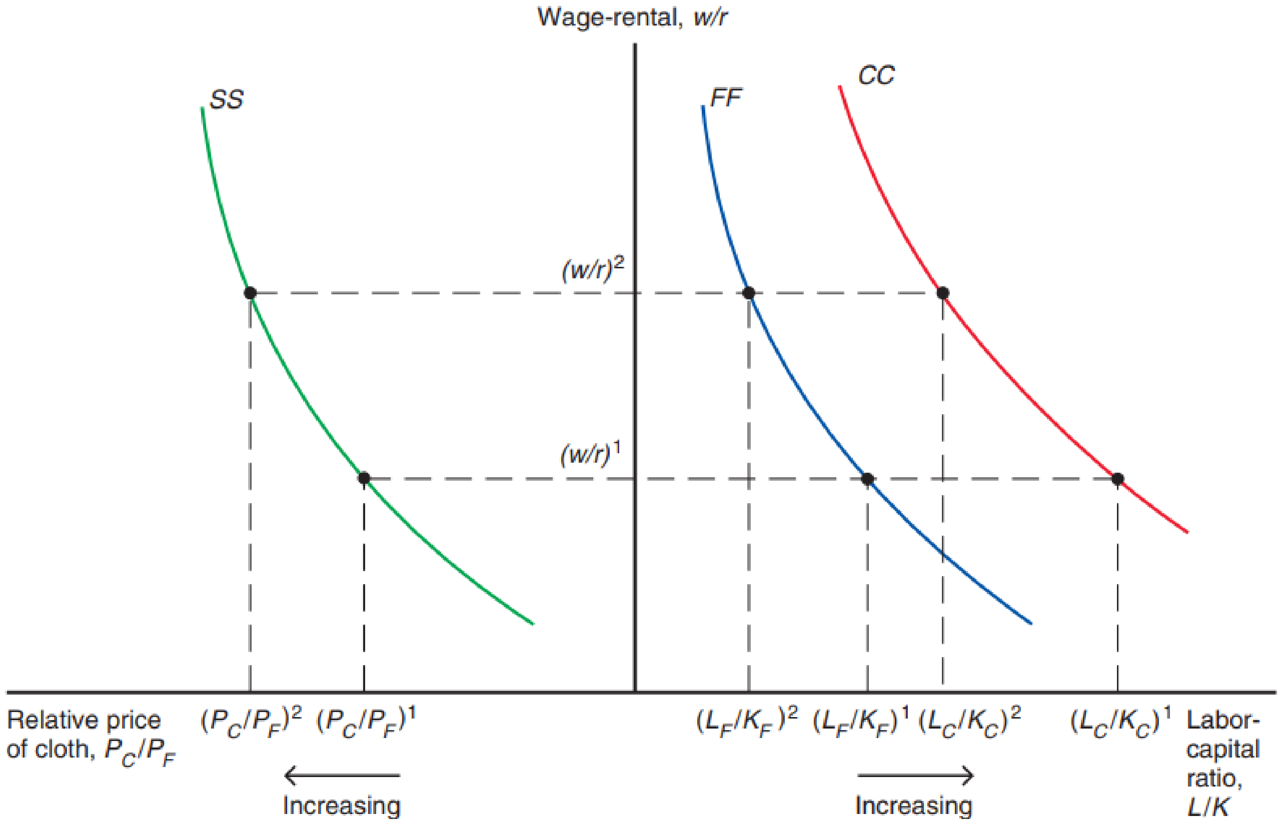


Figure 10: From good prices to input choices

Krugman, Obstfeld and Melitz now presume an increase in the economy's labour force. This increase, as explained by the authors, leads to the aggregate ratio L/K of the overall economy to increase. Considering unchanged relative prices (Pc/Pf)1, ratios of labour to capital employed remain constant. How can the economy employ the new labour force in case the relative labour demanded in both sectors does not change from (Lc/Kc)1 and (Lf/Kf)1?

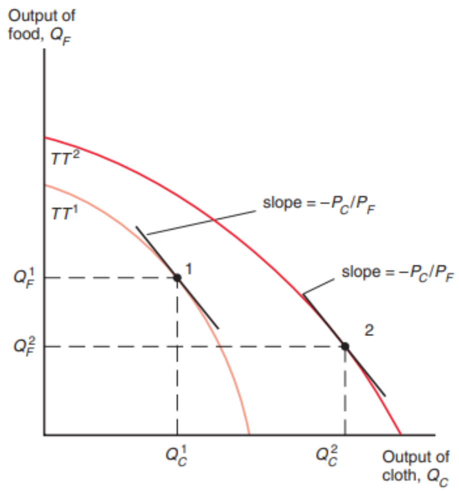


Figure 11: Changes in the output mix

Krugman, Obstfeld and Melitz explain that a new allocation of both labour and capital between industries is necessary. As discussed before, the cloth industry is labour intensive relative to the food industry and thus, at a certain relative price of cloth to food, it always requires a higher ratio of labour to capital employed in production. Therefore, as the authors illustrate, there should be an absolute increase of both labour and capital allocated to the cloth sector without changing the ratios between labour to capital in both sectors. In this situation the overall economy will produce more cloths and less food because it is allocating more capital and labour to the cloth industry. This phenomenon is represented in figure 11.

By exploiting this graph, Krugman, Obstfeld and Melitz introduce the concept of biased expansion of production possibilities. The authors firstly illustrate that now the economy is able to produce more cloths and food than in the previous case. However, the authors show that, although the quantity that could be produced is higher for both cloth and food, the outward shift of the frontier is much larger towards cloth than food. Krugman, Obstfeld and Melitz call it biased expansion of production possibilities. They add that this phenomenon occurs when the improvement of the production possibility frontier is stronger towards a specific sector.

Krugman, Obstfeld and Melitz graphically show in figure 11 that the improvement is so strongly biased in the direction of cloth that if the relative price (Pc/Pf) does not change, the new production-mix of the overall economy results to be at point 2. At this point a dramatic decrease of food produced is registered (Qf2) along with a broad rise in cloth produced (Qc2).

The authors explain that a rise in the labour supply disproportionally increases the production possibility frontier towards cloth. Conversely, if a capital supply increase is registered, the production possibility frontier would be biased towards food. Keeping in mind that cloth production is labour intensive, the authors illustrate that if we are dealing with an economy which is relatively more labour abundant than capital, it will supply cloth relatively better than an economy which has a relative higher supply of capital to labour.

Krugman, Obstfeld and Melitz: *"An economy will tend to be relatively effective at producing goods that are intensive in the factors with which the country is relatively well endowed"*

In all the previous theoretical discussions Krugman, Obstfeld and Melitz assumed that there was no international trade between Home and Foreign countries. From this point on, the authors introduce international trade in their model.

Krugman, Obstfeld and Melitz assume Home country to be labour abundant relative to Foreign country (higher L/K available to the overall economy) and vice versa. Reminding us about what we saw in the previous section, the authors explain that the production possibility frontier of Home country is shifted out more towards cloth production than the production possibility frontier of the Foreign country. Therefore, relative production of cloth to food (RS) in the Home country will be higher than that of Foreign (RS*). In addition, Krugman, Obstfeld and Melitz explain that, since trade makes relative prices to be equal in both countries, the relative price of cloth over food will be the same in each country, represented by point 2 in the illustration below.

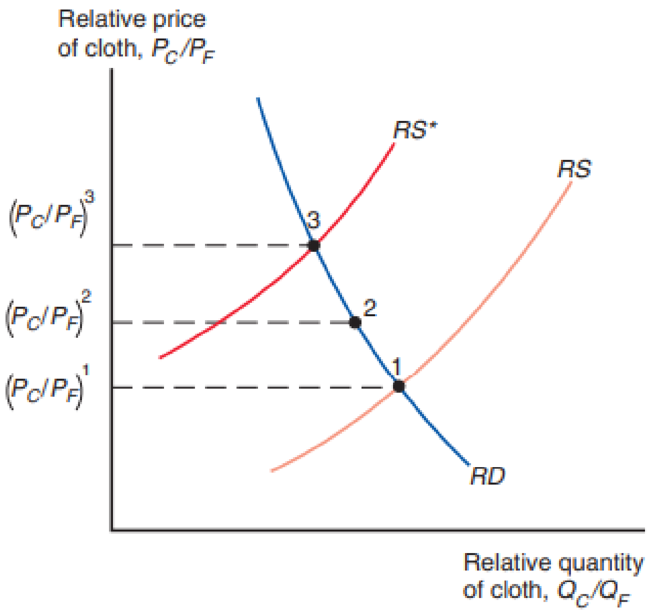


Figure 12: Price convergence caused by trade

In figure 12 Krugman, Obstfeld and Melitz identify as RD the relative demand curve, which is supposed to be the same for both countries. Thus, the relative price of cloth over food in the Home country increases in the case of International Trade and, oppositely, it decreases in Foreign countries. Krugman, Obstfeld and Melitz argue that the economy exports those goods which see a price increase in that economy. Thus, in our example, Home will export cloth (as its relative price rises in Home) and import food. This is because Home is labour abundant and cloth production is labour intensive.

Krugman, Obstfeld and Melitz about the Heckscher-Ohlin Model: "*The country that is abundant in a factor exports the good whose production is intensive in that factor*".

3.2 Trade, Skill-Biased Technological Change and income inequality

In the previous section Krugman, Obstfeld and Melitz illustrate that the distribution of income is remarkably affected by international trade. In their example, they explain that after the introduction of international trade in the economies, Home starts exporting cloth as the country is labour abundant and it sees a rise in the relative price of cloth coming from the new market. Thus, they explain that those people whose income comes from labour are better off, as the ratio (w/k) increases, while those people whose income comes from the use of capital are definitely worse off. The scenario is reversed in the Foreign country. Krugman, Obstfeld and Melitz state:

"Owners of a country's abundant factors gain from trade, but owners of a country's scarce factors lose".

Let us now understand how the authors adapt the Heckscher-Ohlin model to employment and wage inequalities between skilled workers and unskilled workers. Particularly, we will now understand the theoretical impact of technological change and international trade on the previously mentioned inequalities. In their book, the authors adapted the HO model to the US case, however it can also be adapted to almost all developed countries.

Krugman, Obstfeld and Melitz illustrate that since the US is relatively well endowed with high-skilled workers relative to low-skilled ones, international trade can affect high-skilled workers making them better off at the expense of the low-skilled end. In their case study called "North-South Trade and Income Inequality", the authors argued that what is happening is a move towards factor-price equalization. As a matter of fact, based on the factor-model predictions, they highlight that by trading, developed economies, which are relatively capital and highly skilled labour abundant, and newly industrializing economies (NIEs), which are relatively unskilled labour abundant, the wage of high-skilled workers, in developed economies, is increasing at the expense of the wage paid to low-skilled workers.

As we understood when analysing different trends involving wage and employment differentials, inequality has steadily risen since the 1980s. Although international trade played a role in this phenomenon and even though trade between developed and developing countries significantly improved in the economic history, Krugman, Obstfeld and Melitz argue that trade still corresponds to a minor percentage of the total expenditures in developed countries. Specifically, they noticed that in developed economies the export of highly skilled labour, for what concerns skill-intensive industries, and the import of unskilled labour, in labour-intensive industries, still correspond to a minor portion of skilled and unskilled labour supplies. For this reason, the authors argue that trade alone did not play a very significant role in widening wage and employment inequalities. As a matter of fact, the view of Krugman, Obstfeld and Melitz, in addition to other well-known economists, is that new production technologies stressed workers' skills more. The examples made by the authors are computers and new technologies which can be used in as technology-skill complementary, therefore technology complements the work of a skilled person and increases his/her performance (e.g. data visualization tools for high management to monitor KPIs). The authors call this phenomenon "**skill-biased technological change".**

Krugman, Obstfeld and Melitz continued their theoretical discussion by analysing the theoretical impacts of both international trade and technological change on wage and employment inequalities between skilled and unskilled workers. They modified their two-factor production model to consider the effects of technological change, which they defined as skill-biased. They now contemplate two new factors of production which are skilled and unskilled labour. These factors aim at producing two new goods which are high-tech and low-tech goods. From a more practical perspective we can think at these goods as microprocessors (high tech) and shoes (low tech).

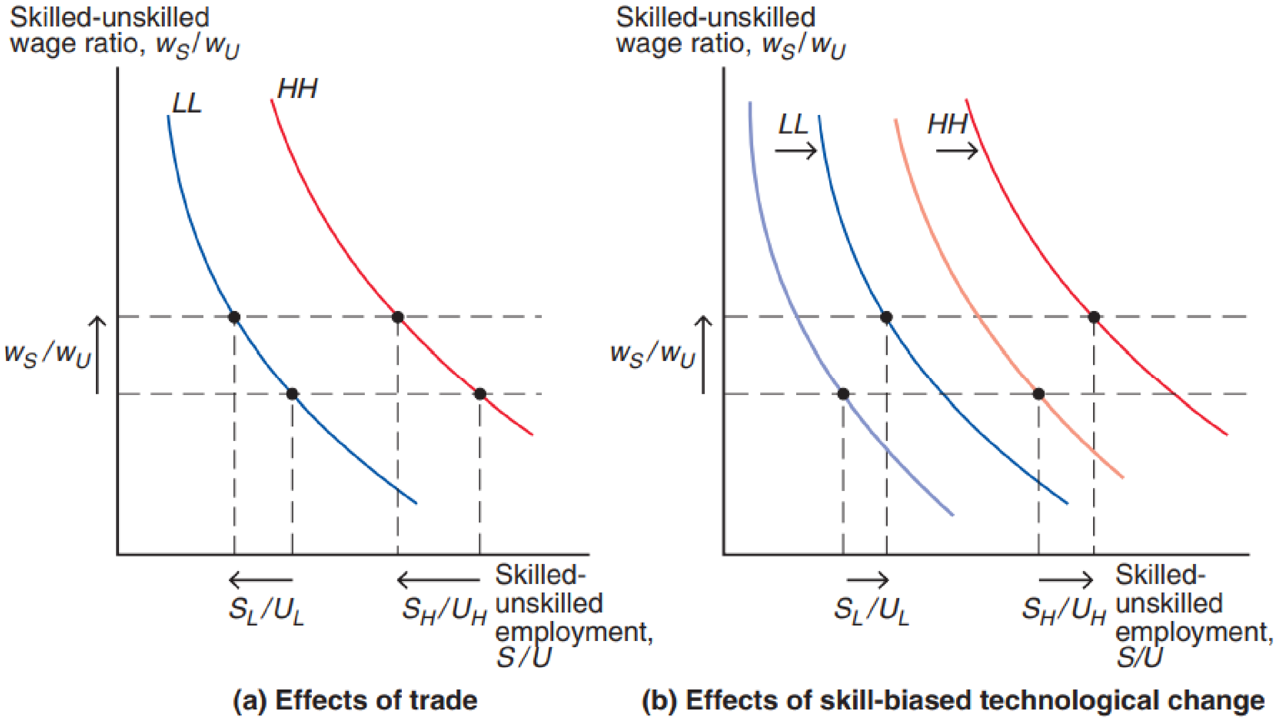


Figure 13: effects of international trade and skill biased technological change on wage and employment inequalities

In figure 13 the authors illustrate how the relative factors demand behaves in the analysed industries. Specifically, they illustrate that the ratio reflecting relative employment between skilled-unskilled workers (S/U) depends on the relative wages (Ws/Wu). This approximates what we saw in the previous discussion regarding cloth and food. Krugman, Obstfeld and Melitz supposed the high-tech industry to be skilled labour intensive thus, the HH curve lay on the right of the LL curve. To better understand the figure above we should keep in mind the SS curve represented in figure 9, which established the positive relationship between the skilled-unskilled wage ratio (Ws/Wu) on the y-axis and the relative price of high-tech goods and low tech goods on the x-axis.

In panel (a) the authors illustrate the effect of an increase in international trade between developed and developing economies. As they illustrate in their book, an increase in the relative price of high-tech goods to low-tech goods leads to an increase in wage inequality between skilled and unskilled workers, represented by the increase in the ratio Ws/Wu along the SS curve. This increase in inequality (relative cost for producers), however, results in a relative employment reduction of skilled workers to unskilled workers in both industries, illustrated by the movements along the curves HH and LL.

Differently from panel (a), in panel (b) Krugman, Obstfeld and Melitz illustrate the effects of technological change on wage and employment inequalities in developed countries. The authors name this technological change as “skill biased” because the relative demand for skilled workers in both the industries will shift out (which means the HH and LL curve shift to the right) and because of its complementarity with skilled workers generates productivity improvements in the high-tech industry. In this discussion Krugman, Obstfeld and Melitz explain that a technological innovation results in a higher skilled-unskilled wage ratio, considering an unchanged relative price of high-tech goods as the SS curve shifts upward. In this case, differently from the previous situation, despite of the increase in the skilled-unskilled wage ratio (relative cost for producers), producers in both industries face the technological change by hiring relatively more skilled workers than unskilled one, as illustrated by the rightward movements of HH and LL. Therefore, the conclusion, reached in this case, is an increase in wage inequality and a higher relative employment between skilled and unskilled workers.

To conclude this section, the theoretical perspective of Krugman, Obstfeld and Melitz argues that international trade per se does not create both wage and employment inequalities between skilled and unskilled workers. Conversely technological change, which results in the so called “skill biased technological change”, is expected to widen both wage and employment inequalities between skilled and unskilled workers through an overall growth of the economy biased towards tech industries which are skill intensive.

4. EMPIRICAL FINDINGS

In this section we will understand whether the theoretical predictions by Krugman, Obstfeld and Melitz proved to be true or not. Specifically, we will analyse different empirical researches, conducted by top economists, in order to clarify the roles played by international trade and skill biased technological change (technological progress) in widening wage and employment inequalities between skilled and unskilled workers in developed countries.

4.1 "Intra-Country Wage Inequality in the OECD Countries". 2018. Manuel Carlos Nogueira and Óscar Afonso

The first empirical research that I will illustrate was conducted by Manuel Carlos Nogueira and Óscar Afonso, two economists from Portugal. I obtained this research from their article "Intra-Country Wage Inequality in the OECD Countries". Their work aims at illustrating the impact of both skill biased technological change (SBTC) and international trade (IT) on wage inequalities in 30 different OECD countries, based on data from 2001 to 2015.

The authors, in this article, studied how these factors contributed to enlarge the wage differential between workers who have completed higher education (skilled labour) and those workers who have a lower level of education (unskilled workers). Nogueira and Afonso grouped different countries in seven clusters, which reflect seven groups of countries which are homogeneous within each group and heterogeneous between them.

- Cluster 1: Australia, Canada, Estonia, New Zealand and Switzerland. This cluster presents homogeneity in terms of low wage inequality and it is the one with countries that heavily invest on R&D. Therefore, the authors expect SBTC to be the main driver of inequality.

- Cluster 2: Slovakia and Hungary. A cluster with high wage inequality countries. These have the lowest rate of R&D expenditure on GDP and they have the highest degree of openness to trade.

- Cluster 3: Luxembourg. The authors did not consider it in their analysis because it is an outlier.

- Cluster 4: the USA, Germany, Japan and Korea. The cluster with most populated countries and the highest rate of R&D investments. The SBTC is expected to be the main cause of inequality by Nogueira and Afonso.

- Cluster 5: Czech Republic, Greece, Portugal and Turkey. Cluster reflecting the poorest countries in the considered sample which share the highest wage inequality rates.

- Cluster 6: Austria, France, Ireland, Italy, Netherlands, Poland, Slovenia, Spain and the UK.

- Cluster 7: Belgium, Denmark, Finland, Norway and Sweden. Cluster with the lowest rate of wage inequality and a high rate of R&D investments.

The analysis will show that both SBTC and IT are significant in enlarging the wage gap in almost all the 30 countries analysed. However, the authors explain that, by looking at individual clusters, some of them are more affected by SBTC, some by IT and just one cluster is simultaneously affected by both the theoretical predictions.

Nogueira and Afonso indicate in Table 1 the variables they used in their analysis. They named the dependent variable WPT-WPS. It represents the wage differential between college educated workers (High skilled) and high school educated workers (Low skilled). The authors defined a set of explanatory variables which explain the dependent ones.

Variable	**Definition**	**Unit**	**Source**
$WPT_{i,t}$ -$WPS_{i,t}$	Wage gap between university graduates and high school graduates in country *i* and year *t*, in real terms	Index	OECD Education at a glance
$SBTC_{i,t}$	Research and development spending as a percentage of GDP in country *i* and year *t*	Percentage	OECD World Bank
$Trade_{i,t}$	International trade measured by the degree of openness, i.e. the sum of exports and imports as a percentage of GDP, in country *i* and year *t*	Percentage	OECD World Bank
$FDI_{i,t}$	Share of stock of foreign direct investment on GDP in country *i* and year *t*	Percentage	OECD World Bank
$Immigration_{i,t}$	Total number of immigrant workers as a percentage of the labour force in country *i* and year *t*	Percentage	OECD World Bank
$Education_{i,t}$	Education expenditure as a percentage of GDP in country *i* and year *t*	Percentage	OECD World Bank
$GDPpc_{i,t}$	Gross domestic product *per capita* in country *i* and year *t*, in real terms	Value in dollars	OECD World Bank

Table 1: Variables definition

As we can see, in addition to SBTC and International Trade, there are other variables influencing the wage differential, such as FDI, immigration, education and GDP per capita. However, for the purpose of this report, I decided not to consider them in the following discussion.

Nogueira and Afonso defined the skill biased technological change variable as a measure of total R&D spending as a percentage of total GDP by each country (e.g. Manchin and Van Reenen 1998) while international trade as a measure of the degree of openness (Trade) to express trade intensification (e.g. Mathias Thoenig and Thierry Verdier 2003).

Nogueira and Afonso reported in Table 2 the average values of the wage differential, the SBTC and IT for each country. By analysing this table, the authors highlight the US, Portugal, Greece, Hungary and Slovakia as those countries with the highest wage inequality while they highlight Finland, Estonia, Belgium, Sweden and Denmark as those countries with the lowest wage differentials.

Country	WPT-WPS	SBTC	IT	Country	WPT-WPS	SBTC	IT
Australia	33.3947	1.8214	0.4078	Korea	66.2112	3.0682	0.8466
Austria	75.3830	2.2838	0.9736	Luxembourg	55.916	1.6260	2.9083
Belgium	14.1448	1.9415	1.5462	Netherlands	30.4001	1.8919	1.3044
Canada	39.0111	1.9533	0.7182	New Zealand	33.9172	1.1479	0.5939
Czech Republic	73.4576	1.3150	1.2209	Norway	33.858	1.6172	0.7213
Denmark	24.6312	2.5379	0.8989	Poland	36.427	0.6099	0.7252
Estonia	11.4032	1.6878	1.4930	Portugal	92.506	0.9455	0.6677
Finland	8.5151	3.3638	0.7617	Slovakia	86.6301	0.5665	1.6261
France	26.9906	2.1626	0.5283	Slovenia	68.7206	1.6487	1.2503
Germany	28.6245	2.5464	0.7424	Spain	36.317	1.0842	0.5647
Greece	76.8557	0.4830	0.5398	Sweden	20.7474	3.6590	0.8687
Hungary	80.3444	0.9394	1.4393	Switzerland	51.5686	2.7018	0.8621
Ireland	35.9138	1.2862	1.6181	Turkey	65.7066	0.6899	0.4927
Italy	50.8265	1.0923	0.5139	The United Kingdom	72.2204	1.7731	0.5639
Japan	36.4698	3.3856	0.3088	The USA	90.2564	2.6902	0.2536

Table 2: Average variables value for the sample considered from 2001 to 2015

Based on the theoretical HO model predictions, Nogueira and Afonso explain that the SBTC variable is expected to increase the wage differential between skilled and unskilled workers. For what concerns the international trade variable, instead, they explain that the effects of this variable on wage differentials are ambiguous and mainly depend on a country's specialization. They expect the wage inequalities to be higher in countries specializing in high-tech products which produce and export these types of goods. Therefore, the authors expect those countries, which are relatively skill abundant, to present higher wage differentials.

Cluster	Cluster 1	Cluster 2	Cluster4	Cluster 5	Cluster 6	Cluster 7
Intercept	1.70945***	5.45850***	1.12967***	3.35345***	4.940560***	1.48756***
ln SBTC	0.13709*	-0.17500***	0.09896	-0.24427***	-0.125594	0.02273**
lnTrade	-0.17323	0.21008**	0.15382***	0.32377***	0.100570**	0.01155*
ln Immigration	0.14482*	-0.23277	0.04319	-0.20730**	0.044640	0.10837
ln Educationexpenditures	0.16350**	0.53210***	0.23913***	0.12108*	0.183565***	0.38735***
ln FDI	0.02502*	-0.00600	-0.01072	-0.03339	0.006579	0.00344
ln GDPpc	-0.18603**	-0.08400***	-0.07350**	-0.04046**	-0.016350**	-0.05735***
LSDV R-squared	0.87007	0.94020	0.89247	0.73867	0.931454	0.98056
F-statistic (*p*-value)	0.00112	<0.00010	<0.00010	<0.00010	<0.000100	<0.00010

Note: ***, **, and * denote statistical significance at the 1%, 5% and 10% level of significance, respectively. We do not consider the analysis for cluster 3 since it is composed by just one country and presents an insufficient number of observations to obtain estimates.

Table 3: Estimation results grouped by clusters

Results obtained by Nogueira and Afonso in their cluster analysis are shown in table 3. In these results the authors highlight different significance for both SBTC and international trade for different clusters. Here are the most important points to take away.

As they expected, cluster 1, which is composed of countries that heavily invest in R&D activities, is strongly and mainly affected by SBTC. As a matter of fact, the related coefficient presents a positive and statistically significant value. Moreover, other things equal, a rise of 1% in R&D/GDP ratio widens the wage gap between skilled and unskilled workers by 0.137%. The authors did not provide any additional comments regarding international trade for this cluster as the IT coefficient does not reveal high statistical significance.

For what concerns cluster 2, a cluster composed of small countries with high rates of wage inequality, Nogueira and Afonso highlight the fact that international trade plays a predominant role in increasing wage inequality. As they illustrate in their article, the related coefficient shows a very high and statistically significant value and, other things equal, a 1% increase in the degree of openness to trade generates a 0.21% increase in wage differential. However, what seems to contradict the theory is the expected effect of SBTC. As a matter of fact, the authors expect the SBTC effect to be negative and statistically significant, conversely to the theoretical predictions.

Regarding cluster 4, a cluster represented by highly industrialized countries, Nogueira and Afonso argue that the theoretical effects provided by the HO model are evident. As we can see in table 3, both the coefficients are positive, suggesting that the HO model predictions are verified. The SBTC coefficient is positive; for each additional 1% of R&D investments, the wage inequality is expected to rise by 0.098%. However, particular attention should be given to the international trade coefficient, which is remarkably positive and statistically significant. The authors argue that goods imported from unskilled labour abundant countries negatively affect unskilled workers in the skill abundant country. Therefore, in this cluster, international trade is supposed to be the main driver of inequality and, other things equal, the authors expect the wage inequality to rise by 0.153% for each additional 1% of international trade openness.

Cluster 5 shows a low R-squared value and therefore it will not be discussed.

Nogueira and Afonso, similarly to what observed in Cluster 2, explain that international trade is the main source of wage inequality for those countries included in cluster 6. Indeed, table 3 presents a high and statistically significant value of international trade coefficient on wage inequalities. Specifically, if the degree of international trade openness increases by 1%, the wage inequality between skilled and unskilled workers is expected to rise by 0.10%. No comments were added for the coefficient related to SBTC as it does not show a great statistical significance.

Finally, for what concerns cluster 7, a cluster led by Nordic countries, Nogueira and Afonso explain that both IT and SBTC are responsible for widening wage differentials, however the largest contribution is provided by the technological change. Both the coefficients associated to IT and SBTC register a positive and statistically significant value, clearly in line with the theoretical predictions of the HO model. However, the authors illustrate that when R&D investments and IT openness improve by 1%, the wage inequality rises by 0.0227% and 0.0115% respectively. Therefore, in this cluster the wage gap due to technological change nearly doubles the one generated by international trade openness.

To finalize their discussion, Nogueira and Afonso identify cluster 7 as that cluster which better fits the theoretical predictions; thus, where both SBTC and international trade are significant in widening wage inequalities. However, when Nogueira and Afonso consider OECD countries all together, they recognise in international trade the main driver for wage inequalities. Therefore, as they explain at the end of their work, if we examine each cluster separately, the conclusions differ based on the economic reality of each country.

4.2 “Do low-skilled workers gain from high-tech employment growth? High-technology multipliers, employment and wages in Britain”. 2019. Neil Lee, Stephen Clarke

Nogueira and Afonso recognised international trade to be the main drive of wage inequality in those countries included in cluster 6. As previously mentioned, they did not add any comment regarding the impact of SBTC on wage inequalities as, although its coefficient proves to be negative, it does not show a good statistical significance. Cluster 6 is a group of advanced countries encompassing Austria, France, Ireland, Italy, Netherlands, Spain and the United Kingdom. Therefore, it could be interesting to further analyse the effects of the skill biased technological change on one of these countries. This is the reason why I will illustrate the empirical findings of Neil Lee and Stephen Clarke which were presented in their research called: “Do low-skilled workers gain from high-tech employment growth? High-technology multipliers, employment and wages in Britain”. This research aims at illustrating how employment rates and wage rates of low and mid skilled workers were affected by high-tech growth, in the UK, from 2009 to 2015.

In the introduction section, Lee and Clarke compared two different points of view of the economic literature. On one hand, they illustrate that there is an optimistic view regarding the impact of high-tech growth on low skilled workers. As a matter of fact, the authors explain that there have been studies that define high technology as a tradable sector, which can create jobs in the non-tradable local economy, through the so called “Multiplier effect”. At this point, Lee and Clarke mentioned previous works such as (North, 1955; Tiebout, 1956) and they highlight the works carried out by Moretti in 2010 and 2013 for the US, which illustrate that for each additional job created in the high-tech industry, 4-5 non-tradable service jobs will be created. Conversely, Lee and Clarke also show that other studies contested the optimistic view. They explain that there have been researches which analysed high tech economies and illustrated strong wage inequalities between skilled and unskilled workers in those economies. To provide an example, Lee and Clarke referred to the research conducted by Saxenian (1983), which aims at illustrating the problems for low skilled workers in the Silicon Valley. Therefore, as the authors explain, although this literature shows that high tech growth could create jobs for unskilled workers, it also shows that these new jobs recognise low wages, negatively affecting the economic possibilities of unskilled workers, particularly when high and growing housing costs are considered.

Lee and Clarke initialize their work by analysing the empirical evidence that studies the effect of high-tech growth on the employment rate of unskilled workers. To do this, they define their regression model described by the following equation:

$$\triangle \mathrm{NonTrade}_c = \alpha + \beta_1 \triangle \mathrm{Tradeable}_c + \gamma X_c + \varepsilon_c$$

This model considers some items that are out of our interests, thus I will only illustrate those significant variables and coefficients which are in line with the purpose of this report.

$\triangle \mathrm{NonTrade}$ is the dependent variable, it represents the change in the log number on Non-tradable jobs. Therefore, it approximates the variation of unskilled jobs between 2009 and 2015.

△Tradeable is the change in log number of tradable high-tech jobs and thus, it approximates the variation of skilled jobs in the high-tech sector, between 2009 and 2015.

The crucial coefficient is β, the so-called "multiplier". Lee and Clarke explain that, if it results to be positive, the growth in high-tech (growth of highly skilled jobs) is followed by a growth in non-tradable (growth of unskilled jobs) which will be proportional to this coefficient.

Impact of high-technology industries on non-tradeables, 2009-2015.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	△Non-tradeable jobs + self-employment, 2009-2015								
Estimator	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Sample	Full	Full	No Outlier	Full	Full	No Outlier	Full	Full	No Outlier
Growth in high-tech and digital, 2009-15	0.0754*	0.0655	0.0687	0.110**	0.101*	0.124**	0.358***	0.320**	0.312**
	(0.0435)	(0.0431)	(0.0434)	(0.0561)	(0.0547)	(0.0525)	(0.129)	(0.162)	(0.159)
High skill %, 2009		−0.0487	−0.0257		−0.0596	−0.0423		−0.127	−0.0987
		(0.141)	(0.140)		(0.133)	(0.131)		(0.142)	(0.138)
Unemployment %, 2009		−0.417	−0.391		−0.385	−0.342		−0.190	−0.173
		(0.340)	(0.329)		(0.326)	(0.317)		(0.359)	(0.355)
Total employment (ln), 2009		0.0102	0.00923		0.00961	0.00823		0.00575	0.00486
		(0.00698)	(0.00697)		(0.00688)	(0.00687)		(0.00905)	(0.00893)
Constant	0.0180	−0.0588	−0.0547	0.0112	−0.0584	−0.0539	−0.0378	−0.0554	−0.0511
	(0.0264)	(0.0790)	(0.0777)	(0.0270)	(0.0754)	(0.0739)	(0.0418)	(0.0809)	(0.0791)
Multiplier	0.43	–	–	0.63	0.58	0.71	2.06	1.84	1.79
First stage results									
Bartik Shift-Share				0.745***	0.734***	0.753***			
				(0.0710)	(0.0724)	(0.0738)			
Pre-WW1 Schools of Art & Design							0.0311***	0.0314***	0.0314***
							(0.00712)	(0.00883)	(0.00885)
R-squared	0.156	0.170	0.171						
Kleibergen-Paap Wald F statistic				110.2	102.9	104.2	18.92	12.64	12.66
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	182	182	181	182	182	181	182	182	181

Note: Robust standard errors reported in parentheses. Columns 3, 6, and 9 exclude Darlington, an outlier. Dependent variable: growth in employment in non-tradeable employment and self-employment, 2009–2015. *p < 0.1. **p < 0.05. ***p < 0.01.

Table 4: Empirical impact of High-tech sector growth on low-tech industries

Table 4 presents the results from the regression of the previous model. Columns 1,2,3 present the results using an OLS estimator (Ordinary Least Squares). Lee and Clarke, however, explain that results from OLS are weak, as they are statistically significant only at 10% level. To improve this data, the authors decided to use the more robust "instrumental variable" (IV). By doing so, results are more statistically significant. These are shown in column 4 and 5, with and without controls but, as the authors indicate, the best model is illustrated in column 6. Through this model Lee and Clarke obtained a multiplier equal to 0.71, indicating that if 10 high-tech jobs are created (High skill job), 7 new non-tradable jobs (Unskilled jobs) evolve.

The authors then compared their results to the ones obtained by Moretti. They found that 0.71 is much lower than 4-5 indicated by Moretti for the US. As Lee and Clarke explain there are different reasons at the basis of this difference. However, the important point to remark in this discussion is the statistically significant positive relationship between high tech job growth and unskilled job growth.

Following the analysis regarding the effects of the growth of high-tech jobs on the growth of low skilled jobs in UK, Lee and Clarke now examine the effects of high-tech growth on low skilled workers wage variations. In order to better reflect the real purchasing power variation, the authors decided to define their model considering coefficients regarding inflation and housing costs. The model defined is the following:

$$ln(HourlyPay_{c\ t}) = \alpha + \beta_1 Tech_{c,t} + \gamma\ X_{c,t} + \varphi_c + \delta_t + \varepsilon$$

This is an advanced model which considers some factors that are not in the interests of our discussion, such as local inflations or local housing price change. Therefore, I will only discuss a part of the overall results, the part that illustrates the relationship between low skilled workers wage variation and high-tech industry growth.

Those variables that are part of our interests are ln(HourlyPay) and Tech. ln(HourlyPay) is the logarithm of hourly pay for both low skilled and middle skilled worker (We will only consider the first item). Tech is variable representing the logarithm of the total employment in high tech industries. It approximates the high-tech industry growth.

Lee and Clarke illustrate the results obtained from the regression model in table 5. They explain that there is clear evidence that the growth of the high-tech industry decreases the real wage paid to low skilled workers. As a matter of fact, in columns 1,2,3,4 they indicate the different negative, and statistically significant, coefficients resulted from the four models considered. This negative impact is even worse in case the authors account for housing costs, as shown in columns 2 and 4, reflecting a lower purchasing power due to inflation and increased housing costs.

Dependent variable	(1) Low-skilled wages	(2)	(3)	(4)	(5) Growth in medium-skilled wages, 2009-2015	(6)	(7)	(8)
Estimator	2SLS △ 2009-2015	2SLS △ 2009-2015	2SLS Annual Panel	2SLS Annual Panel	2SLS △ 2009-2015	2SLS △ 2009-2015	2SLS Annual Panel	2SLS Annual Panel
Inflation measure	RPI	RPI with local housing costs	RPI	RPI with local housing costs	RPI	RPI with local housing costs		
High-tech and digital emp.	−0.166**	−0.185**	−0.0814**	−0.0927**	0.205***	0.210***	0.295**	0.284**
	(0.0744)	(0.0825)	(0.0360)	(0.0375)	(0.0718)	(0.0809)	(0.120)	(0.120)
High-skilled workers (%)	0.403***	0.360**	0.211***	0.160***	−0.350*	−0.433**	0.0123	−0.0384
	(0.153)	(0.165)	(0.0222)	(0.0228)	(0.194)	(0.209)	(0.147)	(0.147)
Unemployment rate (%)	−0.00382	0.165	−0.158*	−0.160*	−0.267	−0.153	0.0497	0.0472
	(0.321)	(0.379)	(0.0896)	(0.0864)	(0.375)	(0.454)	(0.259)	(0.250)
Total employment (log)	−0.00711	−0.0113	0.121	0.0418	−0.00291	−0.00773	0.0154	−0.0639
	(0.00714)	(0.00829)	(0.0965)	(0.0668)	(0.00813)	(0.00976)	(0.118)	(0.147)
Constant	−0.0213	0.0284	1.481	−2.114**	0.133	0.197*	−0.398	−3.993*
	(0.0907)	(0.101)	(1.297)	(0.895)	(0.0988)	(0.112)	(1.714)	(2.126)
First stage results								
Bartik Shift-Share	0.734***	0.703***	0.336***	0.336***	0.734***	0.703***	0.336***	0.336***
	(0.0724)	(0. 0942)	(0.0542)	(0.0542)	(0.0724)	(0.0942)	(0.0542)	(0.0542)
R-squared								
Kleibergen-Paap Wald F statistic	102.9	86.4	38.5	38.5	102.9	86.4	38.5	38.5
Region dummies	Yes	Yes			Yes	Yes		
TTWA Fixed effects			Yes	Yes			Yes	Yes
Year Fixed effects			Yes	Yes			Yes	Yes
Observations	182	160	1,120	1,120	182	160	1,120	1,120
Number of TTWA			160	160			160	160

Note: Standard errors reported in parentheses, clustered on region in FE models. Dependent variable: growth in hourly pay for low skilled (columns 1–4) or medium-skilled (columns 5–8) not working in high-tech. IV = shift share based on 2009 local industry shares and national growth rate. Controls are initial year values for columns 1, 2, 5 and 6, city/year values for models estimated with fixed effects.
*p < 0.1. **p < 0.05. ***p < 0.01.

Table 5: Empirical impact of High-tech sector growth on wage paid to low-skilled and middle-skilled workers

Lee and Clarke conclude their analysis illustrating their main findings.

In line with the optimistic perspective discussed at the beginning of their analysis, the authors conclude that there is a positive relationship between the growth of the high-tech industry and the employment rate of unskilled workers. They remind the reader of the coefficient that links these two variables, which is equal to 0.71. Therefore, as mentioned before, if the high-tech industry generates ten new jobs, 7 new non-tradable jobs will be created and allocated to unskilled workers.

The second main central finding provided by this research relies on the relationship between the growth of the high-tech industry and wage variations of unskilled workers. This finding, differently from the previous one, is in line with the second and pessimistic perspective discussed at the beginning of the analysis. As a matter of fact, the authors found a negative and statistically significant relationship between the two variables considered. Therefore, if we compare these results to the ones obtained for the UK (cluster 6) by Nogueira and Afonso, we can clearly note a divergence. Specifically, Nogueira and Afonso found a negative but statistically insignificant relationship between SBTC and wage inequality for cluster 6. This relationship, however, could be reconsidered when analysing the empirical research by Lee and Clarke, which, in line with the HO model predictions, argues that the growth of the high tech industry in the UK leads to a widen wage inequality between skilled and unskilled workers in the economy.

4.3 “Identifying the Multiple Skills in Skill-Biased Technical Change”. 2019. Seth Gordon Benzell, Erik Brynjolfsson, Frank MacCrory and George Westerman.

In their article, Manuel Carlos Nogueira and Óscar Afonso illustrate that, similarly to cluster 6, wage inequalities in cluster 4 are significantly impacted by international trade. These economists also found that wage inequalities in cluster 4 are impacted positively (the inequality increases) by SBTC, although the coefficient analysed to explain this relationship shows a low statistical significance. Indeed, this coefficient records a value equal to 0.09896, indicating a positive relationship. However, its low statistical significance did not allow Nogueira and Afonso to provide any conclusions about the effect of SBTC in this cluster. Cluster 4 incorporated major countries such as the US, Germany, Japan and Korea. This cluster represents most populated countries with the highest rate of R&D investments, in the samples considered by Nogueira and Afonso. Therefore, as the authors illustrate in their article, these factors may indicate the SBTC theory to be an important explanation for wage inequalities between skilled and unskilled workers.

These are the reasons why I decided to include certain in my report some results referenced by Seth Gordon Benzell, Erik Brynjolfsson, Frank MacCrory and George Westerman in their work called “Identifying the Multiple Skills in Skill-Biased Technical Change”. These American economists characterized American occupations, through a statistical analysis, to provide some evidence regarding wage and employment growth diversified by skill intensive occupations.

At the beginning of the introduction section Benzell, Brynjolfsson, MacCrory and Westerman explain that, under the conventional theory of skill biased technological change, the jobs which suffer more from low wage and employment growth are those which are not complemented by new technology but, instead, substituted. Therefore, the aim of Benzell, Brynjolfsson, MacCrory and Westerman is to analyse how skills interact with technological change in order to identify which are those skills that better pay back in terms of wage and employment growth, in relation to technological change.

Eight different skills are analysed in the article. These skills, as the authors explain, synthesize an occupation and they will be provided with a score, and relative percentile score, for each occupation studied in the sample considered. In addition, the authors estimated the use of ITC capital for different industries to understand how an industry is affected by and engaged with technological change. Benzell, Brynjolfsson, MacCrory and Westerman define the information and technology capital intensity of an industry by dividing the information and technology capital by the total capital stock. The ITC capital that they considered refers to Computers, mainframes and accessories, software, communications equipment and communications structures.

In the following list and tables there are the analysed skills, their absolute scores by occupation and their relative percentile scores by occupation.

- Physicality (PHYS): Arm-Hand Steadiness; Multilimb Coordination...
- Technical Sophistication (TECH): Repairing Electronic Equipment; Technology Design...
- Perception (PERC): Speed of Closure; Flexibility of Closure...
- Leadership (LEAD): Scheduling Work and Activities; Coordinating the Work...
- Cooperation (COOP): Cooperation; Concern for Others; Social Orientation...
- Initiative (INIT): Achievement/Effort; Persistence; Initiative; Independence...
- Mathematics (MATH): Number Facility; Mathematical Reasoning...
- Teaching and Education (EDUC): Learning Strategies; Instructing...

	PHYS	TECH	PERC	LEAD	COOP	INIT	MATH	EDUC
Dish Washer	0.75	0.11	-0.78	-0.15	-0.62	-1.76	-1.08	0.06
Chief Executive	-0.80	0.57	-0.82	1.67	0.94	1.04	1.82	-0.26
Landscape Architect	-0.95	-0.83	0.79	2.00	-2.10	-0.40	0.17	-1.10
Policeman	1.24	-0.65	1.49	0.30	0.88	1.03	-0.64	0.24
Detective	0.54	-0.39	1.44	-0.33	0.21	0.57	-0.28	0.78
Chemist	-0.74	2.12	-0.89	-1.35	-0.51	1.06	0.19	0.09
Economist	-1.32	-0.82	-0.51	-0.33	-1.32	1.00	1.65	-0.57

Table 6: Scores of different occupational skills for occupations of interest.

	PHYS	TECH	PERC	LEAD	COOP	INIT	MATH	EDUC
Dish Washer	67.7	77.5	32.3	58.2	15.0	7.8	13.4	77.3
Chief Executive	25.5	85.4	30.4	94.0	73.7	93.8	92.5	58.5
Landscape Architect	19.0	37.0	86.4	96.3	.3	42.3	47.1	17.4
Policeman	86.7	40.7	96.8	73.7	70.5	93.1	24.5	81.9
Detective	56.8	57.0	96.7	50.0	42.9	82.8	34.8	90.9
Chemist	26.9	99.6	27.5	10.7	17.4	94.0	47.2	78.5
Economist	3.1	37.1	42.0	50.1	4.0	92.9	87.1	38.5

Table 7: Percentiles scores of different occupational skills for occupations of interest

Benzell, Brynjolfsson, MacCrory and Westerman defined their regression model as follow:

$$Y_{j,i,t} = \sum_{F=1}^{8} \beta_F F_j + X_i + \epsilon_{j,i,t}$$

	(1) Median Wage	(2) Median Wage	(3) Wage Skewness	(4) Wage Skewness
Physical	-4.181^{***}	-3.521^{***}	-0.003	-0.002
	(0.512)	(0.453)	(0.004)	(0.003)
Technology	0.604	-0.067	-0.019^{***}	-0.020^{***}
	(0.570)	(0.608)	(0.003)	(0.003)
Perception	0.914^{*}	0.486	-0.010^{*}	-0.006^{*}
	(0.371)	(0.340)	(0.004)	(0.003)
Leadership	3.967^{***}	4.063^{***}	0.006	0.007^{*}
	(0.630)	(0.657)	(0.004)	(0.003)
Cooperation	-1.649^{**}	-1.179^{*}	-0.001	0.005
	(0.543)	(0.592)	(0.004)	(0.003)
Initiative	4.685^{***}	4.449^{***}	0.020^{***}	0.018^{***}
	(0.503)	(0.447)	(0.005)	(0.004)
Math	1.802^{***}	1.671^{***}	0.005	0.000
	(0.405)	(0.437)	(0.004)	(0.003)
Educating	2.327^{***}	2.524^{***}	0.005	0.012^{***}
	(0.526)	(0.533)	(0.004)	(0.003)
Industry FE		X		X
Constant	21.508^{***}	20.874^{***}	0.076^{***}	0.078^{***}
	(0.650)	(0.573)	(0.004)	(0.004)
Observations	112,451	112,451	112,451	112,451

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Estimation results

Where j,i,t recognise the occupation, the industry and the year (from 2006 to 2016) respectively. Xi identifies the so-called industry fixed effects. The authors illustrate the results from the regression in table 8. This regression provides results regarding the wage variation Y, in occupation j and industry i, based on the intensity of different skills Fj. The analysis presents results without control on the industry in the first column while results with industry control are presented in the second column; it also presents results of "wage skewness" but these will not be considered in our discussion.

Based on this table, on one hand Benzell, Brynjolfsson, MacCrory and Westerman highlight that both physical and cooperation intensive occupations register a remarkably negative, and statically significant, wage growth. On the other hand, the authors illustrate that occupations which are intensive in leadership, math and education record a high, and statistically significant, wage growth.

Benzell, Brynjolfsson, MacCrory and Westerman explain that the relationship between occupational skill intensity and wages is due to scarce and valuable skills. An abundant portion of American citizens can perform manual and physical intensive activities. Skills such as physical and cooperation are not particularly valuable, and these are easily found in the labour market. Thus activities, such as quality control, have access to a large supply of personnel, recognising lower salaries. Therefore, these skills generally represent job occupations managed by unskilled workers.

Conversely, there are fewer Americans who can perform leadership, math or education intensive activities. Thus, these are skills which are intensive in those job occupations dedicated to skilled workers.

Benzell, Brynjolfsson, MacCrory and Westerman then shift their focus on how technology is affecting occupational skill characteristics in terms of wages and employment rates. Tables illustrated below refer to the results obtained by running the previously mentioned model. However, in this regression the authors modified it to highlight the results for bottom/top 40 percentiles of the analysed skills, therefore to further illustrate the difference between unskilled and skilled workers. In addition, Table 9 shows results based on the repetitiveness of the occupation. We can approximate high repetitive occupations to low-skilled occupations and low repetitive occupations to high-skilled occupations.

Through the analysis of table 9, Benzell, Brynjolfsson, MacCrory and Westerman highlight the fact that technology, educating, cooperation and leadership intensive occupations see a high wage increase when non-routine, therefore at the top 40 percentiles. This wage growth, however, did not register the same positive values for routine occupations. As a matter of fact, in almost all the considered skills, the wage growth registered a decrease. Particular attention is given to physical and cooperation intensive occupations with high levels of routine, which could well represent unskilled workers in the manufacturing sector. Indeed, these types of occupations saw a remarkable wage decrease, specifically physical intensive occupations registered a -0.239 in the median hourly wage, while cooperation intensive occupations recorded a -0.103.

In the output illustrated in table 10, differently from table 9, Benzell, Brynjolfsson, MacCrory and Westerman organized jobs based on their respective intensity of computer usage. In this table, the authors stress the fact that leadership and initiative occupations, when intensively use computer, recognise a significant wage growth rate but, conversely, cooperation jobs recognise a good wage growth rate in case the job is not computer intensive. The economists explain that this phenomenon is due to the complementarity of technology for leadership and initiative intensive occupations, as it aims at increasing their performances (high skilled workers). In contrast, technology aims at automatizing and robotizing the elementary skills required in cooperation and physically intensive jobs (low skilled workers), which registered deep wage drops.

	(1) ΔWage	(2) ΔWage	(3) Δln(Emp)	(4) Δln(Emp)
Physical	−0.008	−0.239	−0.056**	−0.009
	(0.144)	(0.140)	(0.019)	(0.029)
Technology	0.160	−0.259	0.002	−0.002
	(0.133)	(0.181)	(0.017)	(0.041)
Perception	−0.136	−0.162	0.052*	0.070
	(0.130)	(0.141)	(0.021)	(0.042)
Leadership	0.367*	0.219	−0.001	0.055*
	(0.154)	(0.151)	(0.032)	(0.025)
Cooperation	0.138	−0.103	0.121***	0.035
	(0.117)	(0.148)	(0.024)	(0.034)
Initiative	−0.027	0.022	−0.050*	0.009
	(0.120)	(0.117)	(0.025)	(0.026)
Math	−0.057	−0.034	−0.022	0.034
	(0.093)	(0.142)	(0.016)	(0.040)
Educating	0.185	−0.160	0.008	0.041
	(0.130)	(0.165)	(0.039)	(0.039)
Constant	0.411*	0.578***	0.051*	−0.074*
	(0.171)	(0.151)	(0.020)	(0.036)
Repetitiveness Split	Low	High	Low	High
Observations	4,057	4,561	4,057	4,561

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Estimation results controlling for repetitiveness

	(1) ΔWage	(2) ΔWage	(3) Δln(Emp)	(4) Δln(Emp)
Physical	0.322*	−0.380*	−0.027	−0.004
	(0.136)	(0.158)	(0.042)	(0.037)
Technology	0.116	−0.195	−0.055*	0.029
	(0.068)	(0.149)	(0.026)	(0.025)
Perception	−0.044	−0.129	0.007	0.033
	(0.039)	(0.110)	(0.019)	(0.024)
Leadership	0.145	0.373**	0.009	0.050*
	(0.078)	(0.134)	(0.045)	(0.021)
Cooperation	0.140*	−0.047	0.098***	0.050
	(0.060)	(0.127)	(0.028)	(0.031)
Initiative	−0.252**	0.310	−0.050	−0.012
	(0.082)	(0.185)	(0.033)	(0.039)
Math	−0.229***	0.135	−0.029	0.010
	(0.043)	(0.120)	(0.020)	(0.034)
Educating	0.009	−0.151	−0.017	0.065
	(0.088)	(0.182)	(0.048)	(0.045)
Constant	−0.091	0.525***	−0.036	−0.024
	(0.181)	(0.111)	(0.046)	(0.022)
Computer Use Split	Low	High	Low	High
Observations	2,877	6,062	2,877	6,062

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Estimation results controlling for computer use intensity

In the conclusion section, Benzell, Brynjolfsson, MacCrory and Westerman emphasize that leadership intensive occupations (high skilled workers) see a high wage growth rate more pronounced in occupations and industry which are computer use intensive or which have a significant ITC investment.

"This is consistent with our hypothesis that technological change is boosting the abilities and wages of managers especially in high-tech industries, while individuals who only have cooperation skills are finding refuge in low-tech industries and occupations."

Conversely, Benzell, Brynjolfsson, MacCrory and Westerman remark the negative relationship between physical intensive occupations (low skilled workers) and both their wage and employment growth rate. The economists argue that this phenomenon is reflected by robotic automation. Moreover, a key statement of this research is "Splitting industries and occupations by ITC use, we find further support for these hypotheses: the decrease in wages for physical jobs and increase in wages for leadership jobs are driven by high-tech occupations and industries, while the increase in cooperation intensive jobs is concentrated in low tech occupations and industries". Therefore the results obtained in this research are clearly in line with the theoretical predictions of the HO and the results obtained by Nogueira and Afonso regarding the impact of SBTC on inequalities between skilled and unskilled workers.

In the previous articles analysed we focused our attention on the technological change, resulting in the so-called skill biased technological change which affects wage and employment inequalities between skilled and unskilled workers. As we understood in the theoretical review section, however, unskilled workers are also affected by international trade. Therefore, the aim of the following researches is to illustrate how improved international trade have affected wage and employment inequalities between skilled and unskilled workers in developed economies.

4.4 "The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade". 2016. David H. Autor, David Dorn, and Gordon H. Hanson

Autor, Dorn and Hanson begin their discussion by reminding the reader what we saw in the theoretical review. They highlight the fact that international trade is not Pareto improving.

Specifically, based on Krugman & Obstfeld (2008, p. 64), "Owners of a country's abundant factors gain from trade, but owners of a country's scarce factors lose... [C]ompared with the rest of the world the United States is abundantly endowed with highly skilled labor and (...) low-skilled labor is correspondingly scarce. This means that international trade tends to make low-skilled workers in the United States worse off—not just temporarily, but on a sustained basis.".

In their research, Autor, Dorn and Hanson analyse how US wages and employment inequalities change with respect to improved international trade between US and China. They studied this relationship because they explain that international trade with China provides an excellent example for analysing how large trade shocks impact skilled-unskilled workers in advanced economies. As a matter of fact, although these countries could well represent an example of the "extreme" effects provided by international trade, the results can be approximated to other developed countries (Japan, EU countries, Canada ...) and developing (Taiwan, Vietnam, Bangladesh ...) countries. As the authors explain, we will see that in addition to positive effects on both sides of the economies involved, international trade also shows significant negative effects on unskilled workers.

Autor, Dorn and Hanson start their empirical research by illustrating that a contraction in those US sectors more subjected to import competition, will be seen due to better Chinese production capabilities and costs reduction of international trade. They highlight this point by summarizing the results obtained by Bernard et al. (2006) and showing the empirical results obtained by Acemoglu (2016).

Autor, Dorn and Hanson explain that Bernard et al. (2006), based on American manufacturing data from 1977 to 1997, found high rates of plant exit and employment reductions in those sectors more exposed to trade with low wage countries. Moreover, a significantly large employment reduction was observed among the remaining plants.

For what concerns the illustration of Acemoglu's (2016) results, Autor, Dorn and Hanson explain that this research complements the results obtained by Bernard et al. (2006) and it widens the time covered, analysing the interval from 1991 to 2011. Here is the statistical model used by Acemoglu (2016) in his research:

$$\Delta L_{j\tau} = \alpha_\tau + \beta_1 \Delta IP_{j\tau} + \gamma X_{j0} + e_{j\tau}.$$

For the purpose of this report, I decided to only illustrate the results of the following variables. This is an advanced model which also considers other variables out of the interests for this discussion.

- Ljτ: which is defined by the product between 100 and the annual logarithmic employment change in industry j over the subperiod t.
- IPjτ: which is defined by the product between 100 and the annual change in import penetration from China to the US in the jth manufacturing sector over the tth time period.
- β1: which provides information about how significant the exposure of an industry employment is with respect to import penetration from China.

	1991–2011		1991–1999	1999–2011	1999–2007	2007–2011
	Mean (SD)	Median	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
100 × Annual Δ in US exposure to Chinese imports	0.50 (0.94)	0.14	0.27 (0.75)	0.66 (1.33)	0.84 (1.61)	0.30 (1.68)
100 × Annual log Δ in employment (manufacturing industries)	−2.71 (3.07)	−2.05	−4.32 (3.85)	−0.30 (3.49)	−3.62 (4.15)	−5.73 (5.02)

[a]Statistics are based on 392 four-digit manufacturing industries. The change in US exposure to Chinese imports is computed by dividing 100 times the annualized increase in the value of US imports over the indicated period by 1991 US market volume in that industry. Employment changes are computed in the County Business Patterns. All observations are weighted by 1991 industry employment. Table adapted from table 1 in Acemoglu et al. (2016).

Table 11: Industry-level changes in Chinese import exposure and US manufacturing employment

In their empirical work Autor, Dorn and Hanson, illustrate table 11 which was taken from Acemoglu et al (2016). By looking at this table, the authors explain that an average import exposure growth rate was registered each year from 1991 to 2011 and it was equal to 0.5 percentage point per year. By individually analysing each period, the economists highlight the fact that from 1999 to 2007 this number was equal to 0.84% increase per year and it was much higher than in 1991 - 1999, period in which the average import exposure growth rate registered a 0.27% increase per year. The authors highlight that this remarkable growth reflects the effects of Chinese accession to the WTO. However, through 2007 – 2011 the import exposure growth rate registered a lower value than in the previous period, reaching a 0.30% growth rate per year due to the negative effects of the global financial crises on international trade.

By analysing the second row from table 11 Autor, Dorn and Hanson recognise a radically different trend in the American manufacturing employment rate. Conversely to the import exposure growth rate, the authors indicate that the reduction of the American manufacturing employment, resulting in the American manufacturing employment decline, accelerated in the period analysed. As a matter of fact, as we can see in the table, the economists recognise an employment rate reduction equal to 2.71 log points per year through the period 1991 – 2011. Specifically, by looking at individual periods, the authors recognised a 4.3 log points employment reduction per year through 1991 – 1999, an annual employment contraction of 3.62 log points between 1999 and 2007 and an employment drop equal to 5.7 log points per year through the 2007 – 2011.

Keeping in mind the results illustrated above, Autor, Dorn and Hanson tried to understand the effects of international trade on wage differentials between skilled and unskilled workers. In table 12, taken from Autor et al. (2013) and extended by Chetverikov et al.(2016), the economists reveal that those industries more affected by import competition, present significant decreases in average weekly wages (Column 6).

a. Δ Fraction of working age population in manufacturing, unemployment, and NILF			
Employed in manufacturing	**Employed in non-manufacturing**	**Unemployed**	**NILF**
(1)	(2)	(3)	(4)
−0.60***	−0.18	0.22***b	0.55***
(0.10)	(0.14)	(0.06)	(0.15)
b. Δ Log population, log wages, annual wage, and transfer income			
Δ Log CZ population (log points)	**Δ Average log weekly wage (log points)**	**Δ Annual wage/salary income per adult (US$)**	**Δ Transfers per capita (US$)**
(5)	(6)	(7)	(8)
−0.05	−0.76***	−549.3***	57.7***
(0.75)	(0.25)	(169.4)	(18.4)

Abbreviations: CZ, commuting zone; NILF, not in labor force.
[a]$N = 1{,}444$ (722 CZs times two time periods (1990–2000 and 2000–2007). Employment, population, and income data are based on US Census and American Community Survey data; transfer payments are based on BEA Regional Economic Accounts. All regressions control for the start of period percentage of CZ employment in manufacturing, college-educated population, foreign-born population, employment among women, employment in routine occupations, average offshorability index of occupations, and Census division and time dummies. Models are weighted by start of period CZ share of the national population. Robust standard errors in parentheses are clustered on state. Table adapted from Autor et al. (2013a).
[b]$*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 12: Import competition and outcomes in US local labor markets (1990–2007)

Autor, Dorn and Hanson then explain the most significant results obtained by the quantile regression run by Chetverikov et al (2016). Specifically, as the authors present in their research, Chetverikov et al (2016) states that these wage reductions are mainly focused on those workers at the bottom four wage deciles, therefore resulting again in a widening wage inequality between skilled and unskilled workers.

In their final section Autor, Dorn and Hanson highlight another very important finding. Although increased trade significantly affected the careers of both high skilled and low skilled workers (in the article they are recognised as top/bottom paid terciles), especially in the manufacturing sector, a crucial difference in their patterns of adjustment can be identified. As a matter of fact, the authors found that high skilled workers leaving imports competition exposed sectors, were hired in other industrial areas less threatened by imports competition and without suffering wage losses. Conversely, low skilled workers were mainly relocated within manufacturing sectors which are still negatively impacted by imports competition exposure and, moreover, they suffered from wage losses due to their change to alternative employment.

4.5 "The 1990s trade and wages debate in retrospect". 2018. Adrian Wood

The analysis conducted by Autor, Dorn and Hanson, provided us with the idea that international trade affected those American industrial sectors that were more subjected to the pressure from import from low wage countries. Specifically, we understood that this pressure resulted in a constant decrease in employment and wage rates in those affected sectors. However, as these authors previously explained based on Chetverikov et al (2016), these reductions were mainly focused on those workers at the bottom four wage deciles, namely the unskilled workers.

Nogueira and Afonso, in their article "Intra-Country Wage Inequality in the OECD Countries", recognised the international trade to be a significant cause of wage inequality, between skilled and unskilled workers, in most of the OECD countries. Although these results, in addition to the ones delivered by Autor, Dorn and Hanson, already recognise a clear growing disparity between skilled and unskilled workers in developed countries, such as the US, I wanted to illustrate the empirical analysis performed by Adrian Wood in order to further illustrate this phenomenon from a statistical and numerical perspective in the overall OECD countries.

In this research, Adrian Wood attempts to reconsider the debate that occurred in the 1990s. This is a period in which major economists, as he explains, concluded that increasing international trade with low wage countries was not negatively affecting low skilled workers in advanced countries in a significant measure. It is interesting to note, however, that Adrian Wood and other top economists indicate this phenomenon as a key driver for Brexit, Trump and political extremism in Europe.

For the purpose of this report I will only analyse section 3 of “The 1990s trade and wages debate in retrospect”. A section in which Adrian Wood reviewed how low skilled workers in advanced countries have been harmed, from an economic perspective, by international trade with less developed countries, such as China, Taiwan, Vietnam or Thailand.

Adrian Wood starts the discussion of section 3 by referencing Acemoglu’s et al. (2016) research, which found that the expanded Chinese imports were estimated to create a loss of 1.4 million jobs in the overall American manufacturing employment between 1999 and 2011. Moreover, it was projected to decrease American employment in all sectors by 2.6 million jobs.

It is important to note that, although Adrian Wood reported impact evaluations on labour market demand for the OECD countries (North) of increasing export from non-OECD countries (South) in 2011, he obtained results similar to the ones specific for the individual American labour market.

Results obtained by Wood illustrate that, on the one hand imports from the South (Developing countries) create a loss of 18 million in manufacturing jobs while, on the other hand an increased exports from the North (Developed countries) to the South produced 6.4 million new manufacturing jobs. Therefore, the final loss of manufacturing jobs was equal to 11.5 million, which corresponded to 15% of total manufacturing employment in 2011, as indicated by Adrian Wood.

Differently from the results obtained in the manufacturing industry, Wood indicates that exports from the South have a minimal effect on the Northern net overall demand change in service industries. As a matter of fact, the economist estimated a net effect equals to -0.6 million jobs, which is the result of 7.9 new million jobs created by new export opportunities for Northern countries and 8.6 million jobs lost by import competition from the South.

	Manufacturing			Services			Combined
	More Northern exports	Less import substitution	Net effect	More Northern exports	Less import substitution	Net effect	Net effect
Absolute (million person-years)							
Skilled labour	2.5	−0.5	2.0	3.4	−0.7	2.7	4.8
Unskilled labour	3.9	−17.5	−13.6	4.5	−7.9	−3.4	−16.9
Total labour	6.4	−18.0	−11.5	7.9	−8.6	−0.6	−12.2
Proportionate (%)							
Total relative to actual employment			−15.1			−0.1	−2.1*
Skilled relative to all skilled employment			2.0			2.6	4.6
Unskilled relative to all unskilled empt			−2.9			−0.7	−3.7
Skilled/unskilled economy-wide			5.1			3.4	8.6

Note: *Relative to employment in whole economy (including primary sector).

Table 13: The empirical effects of North–South) trade (Developed – Developing countries) on the employment growth rate in the North

Keeping these overall employment changes in mind, Adrian Wood then clearly separates the impact of international trade between Northern and Southern countries on low skilled and high skilled workers. Specifically, he assumed high skilled workers to be college educated workers and low skilled workers to be non-college educated workers.

By implementing this division, impacts of international trade on employment changes are very disproportioned. Adrian Wood states "In both sectors, the net effect of the South's non-primary exports is to increase the demand for skilled (college-educated), relative to unskilled, labour."

Results obtained by Wood are clear. New high skilled jobs created by new Northern exports opportunities create a positive net effect for high skilled workers in the manufacturing industry (+2.5 – 0.5 = +2.0 million jobs). However, as the author indicates, these new jobs are totally overshadowed by a dramatic net loss of unskilled manufacturing jobs (+3.9 – 17.5 = -13.6 million jobs), thus, creating a net labour loss in manufacturing equals to 11.5 million workers.

The situation in the service sectors was slightly different from what happened in the manufacturing industry. In the service sectors Adrian Wood does not recognise an overall dramatic change like in the manufacturing industry, however, he still recognises a significant unskilled jobs reduction equals to 7.9 million jobs, due to larger imports from low wage countries. This loss was only partially covered by the new 4.5 million unskilled jobs generated generated by a higher northern export, resulting in an overall unskilled jobs loss equal to 3.4 million.

Results related to skilled workers in service sectors are similar to those obtained for skilled workers in the manufacturing industry. In this case new skilled job positions generated by higher exports from the North (developed countries) were 3.4 million while the loss, resulting from higher imports form the South, (developing countries) was equal to 0.7 million. Therefore, the overall change of skilled jobs reached 2.7 new million skilled jobs created.

Reminding us about the HO model and the theoretical impact of international trade on wage and employment inequalities between skilled and unskilled workers, we can see a divergence between the theory and the results obtained by Nogueira and Afonso and Adrian Wood. As a matter of fact, in the theoretical review section, we saw that "international trade per se does not create both wage and employment inequalities between skilled and unskilled workers". Although the HO model predicts a higher relative wage inequality between skilled and unskilled workers in developed countries (confirmed by Nogueira and Afonso), it also predicts a lower high skilled relative to low skilled employment.

The latter prediction seems to diverge from the results obtained by Adrian Wood regarding the changes in the relative employment between skilled and unskilled workers. Adrian Wood estimated first an increase of 4.6% in new skilled job positions through the analysed time period. Specifically, as we can see in the previous table, this number is further divided in a 2.0% rise in the manufacturing industry and a 2.6% rise in the service industry. Results are different for unskilled workers. In this case Adrian Wood estimated a decrease of 3.7% in those job positions available for unskilled workers through the analysed time period. This percentage is divided into relative losses of 2.9% regarding the manufacturing sector and 0.7% regarding the service industry. However, the most meaningful number provided by Wood lays on the overall relative demand for skilled-unskilled workers which registers a growth of 9%, diverging from the theoretical predictions provided by the HO model.

As mentioned by Adrian Wood, his article illustrates that improved international trade between the South (developing countries) and the North (developed countries) had significant effects on low skilled workers living in the North. However, Wood also states that, although it is difficult to quantify, there is another way through which international trade have influenced the inequalities between skilled and unskilled workers in developed economies. This is identified by the effects of international trade on productivity or technological change. As a matter of fact, as argued by Wood, although the economic literature (OECD, 2017; WTO, 2017) identifies technological improvements to be the main responsible for the decrease of unskilled manufacturing employment in developed economies, these developments were boosted by growing international trade. Specifically, Adrian Wood recognises the low-cost imports from developing countries to stimulate what Acemoglu (2003) and Wood (1994) call "defensive innovation" in developed economies. In addition, in Wood(1994) the author argued "trade-induced productivity change had at least doubled the direct effects of North–South trade on manufacturing employment and the relative demand for skilled workers, but the true effect could be either smaller or larger".

These are the reasons why I decided to illustrate the results provided in the following article "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity" by Nicholas Bloom, Mirko Draca and John Van Reenen.

4.6 "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity". 2011. Nicholas Bloom, Mirko Draca and John Van Reenen

In this research Bloom, Draca and Van Reenen studied the impact of Chinese imports competition on technological change in twelve European countries from 1996 to 2007. Here are their main findings:

- Competition from Chinese imports increased technological change within European firms by increasing innovation, total factor productivity (TFP) and management practices. Firms dealing with high levels of imports competition from China generate more patents, invest more on R&D and IT and increase their total factor productivity.
- Competition from Chinese imports led to an employment rearrangement in firms in the direction of more technologically advanced companies. Specifically, it shrinks employment levels and survival probabilities in less technologically advanced firms.

Bloom, Draca and Van Reenen also underlined that these effects weighted for 15% of European technological upgrade from 2000 to 2007. They led to a reduction in employment and in the share of unskilled workers and, moreover, the innovation increase more in those firms and industries which were more impacted by reductions in barriers to Chinese imports.

Therefore, Bloom, Draca and Van Reenen integrated the effects of trade on survival and innovation. As they explain, this combination is the cause of technological upgrading in those industries most affected by Chinese imports.

The authors present their core results in table 14, which illustrates the technological change within European firms caused by increased imports from China. The authors developed five different models which consider five different dependent variables. It is important to highlight the fact that all the following relationships have a strong statistical significance, as the least significant relationship presents a 5% statistical significance.

Bloom, Draca and Van Reenen, in column 1, set the patents issued by a firm as dependent variable of the model. As we can see, when Chinese imports increase by 10%, there is a 3.2% increase in patents issued by a firm. In line with the previous results, column 2 shows the positive and significant relationship between IT intensity and imports from China while column 3 shows the positive and significant relationship between R&D investments and the same imports competition. Bloom, Draca and Van Reenen note that a 10% increase in Chinese imports competition results in a 3.6% increase in IT intensity, a 12% increase in R&D investments and a 2.6% in total factor productivity.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	**Δln(PATENTS)**	**Δln(IT/N)**	**Δln(R&D)**	**ΔTFP**	**ΔMANAGEMENT**
Estimation method	**5 year diffs**	**5 year diffs**	**5 year diffs**	**5 year diffs**	**3 year diffs**
Change in Chinese Imports ΔIMP_{jk}^{CH}	0.321*** (0.102)	0.361** (0.076)	1.213** (0.549)	0.257*** (0.072)	0.814*** (0.314)
Sample period	2005-1996	2007-2000	2007-1996	2005-1996	2010-2002
Number of Units	8,480	22,957	459	89,369	1,576
Number of country by industry clusters	1,578	2,816	196	1,210	579
Observations	30,277	37,500	1,626	292,167	3,607

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country by four-digit industry pair in parentheses (except columns (3) and (5) which are three-digit industry by country). All changes are in five-year differences, e.g. ΔIMP_{jk}^{CH} represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair (except column (5) which is in three-year long differences). All columns include a full set of country by year dummies. *Δln(PATENTS)* is the change in *ln(1+PAT), PAT* = count of patents. *IT/N* is the number of computers per worker. *R&D* is expenditure on research and development. TFP is estimated using the de Loecker (2007) version of the Olley-Pakes (1996) method separately for each industry based on 1.4m underlying observations (see Appendix C) and *Management* is the average score on the 18 Bloom and Van Reenen (2007) management questions around monitoring, targets and incentives. The 12 countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK for all columns except (4) which only includes France, Italy, Spain and Sweden (the countries where we have good data on intermediate inputs) and column (5) which covers France, Germany, Italy, Ireland, Sweden and the UK. Dummies for establishment type (Divisional HQ, Divisional Branch, Enterprise HQ or a Standalone Branch) are included in column (2). Standard survey noise controls such as interviewer dummies and interview/interviewee controls (e.g. tenure in firm) are included in column (5) as in Bloom and Van Reenen (2007). Units are firms in all columns except (2) where it refers to plants.

Table 14: Technological change caused by increased Chinese imports

The authors highlight the fact that when China joined the WTO in 2001 there was a strong reduction in imports quotas and tariffs on apparel and textiles. These reductions took place in two waves, the first one was in 2002 while the second one occurred in 2005 and allowed China to increase its imports to the EU on apparel and textiles by 240%. The results highlighted by the authors explain that although the sectors affected by the increase in imports were low-tech sectors, European firms in these industries issued 21.638 new patents.

In table 15 Bloom, Draca and Van Reenen show the reallocation effects by analysing how employment grew, in Panel A, and survivals in Panel B with respect to changes of imports from China. In column 1 the authors illustrate the strong negative effect of Chinese imports on the overall employment. Specifically, a 10% raise in Chinese imports is associated with a 3.5% overall employment decrease. Bloom, Draca and Van Reenen, in column 3 and 4, then check for the "patenters" sample which are "firms who had at least one patent since 1978". In this case they noted that firms with a high lagged patent stock saw a lower employment decrease following the rise in Chinese imports. Similar results were found in columns 5 and 6, where the authors used the initial level of IT and total factor productivity. Similarly, the authors determined that high-tech firms are in some way protected from the effects caused by the Chinese import shock. These are results are very important and allowed the authors to state that firms face Chinese imports by investing in innovation but, at the same time, by cutting down on employment.

PANEL A: EMPLOYMENT

Dependent Variable: Employment Growth, $\Delta \ln N$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Technology variable (TECH)		Patent stock	Patent stock	Patent stock	IT	TFP
Sample	All Firms	All Firms	Patenting firms	Patenting firms	IT sample	TFP sample
Change in Chinese Imports	-0.349***	-0.352***	-0.361***	-0.434***	-0.379***	-0.382***
ΔIMP_{jk}^{CH}	(0.067)	(0.067)	(0.134)	(0.136)	(0.105)	(0.093)
Change in Chinese imports*technology at t-5		1.546**		1.434**	0.385**	0.956**
ΔIMP_{jk}^{CH} *$TECH_{t-5}$		(0.757)		(0.649)	(0.157)	(0.424)
Technology at t-5	0.513***	0.469***	0.389***	0.348***	0.230***	0.256***
$TECH_{t-5}$	(0.050)	(0.058)	(0.043)	(0.049)	(0.010)	(0.016)
Number of Units	189,563	189,563	6,335	6,335	22,957	89,369
Number of country by industry clusters	3,123	3,123	1,375	1,375	2,816	1,210
Observations	581,474	581,474	19,844	19,844	37,500	292,167

PANEL B: EXIT

Dependent Variable: *SURVIVAL*	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Technology variable		Patent stock	Patent stock	Patent stock	IT	TFP
Sample	All Firms	All Firms	Patenting firms	Patenting firms	IT sample	TFP sample
Change in Chinese Imports	-0.122***	-0.122***	-0.065	-0.089	-0.182**	-0.189***
ΔIMP_{jk}^{CH}	(0.036)	(0.036)	(0.047)	(0.050)	(0.072)	(0.056)
Change in Chinese imports*technology at t-5		0.391**		0.261**	0.137	0.097
ΔIMP_{jk}^{CH} *$TECH_{t-5}$		(0.018)		(0.114)	(0.112)	(0.076)
Technology at t-5	0.052***	0.040***	-0.006	-0.014	-0.002	-0.003
$TECH_{t-5}$	(0.008)	(0.011)	(0.007)	(0.009)	(0.006)	(0.004)
Survival Rate for Sample (mean)	0.929	0.929	0.977	0.977	0.886	0.931
Number of country by industry clusters	3,369	3,369	1,647	1,647	2,863	1,294
Observations (and number of units)	490,095	490,095	7,985	7,985	28,624	268,335

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation by OLS with standard errors (clustered by country by four-digit industry pair) in parentheses. ΔIMP^{CH} represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. In columns (1) to (4) *TECH* is ln[(1+ the firm's patent stock)/employment]. In column (5) *TECH* is computers per employee *(IT/N)* and in column (6) *TECH* is *TFP*. 12 Countries in all columns except column (6) which is for four countries. In columns (3) and (4) only "patenting firms" (defined as a firm that had at least one European patent between 1978 and 2007) included. Sample period is 2005-1996 for all except column (5) which is 2007-2000. Number of units is the number of firms in all columns except (5) where it is the number of plants. All columns include country by year effects. **In Panel A** the dependent variable is the five year difference of ln(employment). **In Panel B** the dependent variable (*SURVIVAL*) refers to whether an establishment that was alive in 2000 was still alive in 2005 for the HH sample in column (5). In the other columns it is based on Amadeus company status (Appendix B) and is defined on the basis of whether a firm alive in 2000 was dead by 2005.

Table 15: Employment rate and survivals

The highlighted fact presented by Bloom, Draca and Van Reenen in this table is that imports competition from low wage countries seems to boost a quicker technological change while this is not true for what concerns imports competition from high wage countries. The reason explained by the authors relies on the profitability of low-tech goods imported by the south (low wage countries). Specifically, according to this model, the profitability of low-tech goods in the North (high wage countries) is negatively affected by the import from the South and producers are incentivized to improve the quality of their goods by upgrading the technology.

Dependent Variable:	(1) **Δ(Wage bill Share of college educated)**	(2) **Δ(Wage bill Share of college educated)**	(3) **Δ(Wage bill Share of college educated)**	(4) **Δ(Wage bill Share of college educated)**	(5) **Δ(Wage bill Share of college educated)**
Sample	**All**	**All**	**All**	**Textiles & Clothing**	**Textile & Clothing**
Method	**OLS**	**OLS**	**OLS**	**OLS**	**IV**
Change in Chinese Imports, ΔIMP_{jk}^{CH}	0.144*** (0.035)		0.099** (0.043)	0.166*** (0.030)	0.227*** (0.053)
Change in IT intensity $\Delta \ln(IT/N)$		0.081** (0.024)	0.050* (0.026)		
F-test of excluded IV					9.21
Industry Clusters	72	72	74	17	17
Observations	204	204	204	48	48

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. The sample period is 1999-2006. The dependent variable is the five-year difference in the wage bill share of college-educated workers. Estimation is by OLS with standard errors clustered by three-digit industry pair in parentheses. This data is a three-digit industry panel for the UK between 2000 and 2007 (based on aggregating up different years of the UK Labor Force Survey). All manufacturing industries in columns (1) - (3) and textiles and clothing industries sub-sample in columns (4)-(5). IV regressions use Quota removal (the height of the quota in the three-digit industry in 2000 prior to China joining the WTO). All regressions weighted by number of observations in the Labor Force Survey in the industry cell. All regressions control for year dummies.

Table 16: Changes in wages paid to college educated workers due to increased Chinese imports

Bloom, Draca and Van Reenen now move on analysing the effects of technological changes caused by Chinese imports competition on wage growth of college educated workers (skilled workers). The authors decided to consider the UK labor force survey for this analysis because the impact of Chinese imports is widely spread among Europe and they thought the UK to be a representative example. The most significant results highlighted by the authors from table 16 are the following:

Column 1 illustrates that Chinese imports lead to a higher wage-bill share of college educated workers. Here the authors suggest that Chinese trade increases the demand for skills.

Column 2 shows the increase in the share of wages for college workers caused by technological change (IT).

Column 3, instead, integrates both the previous coefficients. In this case the authors highlight that, although the coefficients are lower, they both are significant “suggesting part of the association of IT with skilled workers may be a proxy for the impact of developing country trade.”

In column 4 the authors regressed the model by only considering the textile and apparel industry which well represents a low-tech industry where import competition from low wage countries is harsh. As we can see in this case, the resulted coefficient is higher than in the previous regressions. The authors identified these results to be in line with their model. Specifically, imports penetration from China leads producers to change production, moving from low tech goods to the design and manufacture of new goods. This phenomenon is identified to raise the demand for skilled workers and consequently their wage.

Bloom, Draca and Van Reenen conclude their analysis by summarizing the obtained results. In their paper we have understood the impact of trade on technological change in twelve selected European countries between “Northern” (high wage) and “Southern” (low wage). The authors used firm level data on innovation such as patents, citations and R&D expenses united with data on trade. The first result obtained by the economists is the increased levels of patenting, R&D, IT in those firms which suffered more by the imports from China. In the second significant result the authors show that jobs and survival rate registered a strong decrease in those low-tech sectors which more suffered the Chinese import competition. However, the authors also illustrate that high-tech sectors did not suffer from import competition and they did not register significant job losses. Bloom, Draca and Van Reenen also note that both these phenomena boost technological change and thus, wage and employment inequalities.

5. CONCLUSIONS

Increasing wage inequality between skilled and unskilled workers has been one of the major issues studied by labor economists over the last decades. As John Van Reenen (2011) explains, this interest was enhanced by empirical research which presented significant variations in the wage structure in several countries. As pointed out in his article, wage inequality started its rapid growth in the US and UK in the 1980s but then it also affected most other OECD countries.

Based on Krugman, Obstfeld and Melitz, this report illustrates the theoretical model, namely the Heckscher – Ohlin model, which explains two theoretical reasons at the basis of wage and employment inequalities between skilled and unskilled workers in developed countries. Specifically, both the skill biased technological change and the international trade arguments are significant in widening the wage skilled gap. To understand whether these theoretical arguments came out to be verified, I compared them with several empirical research conducted by well-known economists.

What we understood first is that these factors can differently widen the wage gap in different ways based on the economic reality of each country. As a matter of fact, Nogueira and Afonso identified cluster 7, consisting of Belgium, Denmark, Finland, Norway and Sweden, as that cluster which better fits the theoretical predictions thus, where both SBTC and international trade are significant in widening wage inequalities. However, when Nogueira and Afonso consider OECD countries combined, they recognise in international trade the main driver for wage inequalities and, in some cases, they also detect the impact provided by SBTC to be negligible.

Alternatively, Lee and Clarke, specifically studied the impact of high-tech industry growth on lowly skilled workers in the UK. In their research they conclude that there is a positive relationship between the growth of the high-tech industry and the employment rate of unskilled workers. The coefficient that links these two variables is equal to 0.71, therefore if the high-tech industry generates ten new jobs, 7 new non-tradable jobs will be created and allocated to unskilled workers. The second main central finding provided by Lee and Clarke relies on the negative, and the statistically significant, relationship between the growth of the high-tech industry and wage variations of unskilled workers. In line with the HO model predictions, they argue that the growth of the high-tech industry in the UK leads to a widening wage inequality between skilled and unskilled workers in the economy.

Benzell, Brynjolfsson, MacCrory and Westerman, by analysing the impact of SBTC diverified by skill intensive occupations in the US, report a negative relationship between physical intensive occupations (low skilled workers) and both their wage and employment growth rate. The economists point out that leadership intensive occupations (high skilled workers) see a high wage growth rate more pronounced in occupations and industry which are computer use intensive or which have a significant ITC investment. The economists argue that this phenomenon is reflected by robotic automation, which aim at substituting simple and repetitive activities conducted by unskilled workers and complementing complex activities operated by skilled workers. Therefore, again, their results seem to be in line with the theoretical predictions of the HO model regarding the impact of the SBTC on wage and employment inequalities.

Autor, Dorn and Hanson analysed the effects of international trade with China on wage differentials in the US. Based on Autor et al. (2013), the economists show that those industries more affected by import competition present significant reductions in average weekly wages. However, based on Chetverikov et al.(2016) and in line with the theoretical predictions of the HO model, they states that declines are mainly concentrated on those workers at the bottom four wage deciles, widening wage inequalities between skilled and unskilled workers. Moreover, although increased trade affected the careers of both high skilled and low skilled workers, high skilled workers were hired in other industrial areas less threatened by imports competition and without suffering wage losses, while low skilled workers were mainly relocated within manufacturing sectors still threatened by imports competition in addition to reported wage losses caused by their change to alternative employment.

Although the HO model predicts increasing international trade to increase the relative wage inequality between skilled and unskilled workers in developed countries (confirmed by previous articles), it also predicts a lower high skilled relative to low skilled employment. The second prediction seems to diverge from the results obtained by Adrian Wood regarding the changes in the relative employment between skilled and unskilled workers in OECD countries due to increasing imports from non-OECD countries. As a matter of fact, the most meaningful number provided by Wood relies on the overall relative demand for skilled-unskilled workers in OECD countries which registers a growth of 9%, diverging from the theoretical predictions provided by the HO model.

This divergence, however, seems to be explained by the same Adrian Wood and Bloom, Draca and Van Reenen.

Wood argues that there is another way through which international trade has affected the inequalities between skilled and unskilled workers in developed economies. This is characterized by the impact of international trade on skill biased technological change. As argued by Wood, although the economic literature (OECD, 2017; WTO, 2017) identifies technological change to be the main cause for the reduction of unskilled manufacturing employment in developed economies, this technological change was boosted by improving international trade. Particularly, Adrian Wood identifies in the low-cost imports from developing countries a stimulus to what was confirmed by Bloom, Draca and Van Reenen in their research, and to what Acemoglu (2003) and Wood (1994) call "defensive innovation" in developed economies.

In short, despite all of the research it is clear that with economic development combined with progressive advancement in technology the disproportionate wage gap between skilled and unskilled workers will prevail regardless of efforts by governments. Lowly skilled workers are victims of circumstance. They are caught in a vacuum. Their only way out may be through State sponsored training, development and vocational educational programmes.

6. REFERENCES

Machin, Stephen, and John van Reenen. 1998. "Technology and Changes in Skill Structure: Evidence from Seven OECD Countries."

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2008. "Trends in U.S. Wage Inequality: Revising the Revisionists."

Acemoglu, Daron. 2003. "Patterns of Skill Premia."

Afonso, Óscar. 2012. "Scale-Independent North-South Trade Effects on the Technological Knowledge Bias and on Wage Inequality."

Krugman, Obstfeld and Melitz. 2018. "International Economics theory and policy"

John Van Reenen. 2011. "Wage Inequality, Technology and Trade: 21st Century Evidence"

Goldin, Claudia and Katz, Lawrence F. 2008. "The Race between Education and Technology".

Machin, Stephen and John Van Reenen. 2010. "Inequality: Still Higher, But Labour's Policies Kept it Down"

Atkinson, Tony, Thomas Piketty and Emmanuel Saez .2011. "Top Incomes in the Long Run of History"

Teresa C. Fort Justin R. Pierce Peter K. Schott. 2018. "NEW PERSPECTIVES ON THE DECLINE OF US MANUFACTURING EMPLOYMENT"

The Computing Technology Industry Association. 2020. "The definitive guide to the U.S. tech industry and tech workforce"

Manuel Carlos Nogueira, Óscar Afonso. 2018. "Intra-Country Wage Inequality in the OECD Countries"

Neil Lee, Stephen Clarke. 2019. "Do low-skilled workers gain from high-tech employment growth? High-technology multipliers, employment and wages in Britain"

North. 1955. "location theory and regional economic growth"

Tiebout. 1956. "A pure theory of local expenditures"

Moretti. 2010. "Local multipliers. Am. Econ. Rev. Pap. Proceed."

Moretti. 2013. “The new gwography of jobs mariner”

Saxenian. 1983. “The urban contradictions of Silicon Valley: regional growth and the restructuring of the semiconductor industry”

Seth Gordon Benzell, Erik Brynjolfsson, Frank MacCrory and George Westerman. 2019. “Identifying the Multiple Skills in Skill-Biased Technical Change”

David H. Autor, David Dorn, and Gordon H. Hanson. 2016. “The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade”

Krugman PR, Obstfeld M. 2008. “International Economics: Theory and Policy”

Bernard AB, Jensen JB, Schott PK. 2006. “Survival of the best fit: exposure to low-wage countries and the (uneven) growth of U.S. manufacturing plants.”

Acemoglu D, Autor DH, Dorn D, Hanson GH, Price B. 2016. “Import competition and the Great U.S. Employment Sag of the 2000s.”

Autor DH, Dorn D. 2013. “The growth of low-skill service jobs and the polarization of the US labor market.”

Autor DH, Dorn D, Hanson GH. 2013a. “The China syndrome: local labor market effects of import competition in the United States.”

Autor DH, Dorn D, Hanson GH. 2013b. “The geography of trade and technology shocks in the United States.”

Chetverikov D, Larsen B, Palmer C. 2016. “IV quantile regression for group-level treatments, with an application to the distributional effects of trade.”

Adrian Wood. 2018. “The 1990s trade and wages debate in retrospect”

OECD (2014). Employment outlook 2014.

OECD (2017). Employment outlook 2017.

WTO (2017). World trade report 2017.

Wood, A. (1994). “North-South trade, employment and inequality: Changing fortunes in a skill-driven world”

Nicholas Bloom, Mirko Draca and John Van Reenen. 2011. “Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity”