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EFFECT OF INTERNATIONAL TRADE ON WAGE AND INCOME INEQUALITY IN DEVELOPED AND DEVELOPING COUNTRIES

AMAIA ODRIOZOLA GARMENDIA

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Economía Española, Internacional y Sectorial

Director: ANTONIO GÓMEZ GÓMEZ-PLANA

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ABSTRACT

Whether international trade contributes positively to reduce wage and income inequality within countries has become a controversial issue. This paper aims to analyse the effect of trade openness on wage and income inequality in developed as well as developing countries using cross-sectional and panel data. According to Heckscher–Ohlin model, trade openness increases wage inequality between skilled and unskilled workers in developed countries, while decreasing it in developing countries. Results from the cross-sectional analysis suggest that there exists a positive relationship between trade openness and wage inequality in developed and developing countries. This can be explained by skill-biased technological change. However, results from the panel data analysis also conclude that trade openness contributes positively to reduce income inequality both in developed as well as developing countries. Therefore, trade liberalization seems to have important implications for achieving Sustainable Development Goals. One of the reasons for these different results may lie in the fact that overall household income includes other sources of income such as transfers and capital income apart from wages.

KEYWORDS

Trade openness, wage inequality, income inequality, Heckscher–Ohlin model, cross-section model, panel data model.

RESUMEN

La cuestión de si el comercio internacional contribuye positivamente a reducir la desigualdad salarial y de ingresos en los países se ha convertido en una cuestión controvertida. Este trabajo tiene como objetivo analizar el efecto de la apertura comercial en la desigualdad salarial y de ingresos en los países desarrollados, así como en los países en desarrollo, utilizando datos transversales y de panel. Según el modelo de Heckscher-Ohlin, la apertura comercial aumenta la desigualdad salarial entre los trabajadores cualificados y los no cualificados en los países desarrollados, mientras que disminuye en los países en desarrollo. Los resultados del análisis de sección cruzada muestran que existe una relación positiva entre la apertura comercial y la desigualdad salarial en los países desarrollados y en desarrollo. Esto puede explicarse por el cambio tecnológico que está sesgado a favor del trabajador cualificado. Sin embargo, los resultados de panel llegan a la conclusión de que la apertura del comercio contribuye positivamente a reducir la desigualdad de ingresos tanto en los países desarrollados como en los países en desarrollo. Por consiguiente, la liberalización del comercio parece tener importantes consecuencias para el logro de los Objetivos de Desarrollo Sostenible. El hecho de que los ingresos totales de los hogares incluyen otras fuentes de ingresos, como las transferencias y los ingresos de capital aparte de los salarios puede ser uno de los motivos por los cuales el análisis de la desigualdad salarial y de ingresos tienen distintos resultados.

PALABRAS CLAVE

Apertura comercial, desigualdad salarial, desigualdad de ingresos, modelo Heckscher-Ohlin, modelo de sección cruzada, modelo de datos de panel.

LIST OF ABBREVIATIONS

HLO: Harmonized Learning Outcomes

ILO: International Labour Organization

IMF: International Monetary Fund

ISCO: International Standard Classification of Occupations

UN: United Nations

UNCTAD: United Nations Conference on Trade and Development

UNECE: United Nations Economic Commission for Europe

WTO: World Trade Organization

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1. INTRODUCTION

Trade liberalization creates larger gains than losses for most of the world (García-Algarra et al., 2020). Yet, there are many misconceptions regarding the distributional impact of trade. Indeed, income inequality has become a concern of real matter not merely for developing countries, but also for the developed ones. Moreover, the effect of trade openness on wage and income inequality is a controversial matter due to the mixed findings of different research. On top of that, many research carried out regarding this issue have not taken into account the different level of development of each country and therefore have led to misleading results. Identifying winners and losers from trade is difficult since "gains from international trade are often distributed thinly across the population while losers are concentrated" (Artuc, 2021). Therefore, gains from trade are easily overlooked and losses may be overstated (Artuc, 2021). Moreover, countries with higher trade openness (measured as exports plus imports as a share of GDP) tend to have higher living standards and lower income inequality (Cerdeiro & Komaromi, 2017).

This paper aims to analyse the effect of international trade on (1) wage inequality as well as on (2) income inequality, both in developed as well as developing countries. The Heckscher–Ohlin (H-O) model analyses the effect of trade on the relative returns to different factors of production (Krugman et al., 2018). According to it, as developing countries are usually abundantly endowed with unskilled workers, trade openness should favour unskilled workers more than the skilled ones in the event of trade liberalization. This model therefore predicts a lower gap in wage between skilled and unskilled workers in developing countries. For developed countries, as they are usually abundantly endowed with skilled workers, it predicts that trade openness increases wage inequalities between skilled and unskilled workers. So as to analyse the implications of trade openness for wage inequality, a cross-section model is constructed for developed and developing countries.

Furthermore, a panel data model is created with the objective of analysing the effect of trade openness on income inequality in developed as well as

developing countries, since wage inequality merely accounts for a part of overall income inequality. The effect of trade openness on income inequality within countries has important implications for achieving Sustainable Development Goals, especially for Goal 8 (promote sustainable economic growth, employment and decent work for all), Goal 9 (promote industrialization, innovation and infrastructure) and Goal 10 (reduce inequalities within and among countries). These, also known as Global Goals, were adopted by the United Nations in 2015 as a universal call to action to end poverty, protect the planet, and ensure that by 2030 all people enjoy prosperity.

In this paper, it is firstly explained in section 2 why international trade is so relevant for achieving Sustainable Development Goals (SDG) as well as the evolution of labour income inequality and international trade in the last decades. Then, section 3 presents the Heckscher–Ohlin model and its hypothesis. Section 4 is devoted to analysing the effect of international trade on wage inequality in developed and developing countries using a cross-sectional model for year 2018. It is followed by section 5 which aims to deepen the analysis regarding the effect of international trade on income inequality using a panel data model for years 2007-2018. Lastly, section 6 summarizes the main findings and conclusions of the analysis.

2. THE RELEVANCE OF INTERNATIONAL TRADE

This section aims to give an overview of the relevance of international trade. It is explained how trade can be a useful and efficient tool so as to achieve Sustainable Development Goals, how it affects labour income inequality and the most important changes in the patterns of international trade in the last decades.

2.1. Trade openness and Sustainable Development Goals

International trade has been seen as tool to reduce inequalities across the world. What is more, according to the General Director of the WTO, Ngozi Okonjo-Iweala, “trade is a necessary ingredient for rebuilding a stronger and more inclusive global economy and for reviving progress towards achieving

the Sustainable Development Goals" (World Trade Organization , 2021). Therefore, international trade might pave the way for achieving specially SDG Goals 1, 2, 3, 8, 9 and 10, which are explained in more detail in **Table 1**.

Table 1. *Sustainable Development Goals that international trade may contribute to achieve.*

GOAL		
1	**No poverty**	End poverty in all its forms from everywhere.
2	**Zero hunger**	Change the global food and agricultural system to nourish more than 690 million people who are hungry today.
3	**Good health and well-being**	Ensure healthy lives and promote well-being for all at all ages.
8	**Decent work and economic growth**	Promote inclusive and sustainable economic growth, employment and decent work for all.
9	**Industry, innovation and infrastructure**	Build resilient infrastructure, promote sustainable industrialization and foster innovation.
10	**Reduce inequalities**	Reduce inequality within and among countries.

Source: *United Nations Sustainable Development Goals. Retrieved from: https://www.un.org/sustainabledevelopment/inequality/*

Indeed, trade openness has played a key role in reducing poverty across different countries (International Monetary Fund, 2001). No country has achieved economic success in the last decades, in terms of substantial increases in the living standards of its people, without being open to the rest of the world (International Monetary Fund, 2001). Globally, the number of people living in extreme poverty[1] declined from 36 per cent in 1990 to 9 per cent in 2020. Furthermore, it also concludes that the world is increasingly

[1] Living on less than 1.90$ per person per day (United Nations, 2019).

dependent on international trade for food security because of population growth, climate change and other factors.

Therefore, trade can contribute to achieve specially Goal 1 (no poverty), Goal 2 (zero hunger) as well as Goal 3 (good health and well-being). On top of that, a report by the WTO Secretariat to the High-level Political Forum highlights the role of trade in reducing pre-pandemic poverty in developing and least developed countries, which is also related to Goal 1. The report notes that by making goods more affordable, trade contributes to increasing the purchasing power of the poorest households and to expand economic opportunities for women and youth. It adds that achieving food security goals will be easier if global agricultural markets work well. This is related to Goal 2, Goal 8 (decent work and economic growth) as well as Goal 10 (reduce inequality). Lastly, international trade could be also essential so as to mitigate the negative consequences of the pandemic as well as to ensure a faster and more distributive recovery (World Trade Organization , 2021). These facts are related specially to Goal 8, Goal 9 (industry, innovation and infrastructure) and Goal 10.

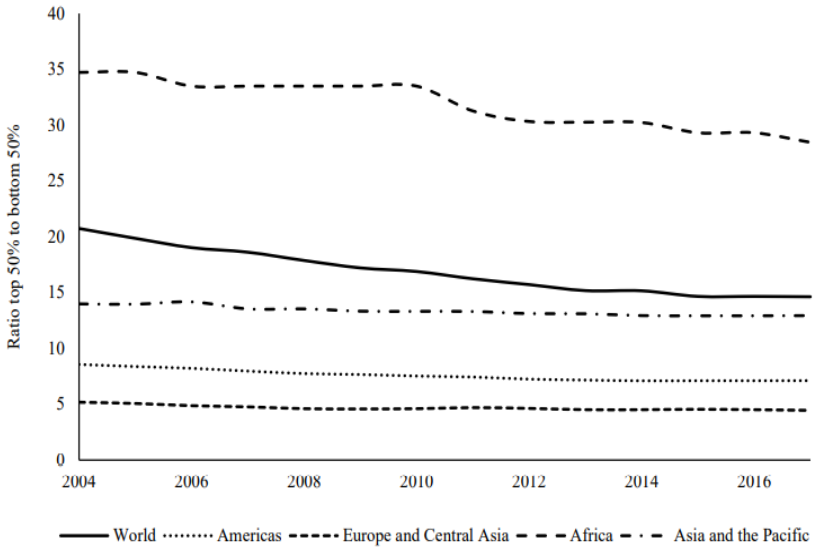
2.2. Trade openness and labour income inequality

International trade affects workers mainly by two channels: it changes the price of goods and services as well as income and job opportunities (Artuc, 2021). Global labour income is unequally distributed across different countries (International Labour Organization, 2019). However, research shows that labour income inequalities have decreased worldwide in the last decades (International Labour Organization, 2019).

Figure 1 can be interpreted as the number of years that the poorest half in the world needs to work on average to earn the same as the richest half in a year. As it can be seen, on average at world level, this ratio shows a decreasing trend. In 2017, the poorest half of the employed population in the world needed to work on average 14 years so as to earn the same as the richest half. However, differences exist across countries. In the case of Africa, this magnitude amounted to 28 years, while in Europe to 4 years. Moreover, the figure also shows that labour income inequalities have remained unchanged on average in Europe and Central Asia, Asia and the Central Pacific as well

as in the Americas since 2004. However, labour income inequalities have decreased in Africa between years 2004 and 2017.

Figure 1. *Number of years that the poorest half in the world needs to work on average to earn the same as the richest half in a year 2004-2017.*

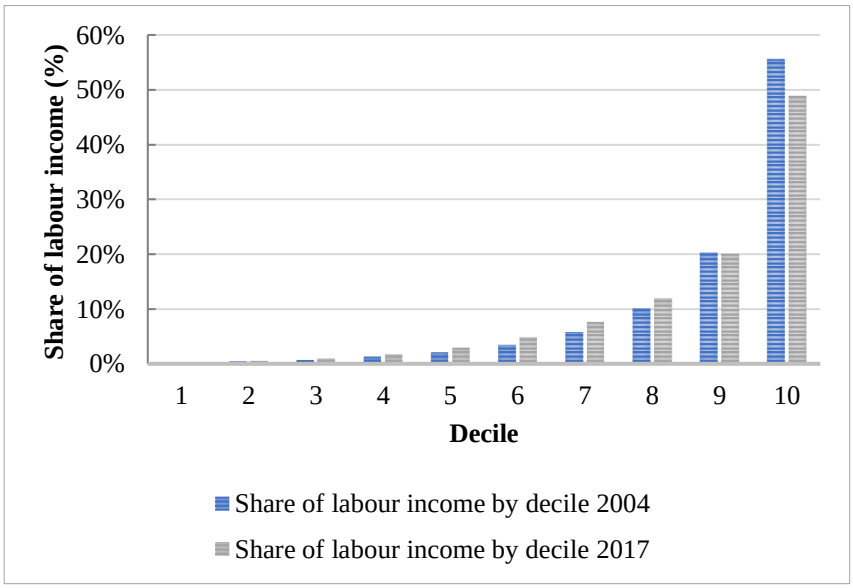


Source: *ILO Department of Statistics, 2019. Retrieved from: "The Global Labour Income Share and Distribution".*

On top of that, these trends can also be shown in **Figure 2**. According to the International Labour Organization (ILO), the poorest 50 per cent of global workers earned merely 4.6 per cent of the world's labour income in 2004, while this amounted to 6.4 per cent in 2017. Therefore, these facts also show a decrease in income inequalities worldwide between years 2004 and 2017.

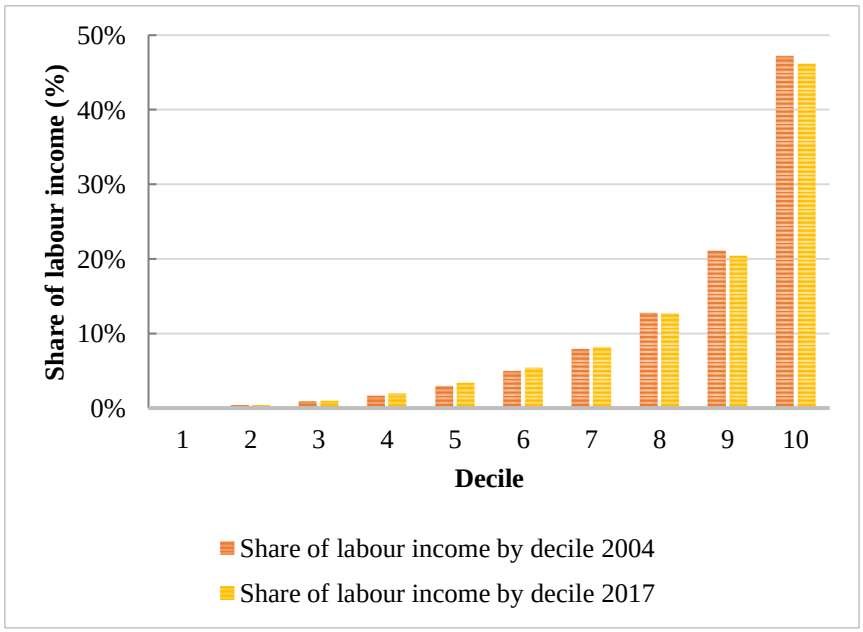
However, not all countries have followed the same pattern. In fact, if China and India are excluded, results show a much lower decrease in income inequalities. The poorest 50 per cent of global workers earned 6.1 per cent of the world labour income in 2004 after excluding these two countries, while this amounted to 6.9 per cent in 2017. This can be seen in **Figure 3**. Therefore, results show that the highest reduction in income inequality have taken place in developing countries (mainly in Africa and Asia). What is more, those having the highest reduction in income inequality, are also the ones which have increased their share of global exports most since 2005.

Figure 2. *World labour income distribution per decile in percentage.*



Source: *ILO Department of Statistics, 2019. Retrieved from: "The Global Labour Income Share and Distribution".*

Figure 3. *World labour income distribution per decile in percentage, after excluding India and China.*



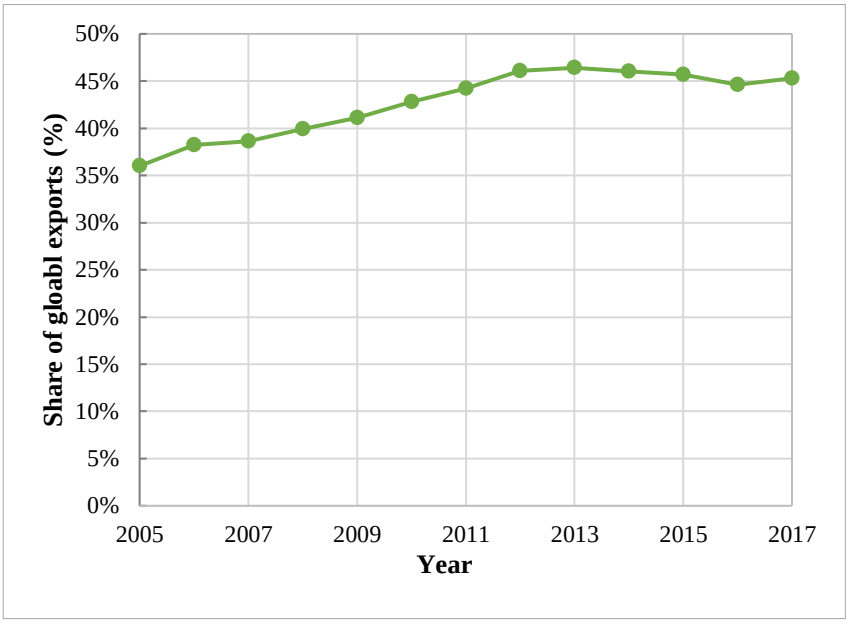
Source: *ILO Department of Statistics, 2019. Retrieved from: "The Global Labour Income Share and Distribution".*

Figure 4 reflects developing economies'[2] share of global exports, in terms of goods and services. The share of global exports was 36% in 2005 for

[2] Those nations that have low living standards, underdeveloped industrial base as well as low Human Development Index (United Nations, 2019, p.9).

developing countries. However, this share amounted to 45.30% in 2017. That is, countries that have suffered a reduction in their income inequality between 2004 and 2017 are those which have increased their share of global exports in the same time period.

Figure 4. *Developing economies' share of global exports.*



Source: *Own elaboration based on data from UNCTAD, 2021*.

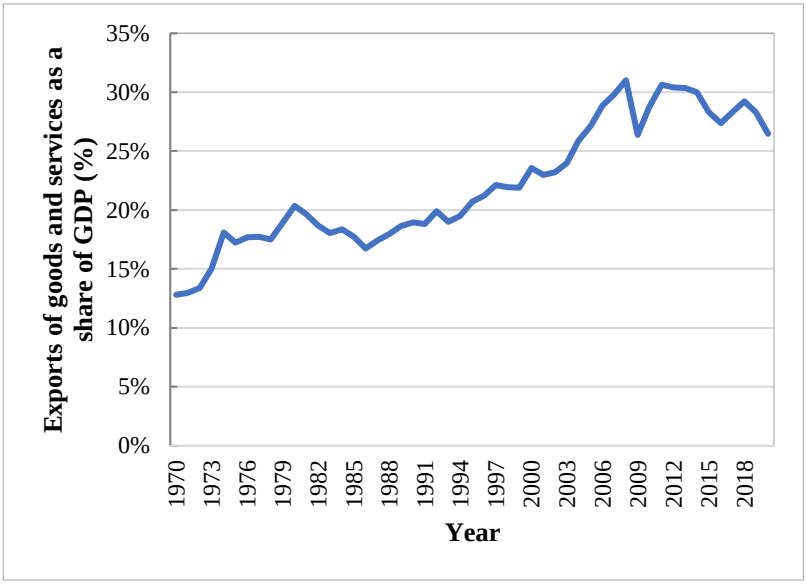
As a consequence, one hypothesis is that trade openness has contributed positively to reduce the income gap between developed and developing countries. According to United Nations, "trade reforms undertaken in developing countries have been accompanied by more rapid economic growth, leading to a reduction in income gaps and lower levels of inequality between countries, observed since the 1990s" (United Nations, 2019). This has been due to faster growth in some developing countries, in particular Brazil, China and India, relative to developed countries, as a consequence of their engagement in rapid and deep trade reforms and rapid integration into world markets, which has reduced the overall income per capita gap between developed and developing countries (United Nations, 2019).

2.3. The evolution of international trade

Analysing the most important changes in patterns of international trade is key since the transformative process has generated gains, but it has also created

distributive consequences. **Figure 5** reflects the value of world exports of goods and services as a percentage of GDP between years 1970 and 2020.

Figure 5. *World exports of goods and services as a percentage of GDP.*



Source: *Own elaboration based on data from the World Development Indicators, the World Bank.*

The export-to-GDP ratio was 12.80% of world GDP in 1970, while it was 26.46% in 2020 (The World Bank, 2020). On top of that, another important change was the increasing importance of global value chains across the world, which also concentrated between 1990 and 2010. According to (Dorn & Levell, 2021), the "China shock", that is, China's dramatic economic expansion, was the main responsible for the mentioned changes in trade patterns. Indeed, China was the largest contributor to the worldwide growth in exports-to-GDP, as well as the largest contributor to rising trade in global value chains. The importance of goods exports from low-income countries increased in 1990 and 2010 as well. Furthermore, this coincided with a decline in trade and communication costs, contributing the expansion of world trade.

3. THE THEORETICAL FRAMEWORK: HECKSCHER-OHLIN MODEL

The neoclassical Heckscher–Ohlin (H-O) model analyses the effect of trade on the relative returns to different factors of production among others. It

assumes two factors of production, two goods and perfect factor mobility across sectors. It states that countries tend to export goods whose production is intensive in factors with which the countries are abundantly endowed. That is, according to the Stolper-Samuelson[3] Theorem, international trade can create winners and losers. Identifying the distributional effects of trade is important, since it has implications for inequality as well as poverty. In a competitive economy, as long as the home economy does not specialize completely, opening to trade leaves at least one factor of production worse off, regardless of the numbers of goods, factors and the degree of factor mobility (Rodrik, 2021). Indeed, it predicts that owners of a country's abundant factors will gain from trade, while owners of a country's scarce factors lose. Therefore, the relative abundance of factors is essential for a country since it determines what will happen with the relative wages after opening for trade. This has important implications for wage as well as income inequality.

According to this theorem, as developing countries are usually abundantly endowed with unskilled workers, trade openness should favour unskilled workers more than the skilled ones in the event of trade liberalization. This theorem therefore predicts a lower gap in wage between skilled and unskilled workers in developing countries. On top of that, the expansion of exports should enable the developing countries to earn foreign exchange, and import raw materials, intermediate goods, capital goods, technology and other items, which can be used to promote economic growth (Urata & Narjoko, 2017).

Regarding developed economies, the H-O theory also predicts that whenever an advanced country follows a trade integration with developing countries, it would experience a rise in wage inequality (Dorn & Levell, 2021).

All in all, the hypothesis is that trade openness reduces real wage gaps between unskilled and skilled workers in developing countries, but it increases real wage gaps between unskilled and skilled workers in developed countries. In other words, the relative factor prices should converge across countries. That is, if wages of skilled workers are rising and those of unskilled

[3] It states that the real wages of skilled-workers rise when the price of skilled worker-intensive industries increase, and the real wages of the opposite factor (unskilled) drop.

workers are falling in the skill-abundant country, the reverse should be happening in the unskilled-abundant country (Krugman et al., 2018). Therefore, a greater trade openness leads to a reduction in wage inequalities in developing countries since they are usually more relatively abundant in unskilled workers relative to skilled. This implies that trade makes the wages of unskilled workers increase relatively more than those of skilled workers. However, as developed countries are usually relatively endowed with skilled workers, trade openness increases more the wages of skilled workers relative to unskilled and therefore their wage gap between unskilled and skilled workers increases.

Empirical studies in 1990s already confirmed that international trade did contribute to the rising skill premium in advanced economies but found that the magnitude of trade's labour market effect was modest (Dorn & Levell, 2021). That is, research shows that trade permanently alters skill demands, it raises demand of high-skilled workers in industrialized countries, while reducing demand for low-skilled workers. Moreover, most economists agreed that the main explanation was skill-biased technological change (Dorn & Levell, 2021). That is, due to the low substitution between skilled workers and capital makes those factors complements in the production. Therefore, technological change in advanced economies takes the form of new and better capital that displace unskilled workers but still require skilled workers (Krugman et al., 2018). Goldin and Katz (1998) analysed how technological change affects the relative demands for skills. They concluded that the shift from factory to continuous process created a capital-skill complementarity.

4. EMPIRICAL ANALYSIS OF THE EFFECT OF INTERNATIONAL TRADE ON WAGE INEQUALITY IN DEVELOPED AND DEVELOPING COUNTRIES: A CROSS-SECTIONAL ANALYSIS FOR 2018

Based on the H-O model previously explained, a cross-sectional model has been created so as to analyse whether the hypothesis mentioned in the previous section can be assumed to be true or not. One of the main reasons

why cross-sectional analysis has been chosen is that it allows to compare many different variables in relation to the dependent variable at the same time across different countries. Indeed, the main purpose of this research is to examine the cross-country relationship between trade openness, the relative abundance of skilled and unskilled workers and wage of skilled workers relative to unskilled workers in developed and developing countries. On top of that, cross-sectional analysis provides a useful springboard for future research. The cross-sectional dimension consists of 62 countries (indicated by subscript *i*). United Nations classifies all countries of the world into one of three broad categories: developed economies, economies in transition and developing economies. Its composition aims to reflect basic country economic conditions. **Table 2** shows the countries that form the database classified by their level of development.

The main reason why these 62 countries have been chosen is that they provide the bases for a heterogeneous sample, which is key so as to analyse how different variables differ across countries with different levels of development. Moreover, no more countries have been included since data was missing for many of them or was not reliable, due to their low level of development. The model is constructed for year 2018, since the COVID-19 pandemic might have affected trade patterns across countries and therefore later years may not correctly reflect the effect that seeks to be analysed. To carry out the econometric analysis, the software Gretl is used. The goal is to find the OLS estimator, that is, to obtain from each model a straight line which is as close as possible to the data points. These are the necessary OLS assumptions: (1) linearity in parameters; (2) random sampling of observations; (3) zero conditional mean; (4) no perfect multicollinearity between independent variables; (5) homoskedasticity and no autocorrelation (Wooldridge, 2013, p.105). If all these assumptions hold, then according to Gauss-Markov Theorem, OLS estimator is Best Linear Unbiased Estimator (BLUE) (Wooldridge, 2013, p.102). These are desirable properties of OLS estimators. Moreover, even if OLS does not require that the error term follows a normal distribution to produce unbiased estimates, satisfying this assumption is key so as to generate reliable estimates.

Table 2. *United Nation's country classification according to economic conditions for countries included in the cross-sectional analysis.*

Developed economies	Economies in transition	Developing economies
1. Austria 2. Belgium 3. Bulgaria 4. Croatia 5. Cyprus 6. Czech Republic 7. Denmark 8. Estonia 9. France 10. Germany 11. Greece 12. Hungary 13. Ireland 14. Italy 15. Latvia 16. Lithuania 17. Luxembourg 18. Malta 19. Netherlands 20. Norway 21. Portugal 22. Slovenia 23. Spain 24. Sweden 25. Switzerland 26. United Kingdom	27. Albania 28. Armenia 29. Serbia	30. Argentina 31. Belize 32. Brazil 33. Costa Rica 34. Curacao 35. Dominican Republic 36. Egypt 37. El Salvador 38. Gambia 39. Guyana 40. Honduras 41. Israel 42. Jordan 43. Republic of Korea 44. Malaysia 45. Mali 46. Malta 47. Mauritius 48. Mexico 49. Mongolia 50. Myanmar 51. Pakistan 52. Panama 53. Paraguay 54. Philippines 55. Sierra Leone 56. South Africa 57. Sri Lanka 58. Thailand 59. Tonga 60. Turkey 61. Viet Nam 62. Zambia

Source: *Development Policy and Analysis Division (DPAD) of the Department of Economic and Social Affairs of the United Nations Secretariat. Retrieved from: https://www.un.org/en/development/desa/policy/wesp/wesp_current/2014wesp_country_classification.pdf*

4.1. Endogenous variable: Relative wage of skilled workers relative to unskilled workers

The dependent variable is wages of skilled workers relative to unskilled workers and it is included as "*Relative wage*" in the model. This research seeks to find out whether trade favours relatively more skilled or unskilled workers in each country. Therefore, the relative wage of skilled workers

relative to unskilled represents the wage gap between skilled and unskilled workers in each country (also known as skill premium). In other words, according to theory, the relative abundance of skilled workers relative to unskilled in a country determines somehow the relative returns of these workers.

The mean nominal hourly earnings of employees by occupation is used as a proxy, retrieved from ILOSTAT. The concept of *occupation* is defined by ISCO-08 (International Standard Classification of Occupations) as a "set of jobs whose main tasks and duties are characterized by a high degree of similarity". The database is formed of different sources, mainly from surveys carried out to households and businesses. It provides the mean nominal hourly earnings converted into the USD as the common currency. Moreover, ISCO-08 classifies each occupation into different levels of skills (low, medium or high). S*kill level* is defined as "a function of the complexity and range of tasks and duties to be performed in an occupation" also according to ISCO-08.

Table 3 shows how ISCO-8 classifies occupations into different skill levels.

Table 3*. Correspondence table between ISCO-08 occupations and broad skill levels.*

Broad skill level	ISCO-08
Skill levels 3 and 4 (high)	1. Managers
	2. Professionals
	3. Technicians and associate professionals
Skill level 2 (medium)	4. Clerical support workers
	5. Service and sales workers
	6. Skilled agricultural, forestry and fishery workers
	7. Craft and related trades workers
	8. Plant and machine operators, and assemblers
Skill level 1 (low)	9. Elementary occupations

Source: *International Standard Classification of Occupations, ILOSTAT. Retrieved from: https://ilostat.ilo.org/resources/concepts-and-definitions/classification-occupation/*

As it can be seen, workers are classified in a total of 9 different occupations. Moreover, these are classified into different skill levels: low, medium and high. Therefore, it is possible to convert the data into the ratio of average wage of skilled workers relative to unskilled by dividing the average wage in

skill levels 3 and 4 (high level) by the average wage of workers in skill level 1 (unskilled level).

4.2. Exogenous variables

4.2.1. R&D intensity

The first independent variable included in the model is the R&D intensity of each country, that is, the domestic expenditure in research and development expressed as a percentage of GDP. It is denoted as "*l_R&D*" since it is in logarithmic form.

Data has been retrieved from the UNESCO Institute for Statistics, from the science, technology and innovation department. This coefficient represents the average USD ceteris paribus effect of increasing the R&D expenditure -to- GDP ratio one percentage point on the relative wages of skilled workers relative to unskilled workers. It is expected that countries which are relatively more intensive in R&D investments have a higher relative wage of skilled workers relative to unskilled. That is, countries investing relatively more in R&D are supposed to be relatively more abundant in skilled workers relative to unskilled, because of the complementarity explained by the skill-biased technological change. Therefore, this coefficient is expected to have a positive sign both, for developed and developing countries.

4.2.2. Living Standards

Moreover, another independent variable is related to the living standards of each country, which is the GDP per capita. Taking this variable into consideration is relevant, since there is evidence regarding the fact that more developed countries usually have higher living standards relative to developing countries and therefore it is expected that also have a higher ratio of skilled workers relative to unskilled. The variable is denoted "*l_GDPpc*" since it is in logarithmic form and is calculated as the gross domestic output of each country divided by the midyear population, converted to USD as the common currency.

Data regarding this variable has been retrieved from the World Bank, specifically from the section of National Accounts. This coefficient represents average USD ceteris paribus effect of increasing the GDP per capita by one

percentage point on the relative wages of skilled workers relative to unskilled workers. As explained previously, it is expected that this coefficient takes a positive value for developed countries as well as developing countries.

4.2.3. Relative abundance of the number of skilled workers relative to the number of unskilled workers

Another independent variable included in the model is the ratio of the number of skilled workers relative to the number of unskilled workers of each country, that is, the relative abundance of the number of skilled workers relative to the number of unskilled. This variable is the key variable so as to check whether H-O prediction regarding the effect of relative abundance of factors of production on their relative wages is fulfilled and it will be proxied by the ratio of the number of workers with upper and post-secondary studies relative to those with lower secondary studies and below in each country, denoted as "*Relative abundance*".

Data regarding this variable has been retrieved from UNESCO Institute for Statistics. Specifically, from the section of International Standard Classification of Education, which provides a framework so as to compare national education systems with those of other countries and to set a benchmark progress towards international goals. This coefficient represents the average USD ceteris paribus effect of increasing the abundance of skilled workers relative to unskilled in one unit on the wages of skilled workers relative to unskilled. It is expected to take a positive value both for developed and developing countries, since the main purpose of the model is to analyse whether being relatively abundant in a factor of production is positively correlated with the returns of that factor, as the H-O model predicts.

4.2.4. Trade openness

Another important variable to take into account when determining the relative wage of skilled workers relative to unskilled workers is the level of trade openness of each country. The trade intensity ratio, that is, exports plus imports divided by GDP is the basic measure for trade openness (Leamer, 1988), and therefore it will be the one used so as to carry out the cross-sectional analysis. The independent variable is denoted "*l_Trade*" as it is in logarithmic form.

Data has been retrieved from the World Bank and the coefficient represents the average USD ceteris paribus effect of increasing the exports plus imports relative to GDP in one percentage point on the relative wages of skilled workers relative to unskilled workers. It is not clear whether this coefficient is expected to be positive or negative since it depends on the level of development of the trading partner as well as the level of development of each country. According to H-O theorem, trade openness reduces real wage gaps between unskilled and skilled workers in developing countries and therefore, the coefficient should take a negative value. However, trade openness is expected to increase real wage gaps between unskilled and skilled workers in developed countries and therefore this coefficient is expected to be positive for them.

4.2.5. Human capital

Lastly, education is fundamental for the development of a country. Indeed, research show that no country can achieve sustainable levels of development without substantial investment in human capital (Ozturk, 2001). Moreover, according to another research carried out by OECD, investing in education increases national wealth levels and leads to economic growth (OECD, 2021). On top of that, it is known that human capital, that is, resources associated with the knowledge and skills of individuals, is a critical component of economic development. In other words, human capital affects economic growth and can help to develop an economy by expending the knowledge and skills for its workers. On top of that, those with more education tend to earn higher salaries. The variable is denoted "*HLO*" refers to the Harmonized Learning Outcomes.

Data has been retrieved from the Harmonized Learning Outcomes database of the World Bank, the section of "Measuring Human Capital Using Global Learning Data" and it enables comparisons of learning process across different countries. The database includes the results from seven different tests that have been combined and made comparable across countries. The HLO (Harmonized Learning Outcomes) data is used so as to calculate the World Bank Human Capital Index combining learning and schooling through the Learning-Adjusted Years of Schooling education component of the index.

This coefficient represents the average USD ceteris paribus effect of increasing the Harmonized Learning Outcomes grade in one point on the relative wages of skilled workers. The sign of this coefficient is expected to be positive for both, developed and developing countries, since countries that invest more in education are supposed to have relatively more qualified workers (and therefore a higher relative wage of skilled workers relative to unskilled).

Appendix 1A provides a description of each variable as well as their source. Moreover, **Appendix 2A** summarizes the main statistics for the variables used in the analysis.

4.3. Models and results

Different models are presented for all countries, developed countries as well as developing countries. For simplicity, economies in transition are considered developing countries. The main results for each model are summarized in **Table 4**.

Model 1 is presented below. $\beta 1$ represents the average USD ceteris paribus effect of increasing the R&D expenditure -to- GDP ratio one percentage point on the relative wages of skilled workers relative to unskilled workers.

$$\text{Relative wage}_i = \beta 0 + \beta 1 \text{l\_R\&D}_i + u_i \ (\textbf{Model 1})$$

As expected, $\beta 1$ takes a positive value for developed, developing and all countries. Moreover, it is statistically significant at a 1% significance level. This implies that countries that are more intensive in R&D also tend to have higher relative wage of skilled workers relative to unskilled.

Model 2 analyses what happens if the variable "*l_GDPpc*" is introduced without "*l_R&D*". $\beta 1$ reflects the average USD ceteris paribus effect of increasing the GDP per capita by one percentage point on the relative wages of skilled workers relative to unskilled workers.

$$\text{Relative wage}_i = \beta 0 + \beta 1 \text{l\_GDPpc}_i + u_i \ (\textbf{Model 2})$$

As expected, it can be seen that $\beta 1$ takes a positive value and is statistically significant both, for developed as well as developing countries. In the case of

the former one, it has a 10% significance level, while the latter one a 5% significance level.

Table 4. *Results from the cross-sectional analysis for 2018.*

Independent / Dependent variable	All countries	Developed countries	Developing countries
Model 1			
Constant	1.988***	2.898***	1.453***
l_R&D	0.864***	0.978***	0.568***
Adjusted R^2	0.486	0.444	0.448
Model 2			
Constant	1.655**	1.750***	1.590***
l_GDPpc	0.478**	0.392*	0.371**
Adjusted R^2	0.374	0.365	0.343
Model 3			
Constant	0.432	1.944	0.647*
l_R&D	0.443***	1.051**	0.584***
l_GDPpc	0.152	0.103	0.129
Adjusted R^2	0.502	0.449	0.448
Model 4			
Constant	0.425***	0.573***	0.760***
l_R&D	0.495***	0.688**	0.582***
Relative abundance	0.119**	0.121*	0.125**
Adjusted R^2	0.536	0.527	0.495
Model 5			
Constant	0.353***	0.800***	0.417**
l_R&D	0.498***	0.717**	0.582***
Relative abundance	0.119**	0.124*	0.127**
l_Trade	0.360***	0.113***	0.080**
Adjusted R^2	0.620	0.631	0.622
Model 6			
Constant	0.346***	0.672***	0.932***
l_R&D intensity	0.333***	0.707**	0.487***
Relative abundance	0.119**	0.125*	0.114*
l_Trade	0.327**	0.111**	0.342**
HLO	0.004**	0.006*	0.001*
Adjusted R^2	0.662	0.653	0.656

Source*: Own elaboration based on results from Gretl. ***p-value<0.01, **p-value <0.05, *p-value<0.1*

Model 3 includes both variables, GDP per capita as well as R&D intensity. $\beta 1$ reflects the average USD ceteris paribus effect of increasing the R&D intensity by one percentage point on the relative wages of skilled workers relative to unskilled workers. $\beta 2$ reflects the average USD ceteris paribus effect of increasing the GDP per capita by one percentage point on the relative wages of skilled workers relative to unskilled workers.

$$\text{Relative wage}_i = \beta 0 + \beta 1 \text{l\_R\&D}_i + \beta 2 \text{l\_GDPpc}_i + u_i \text{ (\textbf{Model 3})}$$

As expected, $\beta 2$ has a positive sign, however, it is not statistically significant. Moreover, $\beta 1$ is positive and statistically significant at a 5% significance level for developed countries. For developing countries, $\beta 1$ is positive and statistically significant at a 1% significance level. Furthermore, it can be seen that introducing the variable "*l_GDPpc"* increases the adjusted R^2 in less than 1% both, for developed as well as developing countries. This implies that the proportion of the variance in the dependent variable that is explained by the independent variables almost does not increase. One of the reasons can be the fact that both independent variables, that is, "*l_GDPpc*" and "*l_R&D*" are correlated among them. Looking at **Appendix 4A**, it can be seen that the Pearson coefficient for them is 0.660, which is quite high.

Model 4 introduces another variable related to the relative abundance of skilled and unskilled workers, that is, "*Relative abundance*". $\beta 2$ represents the average USD ceteris paribus effect of increasing the abundance of skilled workers relative to unskilled in one unit on the wages of skilled workers relative to unskilled.

$$\text{Relative wage}_i = \beta 0 + \beta 1 \text{l\_R\&D}_i + \beta 2 \text{Relative abundance}_i + u_i \textbf{ (Model 4)}$$

As expected, $\beta 2$ is positive and statistically significant both, for developed as well as developing countries. However, the coefficient is statistically significant at a 10% significance level for developed countries, while it is at a 5% significance level for developing countries. This implies that countries with a higher relative abundance of skilled workers relative to unskilled have also a higher relative wage of skilled workers relative to unskilled. Furthermore, it supports the hypothesis and shows that there exists a positive and statistically significant correlation between the relative abundance of

skilled workers relative to unskilled and the relative return of each of them for both, developed and developing countries. Moreover, $\beta 1$ is still positive and statistically significant at a 5% significance level for developed countries, while it is at a 1% significance level for developing countries.

Model 5 introduces a new variable, which is "*l_Trade*". $\beta 3$ reflects the average USD ceteris paribus effect of increasing the exports plus imports relative to GDP in one percentage point on the relative wages of skilled workers relative to unskilled workers.

$$\text{Relative wage}_i = \beta 0 + \beta 1 \text{l\_R\&D}_i + \beta 2 \text{l\_Relative abundance}_i + \beta 3\ \text{l\_Trade}_i + u_i \textbf{ (Model 5)}$$

As expected, $\beta 3$ takes a positive value and is statistically significant at a 1% significance level for developed countries. This supports H-O theory for developed countries, since according to it, trade openness should increase the wages of skilled workers relatively more than those of unskilled workers (since developed countries are relatively more abundant in skilled workers) and therefore these countries should have a higher ratio for the wage of skilled workers relative to unskilled.

However, contrary to expected, $\beta 3$ also takes a positive value and is statistically significant at a 5% significance level for developing countries. This means that the higher the trade openness of a developing country, the higher the ratio for the salaries of skilled workers relative to unskilled. This result is opposite to the expected one, since H-O theory predicts that as developing countries are usually relatively more endowed with unskilled workers, in the event of trade openness, these last ones, that is, unskilled workers should be the ones that benefit the most from trade openness and therefore their wages should increase relatively more than those of skilled workers (and lower the ratio for the salaries of skilled relative to unskilled workers).

Lastly, **Model 6** introduces the variable related to human capital, that is "*HLO*". $\beta 4$ reflects the average USD ceteris paribus effect of increasing the Harmonized Learning Outcomes grade in one point on the relative wages of skilled workers.

$$\text{Relative wage}_i = \beta 0 + \beta 1 \text{l\_R\&D}_i + \beta 2 \text{ Relative abundance}_i + \beta 3 \text{ l\_Trade}_i + \beta 4 \text{ HLO}_i + u_i \textbf{ (Model 6)}$$

Results show that $\beta 4$ is positive and statistically significant at a 10% significance level for developed and developing countries. For the rest of variables, the results have not almost changed. Furthermore, the adjusted R^2 has not increased a lot after introducing the last variable related to human capital, which could also be explained by its high correlation with R&D intensity (Pearson coefficient is 0.637).

Moreover, after constructing and analysing the models, they have been checked for normality of residuals, heteroskedasticity as well as multicollinearity. P-values for the tests can be seen in **Appendix 3A** and the correlation matrix in **Appendix 4A**. When it comes to normality of residuals, Jarque-Bera test is carried out for each of the models. The null hypothesis is that the residuals are normally distributed, against the alternative, that the residuals are not normally distributed. If p-value is lower than 0.05, then the null hypothesis can be rejected, and this implies that the residuals of the model are not normally distributed. As it can be seen, the residuals of the models are normally distributed.

Moreover, homoskedasticity implies that the error has the same variance given any value of the explanatory variable. So as to check this, all models are analysed with White's test. Models with a p-value lower than 0.05 are heteroskedastic and therefore need to be corrected for heteroskedasticity.

Furthermore, multicollinearity is a situation in where two or more predictors are highly linearly related (Gujarati & Porter, 2009, p.320). Assumption 4 implies that no perfect multicollinearity exists between explanatory variables. This implies that no independent variable is a perfect linear function of other explanatory variables. Perfect correlation occurs when two variables have a Pearson coefficient of -1 or +1. That is, when one of these variable changes, the other also changes by a completely fixed proportion. An absolute value for this coefficient higher than 0.7 indicates the presence of perfect multicollinearity. When this happens, OLS cannot distinguish one variable from the other one. This leads to redundancy, that is, two predictors might be

providing the same information about the response variable thereby leading to unreliable coefficients of the predictor. Results show that no perfect multicollinearity exists among explanatory variables, since none of the coefficients takes an absolute value higher than 0.7, even if some are close to it.

All in all, the results in the cross-sectional data support the H-O theory when it comes to the effect of the relative abundance of production factors of a country with the relative returns of that factor in developed as well as developing countries. According to it, countries that are relatively more abundant in skilled workers relative to unskilled also have higher relative wage of skilled workers relative to unskilled.

Moreover, results also support H-O theory when it comes to the effect of trade openness in relative wages of skilled workers relative to unskilled in developed countries. According to it, trade openness increases relative wage gaps between skilled and unskilled workers in developed countries. This has important implications for achieving Sustainable Development Goals, especially Goal 3 (promote well-being for all at all ages) and Goal 10 (reduce inequality within and among countries). These findings could make one think that trade openness is the responsible for increasing wage inequality in advanced economies and that it should not be fostered if Sustainable Development Goals want to be achieved. However, literature explains that trade of advanced economies embodied in skill-intensive exports accounts for a small fraction of the total supply of skilled and unskilled workers and therefore its impact on wage inequality is small.

Instead, the responsible of wage inequality in developed countries are the new production technologies that put a greater emphasis on worker skills, referred to as skill-biased technological change (Krugman et al., 2018). According to a study carried out by OECD, the rising gap between earnings of the high-skilled and those on the low-skilled springs from several factors (OECD, 2011). First, a rapid rise in the integration of trade and financial markets generated a relative shift in labour demand in favour of high-skilled workers. Second, technological progress shifted production technologies in both industries and services in favour of skilled labour.

However, results in the cross-sectional analysis do not coincide with prediction of the H-O theory which argues that trade openness leads to a reduction in the relative wage of skilled workers relative to unskilled workers in developing countries. According to the cross-sectional analysis, a greater trade openness leads to a greater relative wage of skilled workers relative to unskilled, and therefore a higher wage inequality in developing countries. Studies in developing countries that have opened to trade show that this is true in some cases. In Mexico, studies show that the transformation of the country's trade in the late 1980s, increased relatively more the wages for skilled workers and therefore wage inequality (Krugman et al., 2018). Hanson and Harrison (1999) found that low-skilled workers were affected more than proportionately by an increased competition in imports (since Mexico had high protection rates which were reduced significantly). Something similar happened to China after joining the World Trade Organization (WTO). Furthermore, studies analysing the distributive consequences of international trade flows in developing countries suggest that the interplay between trade liberalization and technology adopted determines wage differentials (Meschi & Vivarelli, 2007). Furthermore, they found that skill-biased technological change usually hurts low-skilled workers in developing economies.

On top of that, results also show that the higher R&D intensity of a country, the higher the relative wage of skilled workers relative to unskilled workers. Lastly, countries with a higher level of education also have a higher relative wage of skilled workers relative to unskilled workers. However, research show that skill development is key for reducing inequality and poverty (Grant, 2017). In other words, even if more developed countries have a higher wage inequality (as it can be seen in **Model 2**), education is fundamental for development and economic growth. Therefore, it can be seen as a tool so as to achieve Sustainable Development Goals 1 (no poverty), 2 (zero hunger), 8 (decent work and economic growth), 9 (industry, innovation and infrastructure) and 10 (reduce inequality within and among countries).

Lastly, looking at **Model 6**, it can be seen that the effect of each variable on wage inequality differs across countries. Regarding R&D intensity, it can be that the coefficient analysing the effect of R&D intensity on wage inequality

is higher in developed countries relative to developing. Moreover, the opposite happens with trade openness, which implies that trade openness has a relatively smaller effect on wage inequality in developed countries. Furthermore, the effect of education on wage inequality is also higher in developed countries (since the coefficient takes a higher value). Furthermore, in developed countries, R&D intensity affects wage inequality seven times as much as trade openness does (the coefficient of R&D intensity is almost seven times the coefficient of trade openness). However, in developing countries, the effect of R&D intensity on wage inequality is not even 1.5 times as high as the effect of trade openness.

5. EMPIRICAL ANALYSIS OF THE EFFECT OF INTERNANTIONAL TRADE ON INCOME INEQUALITY IN DEVELOPED AND DEVELOPING COUNTRIES: A PANEL DATA ANALYSIS FOR 2007-2018

Results in the cross-sectional analysis show that there exists a positive correlation between trade openness and wage inequality within developed and developing countries. However, cross-sectional studies cannot be used to infer causality. Therefore, a panel data model is constructed so as to analyse deeper what is the effect of international trade not on wage inequality, but on income inequality within developed and developing countries. Using panel data has several advantages over cross-section data. One of them is that it might make it possible to overcome the problem of bias caused by unobserved individual heterogeneity (Gujarati & Porter, 2009). On top of that, panel data are better able to study dynamics of adjustment, in this case the effect of international trade on income inequality (Gujarati & Porter, 2009). Lastly, panel data reduces estimation bias such as omitted variable bias, simultaneity bias and measurement errors.

Analysing the impact of trade on income inequality has important implications since research shows that even if wage inequality accounts for an important part of overall household income inequality, the latter one also includes other sources of income such as transfers and capital income

(European Parliament Directorate-General for Internal Policies, 2015). It argues that changes in wage inequality explain around one-fourth of the variation in changes in overall income inequality between 2006 and 2011. Indeed, according to OECD, *wage* relates to "remuneration in cash and in-kind paid employees for time worked or work done together with remuneration for time not worked, such as annual vacation and other paid leave or holidays". Moreover, also according to OECD, *income* is defined as "household disposable income in a particular year". "It consists of earnings, self-employment and capital income and public cash transfers; income taxes and social security contributions paid by households are deducted".

Edwards (1997) regressed the GINI coefficient over six indicators of trade openness and concluded that there was no evidence suggesting that trade liberalization had any significant impact on income inequality. Moreover, another research analysed the impact of globalization on income inequality distribution in 60 developed, transitional, and developing countries (Zhou et al., 2011). It concluded that globalization can either improve or worsen income inequality. Furthermore, a research carried out by Cerdeiro and Komaromi (2017) among countries with different levels of development showed that a one percentage point increase in trade openness in a country raises its real income per capita between 2 and 5 percent. On top of that, this research also showed that trade's impact on real income is consistent and significant over time. Other researches concluded that the decrease in the GINI coefficient for these countries was proportional to their openness to trade (García-Algarra et al., 2020).

So as to analyse the implications of trade openness for income inequality in developed and developing countries, a panel data model is presented for years 2007-2018 including 66 countries with different levels of development. **Table 5** shows the countries included in the analysis according to their level of development.

The main reason for choosing that time period and not a wider one is that there was no complete data available for years prior to 2007 and after 2018 for the variables of interest. Although this is a short time series, it is possible to gain interesting insights regarding the topic.

Table 5. United Nation's country classification according to economic conditions for countries included in the panel data analysis.

Developed economies	Economies in transition	Developing economies
1. Australia 2. Austria 3. Belgium 4. Bulgaria 5. Canada 6. Croatia 7. Cyprus 8. Czech Republic 9. Denmark 10. Estonia 11. Finland 12. France 13. Georgia 14. Germany 15. Greece 16. Iceland 17. Ireland 18. Italy 19. Latvia 20. Lithuania 21. Luxembourg 22. Malta 23. Netherlands 24. Norway 25. Poland 26. Portugal 27. Romania 28. Slovak Republic 29. Slovenia 30. Spain 31. Sweden 32. Switzerland 33. Ukraine 34. United Kingdom 35. United States	36. Albania 37. Armenia 38. Serbia	39. Argentina 40. Belarus 41. Belize 42. Bhutan 43. Bolivia 44. Botswana 45. Brazil 46. Chile 47. China 48. Costa Rica 49. Colombia 50. Dominican Republic 51. Ecuador 52. El Salvador 53. Egypt 54. Honduras 55. Indonesia 56. Israel 57. Kazakhstan 58. Kyrgyz Republic 59. Malta 60. Moldova 61. Panama 62. Paraguay 63. Peru 64. Thailand 65. Turkey 66. Uruguay

Source: *Development Policy and Analysis Division (DPAD) of the Department of Economic and Social Affairs of the United Nations Secretariat. Retrieved from: https://www.un.org/en/development/desa/policy/wesp/wesp_current/2014wesp_country_classification.pdf*

Moreover, the set of countries included in the model has slightly changed from the countries in the cross-sectional analysis. Cross-sectional units are denoted with subscript i, while time-series units are denoted with subscript t. In this case, as the panel is balanced (the same time periods are available for all cross-section units), there are a total of 868 observations.

5.1. Endogenous variable: Income inequality

The dependent variable for this model is income inequality, measured by the GINI coefficient. It measures the extent to which the distribution of income (or, in some cases, consumption expenditure) within an economy deviates from a perfectly equal distribution. A Lorenz curve plots the cumulative percentages of total income received against the cumulative number of recipients, starting with the poorest individual or household. The GINI coefficient measures the area between the Lorenz curve and a hypothetical line of absolute equality, expressed as a percentage of the maximum area under the line. Thus, a GINI coefficient of 0 represents perfect equality, while an index of 100 implies perfect inequality. Data for this variable has been retrieved from the World Bank, that is, the GINI coefficient used in the model has been retrieved directly from the World Bank database.

5.2. Exogenous variables

5.2.1. Trade openness

As the main goal is to analyse the effect of trade openness on income inequality, one of the independent variables included in the analysis is trade openness. This variable is the same as used previously in the cross-sectional analysis represents the trade intensity ratio. It is denoted "*l_Trade*", since it is in logarithmic form. The coefficient represents the average ceteris paribus percentage variation in the GINI coefficient when increasing the exports plus imports -to- GDP ratio one percentage point. As explained previously, according to the H-O theory, it is expected that trade openness increases income inequalities in developed countries, therefore this coefficient is expected to be positive for developed countries. However, trade openness is expected to decrease income inequality in developing economies, and therefore the coefficient is expected to be negative for them. However, after seeing the results obtained in the cross-section analysis, it is possible that the coefficient takes a positive value both for developed as well as developing countries.

5.2.2. R&D intensity

Moreover, the cross-sectional analysis also showed that there exists a correlation between the relative wage of skilled workers relative to unskilled

and the R&D intensity of each country. Therefore, it is also interesting to include this variable in the analysis. It is denoted as "*l_R&D*". This coefficient represents the average ceteris paribus percentage variation in the GINI coefficient when increasing the R&D investment -to- GDP ratio one percentage point. According to the results obtained in the cross-sectional analysis, it is expected to be positive both, for developed as well as developing countries since the results concluded that the higher R&D intensity in a country, the higher the ratio for the wage of skilled workers relative to unskilled workers. Therefore, a higher R&D intensity implies higher wage inequality. However, as mentioned before, wage inequality merely accounts for a part of income inequality. Furthermore, R&D is an important factor that drives economic growth and productivity (Ugur et al., 2018). Moreover, productivity is related to relative wages. On top of that, a research carried out regarding this issue showed that R&D investment contributed to income inequalities (Churchill et al., 2021). Due to this fact, it is not clear the value for this coefficient in developed and developing countries.

5.2.3. Living standards

Lastly, the independent variable regarding living standards of each country is included, that is, GDP per capita. This variable is denoted as "*l_GDPpc*". The coefficient represents the average ceteris paribus percentage variation in the GINI coefficient when increasing the GDP per capita one percentage point. According to the results in the cross-sectional analysis, it is expected to take a positive value, both for developed as well as developing countries. Moreover, Kuznets (1955) argued that as countries developed, income inequality increased, peaked and then decreased. Therefore, according to that research, the sign of the coefficient is expected to depend on the level of development of each country.

Appendix 1B summarizes the main statistics for each variable and **Appendix 2B** provides a description of each variable as well as their source.

5.3. Models and results

There are different types of panel models: (1) Pooled OLS Model, (2) Fixed Effects Model and (3) Random Effects Model. In the Pooled OLS Model, the heterogeneity of each subject is subsumed in the term u_{it}. Therefore, it is quite

possible that the error term may be correlated with some of the regressors included in the model (Gujarati & Porter, 2009). In that case, the estimated coefficients may be biased and inconsistent. Firstly, Breusch-Pagan LM Test is carried out. The null hypothesis is that there are no significant differences across units. If p-value is lower than 0.05, then the null hypothesis can be rejected, and Fixed Effects Model or Random Effects Model is preferred over the Pooled OLS Model. **Table 6** shows that the p-values for this test are lower than 0.05 for models 8, 9 and 10. Therefore, Fixed Effect Model or Random Effects Model should be used. The main difference between these two approaches lies in how the unobserved characteristics (individual effects) are modelled. Hausman's Specification Test is carried out so as to analyse which model to use: the Fixed Effect or the Random Effect Model. In this case, the null hypothesis states that Random Effect Model is consistent. If p-value is lower than 0.05, then the null hypothesis can be rejected, and the Fixed Effect Model should be used. As it can be seen in **Table 6**, p-values for this test are lower than 0.05 for models 8, 9 and 10. Therefore, Fixed Effect Model is used.

Under the following assumptions, the Fixed Effect Model will produce consistent and unbiased estimators (Hanck et al., 2021): (1) Exogeneity; (2) the explanatory variables are independent and identically distributed; (3) large outliers are unlikely; (4) there is no perfect multicollinearity between independent variables (Hanck et al., 2021).

The same as in the cross-section analysis, Jarque-Bera Test, White's Test as well as Durbin-Watson Test have been carried out. **Appendix 3B** shows the p-values for each. As it can be seen, there residuals are normally distributed and there is no serial autocorrelation. It also shows the models that had to be corrected for heteroskedasticity. Moreover, **Appendix 4B** provides the correlation matrix for the variables. As it can be seen, there is no perfect multicollinearity between independent variables.

Table 6 provides a summary of the results for each model. **Model 7** aims to analyse whether there is a causal effect between trade openness and the GINI coefficient. $\beta 1$ represents the average ceteris paribus percentage variation in the GINI coefficient when increasing the exports plus imports -to- GDP ratio one percentage point.

Table 6. *Results from the panel data analysis for 2007-2018.*

Independent / Dependent variable	All countries	Developed countries	Developing countries
Model 7			
Constant	4.400***	4.083***	4.590***
l_Trade	-0.196***	-0.137***	-0.228***
Breusch-Pagan LM Test	0.005	0.013	6.771e-06
Hausman's Specification Test	0.015	0.040	0.001
Model 8			
Constant	4.681***	4.735***	4.663***
l_Trade	-0.193***	-0.149***	-0.226***
l_R&D	-0.066***	-0.120***	-0.020***
Breusch-Pagan LM Test	0.042	0.023	0.002
Hausman's Specification Test	8.735e-6	0.006	5.26e-12
Model 9			
Constant	4.486***	4.456***	4.414***
l_Trade	-0.211***	-0.171***	-0.244***
l_R&D	-0.109***	-0.186***	-0.053***
l_GDPpc	0.048***	0.068***	0.050***
Breusch-Pagan LM Test	0.048	0.033	0.029
Hausman's Specification Test	4.596e-5	0.006	3.204e-10

Source*: Own elaboration based on results from Gretl. ***p-value<0.01, **p-value <0.05, *p-value<0.1*

$$l\_GINI_{it} = \beta 0 + \beta 1 l\_Trade_{it} + u_{it} \text{ (\textbf{Model 7})}$$

As expected, $\beta 1$ is negative and statistically signifficant at a 1% significance level for developing countries. This implies that opening for trade contributes to decrease income inequalities within countries in developing economies. However, contrary to expected, $\beta 1$ is negative and statistically signifficant at a 1% significance level also for developed countries. This implies that trade openess contributes to decrease income inequality within countries in developed economies as well.

Model 8 introduces another independent variable, "*l_R&D*". $\beta 2$ represents the average ceteris paribus percentage variation in the GINI coefficient when increasing the R&D investment -to- GDP ratio one percentage point.

$$l\_GINI_{it} = \beta 0 + \beta 1 l\_Trade_{it} + \beta 2 l\_R\&D_{it} + u_{it} \text{ (\textbf{Model 8})}$$

$\beta 2$ is negative and statistically signifficant at a 1% significance level for developed as well as developing countries. This implies that countries that are more intensive in R&D investment also have a lower GINI coefficient and therefore lower income inequality.

Lastly, **Model 9** introduces another independent variable, "*l_GDPpc*". $\beta 3$ represents the average ceteris paribus percentage variation in the GINI coefficient when increasing the GDP per capita one percentage point.

$$l\_GINI_{it} = \beta 0 + \beta 1 l\_Trade_{it} + \beta 2 l\_R\&D_{it} + \beta 3 l\_GDPpc_{it} + u_{it} \text{ (\textbf{Model 9})}$$

As expected, β3 is positive and statistically significant at a 1% significance level for both, developed and developing countries. Moreover, the results for the rest of variables have almost kept unchanged.

In a nutshell, results show that trade openness reduces income inequality both, within developing as well as developed countries. This result contradicts the H-O theory for developed countries, since according to it trade increases the returns of the relatively abundant factor (skilled workers) and therefore increase wage inequality between skilled and unskilled workers. Moreover, research shows that trade openness facilitates technology diffusion, which tends to favour highly skilled labour (Berman et al., 1998). This result has important implications for achieving Sustainable Development Goals. Specifically, for some targets inside Goal 10 (reducing inequalities) such as to "progressively achieve and sustain income growth of the bottom 40% of the population at a rate higher than the national average" (United Nations, 2019). On top of that, opening for trade can bring the opportunities for developing countries to "improve their regulation and monitoring of financial markets and institutions and strengthen the implementation of such regulations" (United Nations, 2019). Furthermore, trade openness can contribute to "ensure enhanced voice for developing countries in decision-making in global international economic institutions". This last target is also related to Goal 2 (zero hunger) since being part of the global trade framework can provide developing economies with the necessary tools to eradicate hunger.

Moreover, results also show that increasing R&D intensity reduces income inequality within developed as well as developing countries. Therefore, results do not coincide with skill-biased technological change previously mentioned (Krugman et al., 2018) since it states that expenditure in R&D increases income inequality by increasing the demand of skilled workers.

Lastly, results conclude that the higher the GDP per capita, the higher income inequality both, in developed as well as developing countries.

6. CONCLUSION

Firstly, the main objectives of this research are to analyse the effect of international trade on (1) wage inequality as well as (2) income inequality in developed and developing economies. Indeed, trade is seen as an essential tool so as to achieve Sustainable Development Goals (SDG) and decrease poverty across countries (World Trade Organization , 2021). Income inequality decreased worldwide between 2004 and 2017. However, the highest reduction has taken place in developing countries (mainly Africa and Asia). In the same period, developing countries' share of global exports increased as well. The neoclassical Heckscher–Ohlin (H-O) model predicts that trade openness reduces real wage gaps between unskilled and skilled workers in developing countries, but it increases real wage gaps between unskilled and skilled workers in developed countries.

Regarding objective 1, a cross-sectional model has been created for year 2018 including 62 countries with different levels of development. Results show that a greater trade openness leads to a greater relative wage of skilled workers relative to unskilled, and therefore a higher wage inequality in developed and developing countries. According to literature, this can be explained by skill-biased technological change, although no variable regarding "technological change" has been included in the model. Moreover, R&D intensity, relative abundance of skilled workers relative to unskilled, as well as human capital of each country are positively correlated with the relative wage of skilled workers relative to unskilled, both in developed and developing countries.

Regarding objective 2, a panel-data model has been used including 66 countries for the period 2007-2018. Contrary to expected, results show that trade openness decreases income inequality both in developed as well as developing countries. Therefore, trade plays a key role in reducing income inequality within developed and developing countries. This finding has important implications for achieving Sustainable Development Goals, especially Goal 10 regarding the reduction of income inequality within and among countries. Moreover, investing in R&D also reduces income inequality in developed and developing countries. Furthermore, results also show that the higher the GDP per capita of a country, the higher income inequality in developed and developing countries.

All in all, the mixed findings regarding the implications of trade openness for wage inequality as well as income inequality suggest that this issue is more complicated than expected. Indeed, wage and income inequality depend on many other country factors. For future research, it would be interesting to include variables related to technological change in the analysis so as to examine the effect of technological change on wage and income inequality in countries with different levels of development. Moreover, analysing the effect of trade openness on income inequality not merely within developed and developing countries, but also among them, would bring some light on whether trade contributes positively to reduce the income inequality among countries with different levels of development and help developing countries in the catch-up process. Moreover, more insights would be gained regarding the effect of trade openness on income inequality by comparing the GINI coefficient before and after taxes and transfers.

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APPENDIX

Appendix 1A. Variable description and source for cross-section analysis.

Variable	Description	Source
Relative wage	Average wage of skilled workers relative to unskilled workers	ILOSTAT
R&D intensity	The level of R&D expenditure as a percentage of GDP	UNESCO
Living standards	GDP per capita in USD	World Bank
Relative abundance	The number of skilled workers relative to unskilled workers	UNESCO
Trade openness	Sum of exports plus imports as a percentage to GDP	World Bank
Human capital	Harmonized Learning Outcomes grade (in points)	World Bank

***Source**: Own elaboration.*

Appendix 1B. Variable description and source for panel data analysis.

Variable	Description	Source
Income inequality	GINI coefficient	World Bank
R&D intensity	The level of R&D expenditure as a percentage of GDP	UNESCO
Living standards	GDP per capita in USD	World Bank
Trade openness	Sum of exports plus imports as a percentage to GDP	World Bank

***Source**: Own elaboration.*

Appendix 2A. Main statistics for variables in the cross-sectional analysis.

Variable		Mean	SD	Min	Max	n
Relative wage	All	2.822	1.005	1.419	5.441	62
	Developed	3.356	0.761	1.699	5.244	26
	Developing	2.547	0.959	1.419	5.441	36
Relative abundance	All	2.9406	2.0029	0.346	7.564	62
	Developed	3.801	2.190	0.637	7.564	26
	Developing	2.5761	1.6645	0.346	7.546	36
l_GDPpc	All	9.3561	1.2843	6.280	11.672	62
	Developed	10.464	0.6325	9.122	11.672	26
	Developing	8.7172	1.0181	6.280	10-647	36
l_R&D	All	4.141	1.2472	1.133	6.208	62
	Developed	5.0736	0.5181	4.047	5.816	26
	Developing	3.688	1.133	1.133	6.208	36
l_Trade	All	4.491	0.450	3.363	5.887	62
	Developed	4.750	0.490	3.924	5.887	26
	Developing	4.326	0.4938	3.363	5.594	36
HLO	All	459.71	90.452	229.34	566.60	62
	Developed	531.25	26.254	452.01	566.60	26
	Developing	413.16	86.361	229.34	555.60	36

***Source**: Own elaboration based on results from Gretl.*

Appendix 2B. Main statistics for variables in the panel data analysis.

Variable		Mean	Standard deviation	Min	Max	n
l_GINI	All	3.564	0.213	3.144	4.106	868
	Developed	3.790	0.453	3.205	4.106	420
	Developing	3.588	0.223	3.144	4.015	448
l_Trade	All	4.412	0.520	3.096	5.940	868
	Developed	4.546	0.516	3.211	5.886	420
	Developing	3.391	0.569	3.096	5.940	448
l_R&D	All	4.459	0.945	1.223	6.203	868
	Developed	4.848	0.676	2.580	5.923	420
	Developing	4.059	0.947	1.223	6.203	448
l_GDPpc	All	9.693	1.026	6.581	11.725	868
	Developed	10.148	0.851	7.661	11.725	420
	Developing	9.261	0.964	6.581	11.225	448

***Source**: Own elaboration based on results from Gretl.*

Appendix 3A. P-values for residual normality and heteroskedasticity tests in the cross-section models.

Test	All countries	Developed countries	Developing countries
Model 1			
Jarque-Bera Test	0.359	0.250	0.378
White's Test	0.091	0.001	0.834
Model 2			
Jarque-Bera Test	0.577	0.336	0.369
White's Test	0.190	0.015	0.860
Model 3			
Jarque-Bera Test	0.791	0.775	0.698
White's Test	0.555	0.323	0.006
Model 4			
Jarque-Bera Test	0.422	0.637	0.423
White's Test	0.556	0.018	0.773
Model 5			
Jarque-Bera Test	0.470	0.628	0.946
White's Test	0.409	0.116	0.523
Model 6			
Jarque-Bera Test	0.445	0.654	0.424
White's Test	0.670	0.191	0.827

***Source**: Own elaboration based on results from Gretl.*

Appendix 3B. P-values for residual normality, heteroskedasticity tests and Durbin-Watson Test in the panel data models.

Test	All countries	Developed countries	Developing countries
Model 7			
Jarque-Bera Test	0.185	0.195	0.113
White's Test	0.001	0.283	0.030
Durbin-Watson Test	2.276	1.995	2.178
Model 8			
Jarque-Bera Test	0.228	0.163	0.126
White's Test	2.231e-30	0.000	0.029
Durbin-Watson Test	2.230	1.779	2.187
Model 9			
Jarque-Bera Test	0.751	0.650	0.064
White's Test	2.212e-38	0.017	0.028
Durbin-Watson Test	2.226	2.100	2.201

***Source**: Own elaboration based on results from Gretl.*

Appendix 4A. Correlation matrix for variables in the cross-sectional analysis.

Variable	Relative abundance	l_GDPpc	l_R&D	l_Trade	HLO
Relative abundance	**1**	**0.612**	0.347	0.016	0.208
l_GDPpc		**1**	**0.660**	0.144	**0.692**
l_R&D			**1**	0.295	**0.637**
l_Trade				**1**	0.131
HLO					**1**

***Source**: Own elaboration based on results from Gretl.*

Appendix 4B. Correlation matrix for variables in the panel data analysis.

Variable	l_GINI	l_GDPpc	l_R&D	l_Trade
l_GINI	**1**	-0.220	-0.326	-0.529
l_GDPpc		**1**	**0.746**	0.175
l_R&D			**1**	0.030
l_Trade				**1**

***Source**: Own elaboration based on results from Gretl.*