



# **Analysing Globalisation and Different Measures of Income Inequality: An ARDL Approach with Evidence for the OECD Countries**

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Dissertação para obtenção do Grau de Mestre em  
**Economia**  
(2º ciclo de estudos)

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**junho de 2020**



# **Acknowledgements**

I would like to thank the following people, without whom I would not have been able to complete this dissertation. My supervisor Prof. Dr. José Alberto Fuinhas, whose knowledge and guidance into the subject matter drove me through this research. My friend Tiago for his consistent support and motivation. My parents, who set me off on the road to this master's degree a long time ago. My brother for the unconditional love and support during the compilation of this dissertation. And finally, a special thanks to my partner, Polina, which the support, encouragement and patience allowed me to conclude this chapter of my life.



# Resumo

A desigualdade é um conceito complexo que está associado a um menor crescimento económico. O coeficiente de Gini tem sido extensivamente aplicado como uma medida padrão da desigualdade de rendimentos. Portanto, é necessário avaliar a adequação de medidas alternativas. Este estudo aplica o rácio 20/20 e o rácio Palma como alternativas ao coeficiente de Gini. A variável da abertura do mercado é estimada como proxy de globalização. O presente estudo aplica as emissões de CO<sub>2</sub>, índice de preços ao consumidor e variáveis de educação como variáveis de controlo. Um painel de dados de 28 países da Organização para a Cooperação e Desenvolvimento Económico foi analisado usando dados anuais para o período de 1993 a 2014. Três modelos foram estimados e a abordagem ARDL foi usada para capturar os efeitos de curto e longo prazo. O estimador Driscoll-Kraay foi utilizado para obter resultados robustos devido à presença do fenómeno de heterocedasticidade, correlação contemporânea, autocorrelação de primeira ordem e dependência transversal. Os resultados sugerem que a globalização aumentou a desigualdade de rendimentos, enquanto as emissões de CO<sub>2</sub> e o índice de preços ao consumidor causaram um impacto negativo na desigualdade de rendimentos, ou seja, promovem a igualdade de rendimentos. Esta evidência deve ser considerada na definição de estratégias de desigualdade, especificamente tornando a globalização compatível com a mitigação da desigualdade de rendimentos.

## Palavras-chave

Desigualdade de Rendimentos; Globalização; Rácio 20/20; Rácio Palma; ARDL



# Resumo Alargado

O aumento da desigualdade de rendimentos é um dos desafios do nosso tempo, que, caso não seja abordado adequadamente, pode levar ao aparecimento de catástrofes políticas e sociais. Apesar do modo como a desigualdade de rendimentos é medida seja uma consideração relevante para a criação de políticas a favor do crescimento económico de um país, ainda não há consenso na sua medição. O coeficiente de Gini, que varia entre 0 e 1, sendo zero a igualdade perfeita e um a desigualdade máxima, tem sido extensivamente aplicado como uma medida padrão de desigualdade de rendimentos. Portanto, é necessário avaliar a adequação de medidas alternativas. Este estudo aplica como alternativas ao coeficiente de Gini, o rácio 20/20, que compara a riqueza dos 20% da população mais rica com a riqueza dos 20% mais pobres, e o rácio Palma, que compara a riqueza dos 10% mais ricos com a dos 40% mais pobres. O aumento da globalização nas últimas décadas tem vindo a ser associado ao aumento das desigualdades de rendimento. É necessário então estudar e analisar a relação entre desigualdade de rendimentos e globalização com o objetivo de se criar medidas de política económica para contrariar os seus efeitos indesejados. Semelhante à desigualdade de rendimentos, também não existe consenso no modo de medir a globalização. Neste caso, a globalização pode ser definida em características sociais, económicas e políticas. Este estudo foca-se na característica económica e estima a variável da abertura do mercado como proxy da globalização.

Este trabalho tem como objectivo contribuir para a literatura atual, medindo o grau de impacto da globalização na desigualdade de rendimentos no curto e no longo prazo para os países membros da Organização para a Cooperação e Desenvolvimento Económico. Adicionalmente, é também feito o estudo do impacto de outros indicadores na desigualdade de rendimentos no curto e no longo prazo.

Para a elaboração do estudo, foi analisado um painel de dados de 28 países pertencentes à OCDE, usando dados anuais para o período de 1993 a 2014. Como proxy da desigualdade de rendimentos, foi criado um modelo explicativo para cada uma das medidas de desigualdade analisadas, coeficiente de Gini, rácio 20/20 e rácio Palma. Como variáveis dependentes foram utilizadas, as emissões de dióxido de carbono em per capita com o propósito de estudar o impacto das alterações climáticas na desigualdade de rendimentos; o índice de preços ao consumidor que reflete as tendências de inflação; a matrícula escolar secundária como proxy da educação e representa a população total matriculada no ensino médio. O conjunto de dados foi então submetido a uma bateria de

testes para analisar as suas propriedades e garantir que o estimador mais adequado é utilizado. Devido à presença do fenómeno de heterocedasticidade, correlação contemporânea, autocorrelação de primeira ordem e dependência transversal, o estimador Driscoll-Kraay foi utilizado para obter resultados robustos. A abordagem ARDL, ao suportar variáveis estacionárias em nível e também nas suas primeiras diferenças, foi usada para capturar os feitos de curto e longo prazo. Os resultados desta investigação revelam grande consistência com a literatura e a teoria económica ao sugerir que o aumento da globalização aumenta a desigualdade de rendimentos, enquanto o aumento das emissões de CO<sub>2</sub> e de o índice de preços ao consumidor, causa um impacto negativo na desigualdade de rendimentos, ou seja, promovem a igualdade de rendimentos. As principais conclusões do estudo sugerem então implicações políticas importantes para reduzir a desigualdade de rendimentos. Relativamente à globalização, os resultados sugerem que deve ser considerado a implementação de sistemas redistributivos como, por exemplo, o programa Transferências Condicionais de Rendimentos. Como o aumento do índice de preços ao consumidor causa uma diminuição da desigualdade de rendimentos, os países membros da OCDE, através dos bancos centrais, devem continuar a manter o controlo dos níveis de inflação. No que diz respeito às alterações climáticas, as medidas a ser implementadas devem considerar o trade-off entre desigualdade de rendimentos e as emissões de CO<sub>2</sub>. Um exemplo de uma medida que possa ser implementada e poderia resolver este trade-off, é um imposto de carbono redistributivo, neutro em receitas. Este imposto iria incentivar a redução de emissões de dióxido de carbono, e simultaneamente, redistribuir as receitas para o melhoria dos serviços públicos usados por famílias pertencentes à classe baixa de rendimentos.



# **Abstract**

Inequality is a complex concept that is associated with lower economic growth. The Gini coefficient has been extensively applied as a standard measure of income inequality. Therefore, there is a need to assess the appropriateness of alternative measures. This study applies the 20/20 ratio and Palma ratio as alternatives to the Gini Coefficient. The trade openness variable as a globalisation proxy is assessed. The present study applies CO<sub>2</sub> emissions, consumer price index and education variables as control variables. A panel data of 28 countries from the Organization for Economic Co-operation and Development was analysed using annual data for the period from 1993 to 2014. Three models were estimated, and the ARDL approach was used to capture the short- and long-run effects. The Driscoll-Kraay estimator was used to attain robust results, given the presence of the phenomena of heteroscedasticity, contemporaneous correlation, first-order autocorrelation and cross-sectional dependence. Results suggest that globalisation has increased income inequality, while CO<sub>2</sub> emissions and consumer price index have impacted income inequality negatively, i.e., promote income equality. This finding should be incorporated into the definition of inequality strategies, specifically by making globalisation compatible with income inequality mitigation

# **Keywords**

Income Inequality; Globalisation; 20/20 Ratio; Palma Ratio; ARDL



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# Acronymous List

CO <sub>2</sub>	Carbon Dioxide Emissions
ARDL	Autoregressive Distributed Lag
OECD	Organisation for Economic Co-operation and Development
EHII	Estimated Household Income Inequality
GMM	Generalised Method of Moment
FDI	Foreign Direct Investment
EU	European Union
SWWID	Standardised World Income Inequality Database
WID	World Inequality Database
GDP	Gross Domestic Product
VIF	Variance Inflation Factor
CIPS	Cross-Section Im-Pesaran-Shin
CADF	Cross-sectionally Augmented Dickey-Fuller
MG	Mean Group
PMG	Pooled Mean Group
RE	Random Effect
FE	Fixed Effect
PCS	Panel-Corrected Standard Errors
OLS	Ordinary Least Squares
ECM	Error Correction Mechanism



# 1. Introduction

Rising income inequality is a widespread concern and the defining challenge of our time, when, not properly addressed, it leads to the appearance of political and social catastrophes. Due to the increase of globalisation in the last 30 years, there is a need to study and analyse the inequality-globalisation relationship.

According to Bourguignon & Morrisson (2002), inequality strongly intensified during Industrial Revolution and rise of the West (Figure 1), i.e., that not only inequality between individuals is much higher today than 200 years ago, but inequalities' composition has also been totally reversed from being predominantly driven by within-national inequalities, to be determined by the differences in mean country incomes (Milanovic, 2011).

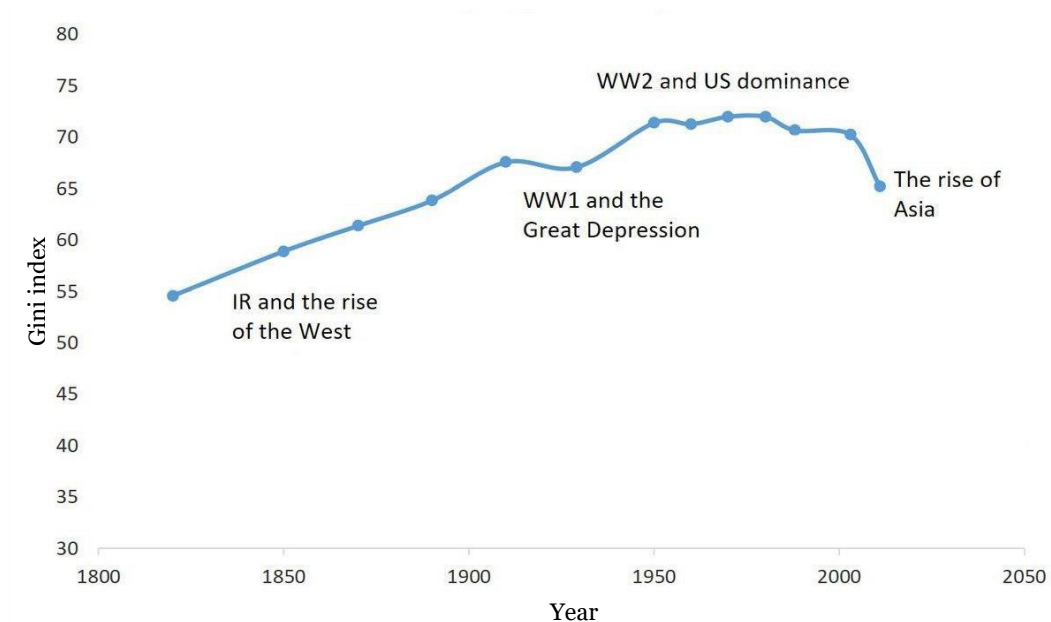


Figure 1. Inequality during the Industrial Revolution and the rise of the West  
(Source: Lakner and Milanovic (2013))

The increase in global mean income combined with the increase in global inequality, made the global inequality extraction ratio, the ratio between actual Gini and maximum feasible Gini which can be interpreted as the share of maximum inequality extracted by the elite (Milanovic et al., 2011), be broadly stable in the last century. This means that during the last 100 years, World War Two and United States dominance, global inequality has increased on the same rate as the maximum feasible inequality, stagnating the global inequality extraction ratio around 70% (Milanovic, 2011). Moreover, more recently, during the rise of Asia, decline moderately.

The measure of inequality is a relevant consideration in which there is still no consensus, and it can be divided into global and partial measures. Global measures include Atkinson index, Generalised Entropy Indices or the Gini coefficient. In contrast, the Palma ratio, the share of the bottom 40% or 20/20 ratio can be designated as partial measures for not accounting full distribution. This research will focus on the standard measure of inequality such as Gini Coefficient, where its range is between 0 and 1, perfect equality and maximum inequality, respectively. Along with the two most used ratios, 20/20 and Palma. While the 20/20 ratio compares the wealth of the 20% wealthiest with the wealth of the 20% poorest individuals, the Palma ratio compares the wealth of the top 10% with the bottom 40%.

As noted above, there was a generalised increase in the world's globalisation levels in the last three decades. Similar to measuring inequality, there still is a lack of consensus in the measure of globalisation. Considering multidimensional globalisation characteristics, several studies (Keohane & Nye, 2000; Fuinhas & Marques, 2017) accept economic, political and social as the main dimensions to study globalisation. However, the economic characteristic of globalisation is the most extensively applied. As economic characteristics, measuring globalisation includes trade openness, foreign direct investment, financial flows and migration across national borders. As most studies that focus on economic characteristics to determine globalisation, this research will apply trade openness as a proxy of globalisation. Considering trade openness as a measure of globalisation is an advantage in the study of the relationship between globalisation and income inequality. Although trade openness has been associated with economic growth, in the income inequality spectrum, trade's impact it still is controversial. As several studies (Marjit & Acharyya, 2003; Chiquiar, 2008) predict that the wage gap between skilled and unskilled labour should be decreased due to trade openness, proceeding to a decrease in inequality. On the other side of the spectrum, disparities in returns to education and skills may arise an increase of income inequality.

This paper aims to study globalisation and different measures of inequality for the countries of Organisation for Economic Co-operation and Development (OECD). The relevance of this study is high since these countries share common goals such as promoting economic growth, prosperity and sustainable development. Also, seeing if the implemented strategies are leading the countries members of OECD to the decrease of inequality reveals further importance of this paper. Additionally, this research aims to check the impact of climate change, education and inflation on income inequality. A panel ARDL model will be applied to perform the analysis. This method allows for a different integration order of variables, such as  $I(0)$  and  $I(1)$  and it is able to provide estimations of the inequality drivers for the short and long run, simultaneously.

The main objective of this study is to contribute to the existent literature by estimating the degree of globalisation impact on income inequality in the short and long run for the countries members of the OECD. A secondary objective was added, to estimate the magnitude of other inequality drivers in the short and long run, also for OECD countries.

This study is organised as follows. Section 2 presents the literature review, which analyses the main existing investigations on this subject. Section 3 presents the data and methodology, where the variables and models to be estimated are presented. The results of this study are presented in section 4 and discussed in section 5. Finally, section 6 presents the main conclusions of the study and proposals for future research.

## 2. Literature Review

In this chapter will be presented the literature review on income inequality and globalisation concepts, along with the analysis of their relationship and economic growth.

There is a plentiful amount of literature on the inequality-growth relationship. While some economists defend the perspective that inequality negatively affects growth and its sustainability (Ostry et al., 2014; Berg; Ostry, 2011), others show that income inequality positively affects growth (Frank, 2009; Partridge, 1997, 2005). However, the inequality-growth nexus is not linear, and some defend that an increase of inequality accelerates growth in high-income countries but slows growth in low-income ones (Lin et al. 2009; Barro, 2000). A few reasons for the existence of nonlinearities in the inequality-growth relationship are the development stage of the countries (Khalifa & El Hag, 2010), income levels (Lin et al., 2006) and the level of poverty within the country (Breuning & Majeed, 2020).

Measuring income inequality has been changing over time. However, the most widely used measure of income inequality is the Gini Index (equation 1), a global measure, in which it is based on the Lorenz Curve. Where the Gini Coefficient has a variance between 0 and 1, equality and complete inequality, respectively.

$$Gini = \frac{\sum_{i=1}^n \sum_{j=1}^n |y_i - y_j|}{2n^2 \bar{y}} \quad (1)$$

In the equation,  $\bar{y}$  denotes the arithmetic mean,  $y$  is the income of person  $i$  and there are  $n$  persons. The reason for the extensive use of the Gini coefficient is that it satisfies a set of principles that income inequality measures need to follow to be considered reliable (Charles-Coll, 2011). Thus, Gini coefficient satisfies the transfer principle (Pigou, 1920; Dalton, 1920) where a transfer from a poor individual to a richer one should translate into an increase in the measure of inequality, the scale independence where it needs to be invariant to an equi-proportional change of the original income; the anonymity principle which is independent of any non-income characteristic of individuals and the population independence where is not influenced by the size of the population. However, the main disadvantage of the Gini measure is that the value can be the same for different sets of distributions, which entangles the analyses and the structure comparison of the income distribution in the different population quantiles (Charles-Coll, 2011). Other income inequality measures that even though do not account for full distribution, have been increasing in inequality studies are the partial measures namely, the Palma Ratio and 20/20

Ratio. Supporting this last statement, according to Cobham & Sumner (2013), between Palma Ratio and Gini Coefficient, Palma is a more useful measure of inequality for policymakers and citizens to track.

$$Palma\ Ratio = \frac{\bar{A}_{i_{top10}}}{\bar{A}_{i_{bottom40}}} \quad (2)$$

While the Palma Ratio (equation 2) compares the share of the wealth ( $\bar{A}$ ) of the top 10% with the share of the wealth of the bottom 40% (Palma, 2006; Palma, 2011), the 20/20 Ratio (equation 3) focuses on the comparison of the wealth of the 20% wealthiest individuals ( $i$ ) with the wealth of the 20% poorest individuals of the population. Meanwhile, for a detailed comparison between these income inequality measures, we can follow the work of Pascoal & Rocha, (2018).

$$20/20\ Ratio = \frac{\bar{A}_{i_{top20}}}{\bar{A}_{i_{bottom20}}} \quad (3)$$

Although literature focusing inequality has been extensively analysed on different branches, there is no consensus on its outcomes and determinants. Indeed, regarding the financial branch, there are studies where high levels of financial development, financial liberalisation and the occurrence of a banking crisis, increase income inequality in a country (de Haan & Sturm, 2017), contradicting the work seen in Bumann and Lensink (2016). Although the focus of our study is the globalisation-inequality nexus, we will also study other indicators that are often discussed in the literature. Following the Kuznets Curve hypothesis (Kuznets, 1995) that postulates an inverted U-shaped relation between per capita income and inequality and given the urgency of the climate change challenge, several studies focused on the impact of income inequality on CO<sub>2</sub> emissions (Hubler, 2017; Liu et al., 2019). However, according to Ravallion et al. (2000) there is a need to address to a trade-off between them. In the manner that inequality-growth relationship may present nonlinearities due to income levels (Lin et al., 2006), the tradeoff between inequality and carbon emissions also depends on income levels (Grunewald et al., 2017); low and middle-income economies, higher income inequality is associated with lower carbon emissions while in upper-middle-income and high-income economies, higher income inequality increases per capita emissions (Grunewald et al., 2017).

According to Goldin & Katz (2007), human capital is an important determinant of income inequality because of higher returns to education. As education determines access to jobs,

pay levels and takes part as a key role as an indication of ability and productivity in the job market, education plays an important role in income inequality. Education literature suggests that the effect on income inequality could be positive or negative, depending on the evolution of rates of return to education, that is, the skill premium (Dabla-Norris et al., 2015). Interestingly, in advanced economies, higher skill premium is associated with widening inequality while in economically more developed countries, skill premium is statistically insignificant (Dabla-Norris et al., 2015).

Similarly, to socio-economic characteristics as education, fiscal and monetary policies, e.g., inflation and consumer price index, are also important determinants of income inequality. As low-income households are generally more vulnerable to increases in the price level as they have a higher portion of cash in total purchases (Albanesi, 2007) relative to other financial assets than high-income households (Erosa & Ventura, 2002). To support the importance of inflation, Easterly and Fischer (2001) present indirect evidence of the distributional consequences of inflation, demonstrating that low-income households are more likely to mention inflation as a top concern.

Turning to the other subject of analysis and the main focus of our study, the globalisation-inequality relationship, we can start by stating that as a progressively globalised world, there has been an exceptional increase in the globalisation research, helping policymakers in the development of growth-promoting policies.

When discussing the way globalisation affects growth, it is important to distinguish between theoretically and empirically. According to Grossman & Helpman (2015), theoretical literature identifies several different possible relations between globalisation and growth. Meanwhile, empirically, even though literature points its positive effect on growth (Fuinhas & Marques, 2017; Gurgul & Lach, 2014), there still is a lack of consensus in this globalisation-growth nexus. The main reason for this, it is defining and measuring globalisation, formulating that globalisation has a multidimensional characteristic (Dreher, 2006). Supporting the challenge of measuring globalisation, in previous studies, trade openness (Frankel & Romer, 1999) and foreign direct investment (Dollar & Kraay, 2001) are used as proxies. Nowadays, accounting the multidimensional globalisation characteristic and accepting economic, political and social as the main dimensions, researchers use as a proxy of globalisation, the Konjunkturforschungsstelle (KOF) Index of Globalisation (Fuinhas & Marques, 2017).

The studies focused on globalisation-inequality relationship, usually use as a proxy the economic characteristics, namely, the trade openness and foreign direct investment, in

which, Kraay (2006) found a strong positive link between trade openness and inequality. According to Asteriou et al. (2014), the financial crisis led to a rise in inequality and the policies to mitigate inequality should be in regards to foreign direct investment.

Focusing on trade, it has been an engine for growth in many countries by promoting competitiveness and enhancing efficiency. Standard trade theory, as Stolper-Samuelson theorem, predicts that trade openness, through tariff reduction, should reduce the wage gap between skilled and unskilled labour in developing countries, resulting in a reduction of income inequality (Asteriou et al., 2014). Meanwhile, on advanced economies, due to disparities in returns to education and skills, trade may aggravate income inequality (Stiglitz, 1998). Other studies also state that income inequality increases with an increase in trade openness (Kanbur, 2015) and the disequalising effects of trade openness decrease as a country grows (Hamori & Hashiguchi, 2012).

Nowadays, still inside the income inequality spectrum, it is already possible to determine who had the largest and smallest gains of globalisation when analysing the changes in real incomes (Lakner and Milanovic, 2013). Figure 2 shows the change in real income between 1988 and 2008 at various percentiles of the global income distribution. One can state that in the past two decades of globalisation, the parts of global income distribution registered the largest gains are the very top of the global income distribution and among the middle classes of emerging market economies.

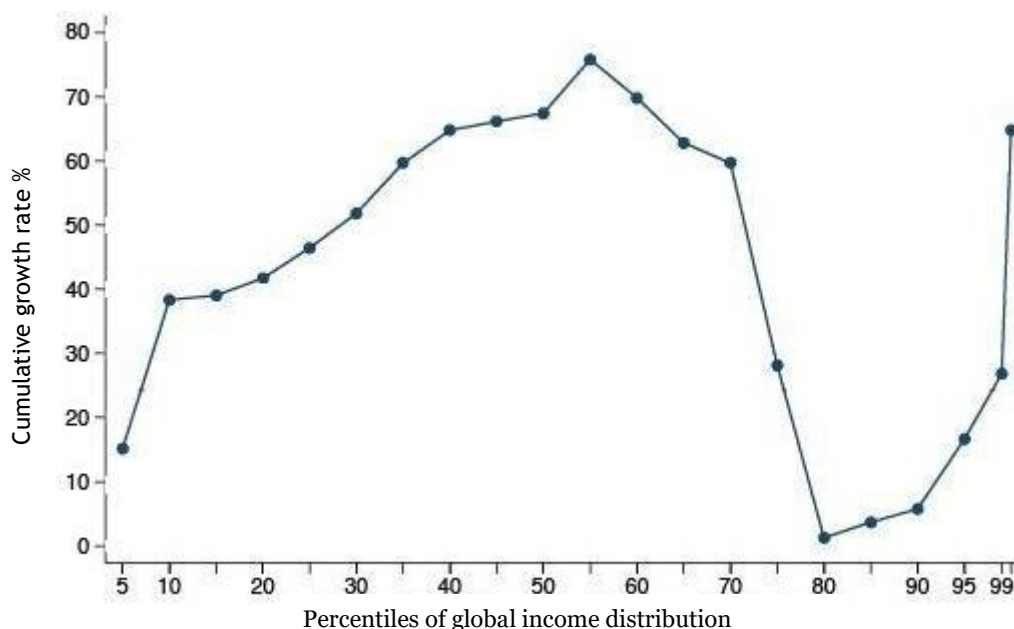


Figure 2. Percentiles of the global income distribution  
(Source: Lakner and Milanovic (2013))

As Figure 2 demonstrates, over those two decades, the top 1% has seen its real income strongly intensify by more than 60%. However, the biggest increase was registered around the 50th and 60th percentile, reaching an 80% real income increase. On the other side, other than the poorest 5%, the ones that registered the smallest gains, are between the 75th and 90th percentiles of the global income distribution, in which the real income gains were none. Following Milanovic (2013), global income distribution has thus changed remarkably and was probably the most profound global reshuffle of people's economic positions.

Even though we are covering some characteristics in the existing ample literature on the relationships inequality-growth and globalisation-growth, as we stated previously, the focus of our study is the globalisation-inequality nexus. When analysing each relationship empirically, we reckon that, in inequality-growth, utmost studies have as a focal point, the financial branch, more specifically, financial development and financial liberalisation. For instance, Furceri and Loungani (2015) demonstrated that financial liberalisation increases inequality with fixed effects method on 149 countries from 1970 to 2010. Jauch and Watzka (2015) demonstrated that more financial development leads to more inequality when controlling for country and time fixed effects, with an unbalanced dataset of up to 138 developed and developing countries over the years from 1960 to 2008. Additionally, using random effects and cross-country regressions for a sample of 121 countries covering 1975-2005, de Hann & Sturm (2017) shows that all finance variables increase income inequality.

Regarding the globalisation-growth relationship, the use of panel data techniques is also becoming more usual on empirical studies, since it has a vast number of advantages over the cross-sectional, and time-series analysis (Hsiao, 2007). Moreover, some studies are handling globalisation as an endogenous variable, strongly increasing the use of dynamic estimators. For example, as per the work of Hamori & Hashiguchi (2012) that studies the effect of financial deepening on inequality. Through a panel data set of 126 countries for the period 1963-2002 and using estimated household income inequality (EHII) data as an inequality measure, demonstrated that inequality increases with an increase in trade openness. The researchers performed a Hausman test in order to choose a fixed-effect model over a random-effect model (Hausman, 1978). Also, a regression with white cross-section robust standard errors was executed to consider heteroskedasticity in the error terms. In order to deal with the endogeneity problem, they estimated each model using the panel dynamic generalised method of moment (GMM) estimators developed by Arellano and Bond (1991), resulting in the same findings previously achieved. Supporting the use of dynamic estimators, we can also follow the work of Asteriou et al. (2014), for the period from 1995 to 2009 and the set of 27 European Union countries. A panel regression was estimated in order to explain income inequality measured by the log of the Gini coefficient

as a function of globalisation measures, trade openness and foreign direct investment. For reasons of robustness, but also in order to consider any dynamic effect and endogeneity problems, the estimation was repeated with the use of the GMM method. Although the results display a reduction in inequality from trade openness in the EU-27, the highest contribution to the average change of inequality comes from FDI. Results are consistent with the fixed effects estimator, suggesting that the results are robust.

Although there is a vast literature that analyses the inequality-growth, globalisation-growth and globalisation-inequality relationships, there is still no consensus, and the discussion about the results remains ambiguous. The econometric techniques, the timespan and sample that researchers choose, may be the main reasons for the diversity seen in the results. Additionally, the globalisation dimensions included in their estimations may also be one reason for the lack of consensus in this matter.

### 3. Data and Methodology

The following chapter is divided in two sections. The first will identify and describe the variables used, along with the sample and timespan. The second section will describe the methodology and reveal the models used.

#### 3.1. Description of the data

For this study, it was used a panel dataset with annual frequency for the period from 1993 to 2014 for twenty-eight (28) countries belonging to the Organisation for Economic Co-operation and Development (OECD). The selected countries are the followings: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom and the United States. Based on data availability criteria, the remaining OECD member countries were excluded. As members of OECD, the countries share the common goal of fostering economic development and co-operation, contributing to the expansion of world trade and promoting economic stability.

Three different variables are used as proxies of income inequality to reach the purpose of analysing globalisation and different measures of income inequality:

- *GC*: Gini index of disposable income from the Standardised World Income Inequality Database (SWIID). As a standard measure of income inequality, the Gini Coefficient has been extensively applied in the inequality literature, for example, in the work of Santiago et al. (2019). For more information in regards the SWIID, we can follow Solt (2016).
- *PR*: Palma ratio has been increasing in inequality studies (Cobham & Sumner 2013). The source of this variable is the World Inequality Database (WID) and consists in dividing the share of income, in constant local and base 2008, from the top 10% (p90-p100) per the bottom 40% (p0-p40).
- *TTR*: 20/20 ratio as an alternative to the Palma Ratio. The source is also the World Inequality Database (WID) and consists in dividing the share of income, in constant local and base 2008, from the top 20% (p80-p100) per the bottom 20% (p0-p20). Follow Pascoal & Rocha (2018) for a detailed comparison between these measures.

Accounting the economic characteristics, in order to analyse globalisation, the following variable is used as a proxy:

- *T*: Trade openness as a percentage (%) of GDP is the sum of exports and imports of goods and services measured as a share of gross domestic product. This variable was extracted from the World Bank and is one of the most common measures of globalisation, seen in plentiful literature as per example, Asteriou et al. (2014).

The source of the control variables was the World Development Indicators (WDI) published by the World Bank, namely:

- *CO2*: Carbon dioxide emissions, per capita, covers emissions from fossil fuel, natural gas and cement manufacturing. Due to the climate change challenge, CO2 emissions per capita has been used, in previous studies as Grunelwald et al. (2017), to research the relationship between income inequality and environmental degradation.
- *CPI*: Consumer price index, base 2010, reflects variations in the cost to the average consumer of acquiring goods and services that may be fixed or changed at specified intervals, such as yearly. This variable is generally calculated by the Laspeyres formula and is used mainly in the financial branch inside the inequality spectrum as in Kim et al. (2011).
- *EDUC*: School enrollment, secondary (% gross) represents the total population enrolled at the secondary school level, which completes the provision of basic education, offering additional subjects and skills, along with more specialised teachers. This variable is used as a proxy of education in the inequality literature as in Bumann & Lensink. (2016).

### 3.2. Methodology

A battery of tests was implemented in order to achieve the purpose of this research, using the econometric software Stata15. As such, to check the adequacy of the data for the use of panel data techniques, the Variance Inflation Factors (VIF) test was executed to verify the existence of linear relationships between the variables. As three different income inequality measures were used, Gini coefficient, Palma ratio and 20/20 ratio, the VIF test is performed for every one of them. The absence of multicollinearity is proved by low VIF statistic values, resulting in a similar mean VIFs of 1.20.

Considering that the sample is based on OECD countries, common shocks are expected, for instance, financial crisis and common policies. To investigate the presence of cross-sectional dependence in each variable, the CD-test developed by Pesaran (2004) was applied. Panel data are a sequence measure of individuals or countries ( $i$ ) over time ( $t$ ). A regression and tests are constructed on a dependent variable ( $y_{it}$ ) and a set of independent variables ( $X'_{it}$ ) for  $I= 1, \dots, N$  and  $t=1, \dots, T$ . The CD-test specification is represented in following Eq. (4)

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left( \sum_{i=1}^{N-1} \sum_{j=i+1}^N \rho_{ij} \right) \quad (4)$$

where  $\rho_{ij}$  is the autocorrelation coefficient. The CD-test is performed under the null of cross-sectional independence.

Considering the presence of cross-sectional dependence, a first-generation panel unit root test is no longer robust to assess the stationary properties of the variables. A second-generation unit root test was applied to verify the integration order of the variables. The Cross-Section Im-Pesaran-Shin (CIPS) test, proposed by Pesaran (2007), is based on a cross-sectionally augmented Dickey-Fuller (CADF) regression and allowed the presence of a single unobserved common factor under the null hypothesis of non-stationarity. Accordingly,  $H_0: b_i = 0$  for all  $i$ . The CADF regression is represented in following Eq. (5)

$$\Delta y_{it} = \alpha_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \varepsilon_{it} \quad (5)$$

where  $\Delta$  denotes the first difference operator,  $\bar{y}$  is the mean of  $y$  and  $\varepsilon$  denotes the error term.

In order to examine the absence of cointegration by determining whether there exists error correction for individual panel members ( $Gt$  and  $Ga$ ) or the panel as a whole ( $Pt$  and  $Pa$ ), the Westerlund test was applied. The second-generation cointegration test developed by Westerlund (2007) uses bootstrapping to obtain robust critical values. The statistics of  $Gt$ ,  $Ga$ ,  $Pt$  and  $Pa$ , are obtained by the Eq. (6), Eq. (7), Eq. (8) and Eq. (9), respectively.

$$Gt = \frac{1}{N} \sum_{i=1}^N \frac{\theta_i}{SE(\hat{\theta}_i)} \quad (6)$$

$$Ga = \frac{1}{N} \sum_{i=1}^N \frac{T\theta_i}{\theta'(1)} \quad (7)$$

$$Pt = \frac{\hat{\theta}_i}{SE(\hat{\theta}_i)} \quad (8)$$

$$Pa = T\hat{\theta} \quad (9)$$

In the equations,  $\theta$  denote error correction parameter, and SE stands for standard deviation. The null hypothesis for the Westerlund test is for all statistics  $H_0: \theta_i = 0$  for all  $i$ . Since the cointegration test determines how the variables are introduced into the model, if the presence of cointegration is observed, the variables are used at the level, if not, the first differences are applied.

In the interest of the study between the globalisation and income inequality relationship, it is beneficial to examine the dynamic effects separately in the short and long run. The Autoregressive Distributed Lag (ARDL) model allows examining the long and short-run impact of independent variables on the dependent ones. This estimator also allows for a different integration order of variables, as  $I(0)$  and  $I(1)$  but not  $I(2)$ . The heterogeneous estimators, such as Mean Group (MG) and Pooled Mean Group (PMG) were not tested or considered due to the reason that the sample is composed of OECD countries. A homogeneous panel should be considered. As stated previously, the Gini coefficient, Palma ratio and 20/20 ratio are used as inequality measures, acknowledging the dependent variables for equations (10), (11) and (12), respectively. The following equations represent the ARDL models, where the short and long-run dynamics can be observed:

$$\begin{aligned}
DLGC_{it} = & \alpha_i + \sum_{j=1}^k \beta_{1ij} DLGC_{it-j} + \sum_{j=0}^k \beta_{2ij} DLT_{it-j} + \sum_{j=0}^k \beta_{3ij} DLCO2_{it-j} \\
& + \sum_{j=0}^k \beta_{4ij} DLCPI_{it-j} + \sum_{j=0}^k \beta_{5ij} DLEDUC_{it-j} + \lambda_{1i} LGC_{it-1}
\end{aligned} \tag{10}$$

$$\begin{aligned}
& + \lambda_{2i} LT_{it-1} + \lambda_{3i} LCO2_{it-1} + \lambda_{4i} LCPI_{it-1} + \lambda_{5i} LEDUC_{it-1} + \varepsilon_{it} \\
DLPR_{it} = & \alpha_i + \sum_{j=1}^k \delta_{1ij} DLPR_{it-j} + \sum_{j=0}^k \delta_{2ij} DLT_{it-j} + \sum_{j=0}^k \delta_{3ij} DLCO2_{it-j} \\
& + \sum_{j=0}^k \delta_{4ij} DLCPI_{it-j} + \sum_{j=0}^k \delta_{5ij} DLEDUC_{it-j} + \omega_{1i} LPR_{it-1}
\end{aligned} \tag{11}$$

$$\begin{aligned}
& + \omega_{2i} LT_{it-1} + \omega_{3i} LCO2_{it-1} + \omega_{4i} LCPI_{it-1} + \omega_{5i} LEDUC_{it-1} + \mu_{it} \\
DLTTR_{it} = & \alpha_i + \sum_{j=1}^k \gamma_{1ij} DLTTR_{it-j} + \sum_{j=0}^k \gamma_{2ij} DLT_{it-j} + \sum_{j=0}^k \gamma_{3ij} DLCO2_{it-j} \\
& + \sum_{j=0}^k \gamma_{4ij} DLCPI_{it-j} + \sum_{j=0}^k \gamma_{5ij} DLEDUC_{it-j} + \theta_{1i} LTR_{it-1} \\
& + \theta_{2i} LT_{it-1} + \theta_{3i} LCO2_{it-1} + \theta_{4i} LCPI_{it-1} + \theta_{5i} LEDUC_{it-1} + e_{it}
\end{aligned} \tag{12}$$

In the equations, the prefixes “L” and “D” denote natural logarithm and first difference, respectively. The subscripts t, i and j denote the time period, country and lag length, respectively.  $\alpha$  denotes the intercept,  $\beta$ ,  $\delta$ ,  $\gamma$  denote the estimated parameters for the short-run,  $\lambda$ ,  $\omega$ ,  $\theta$  denote the estimated parameters for the long-run and finally,  $\varepsilon$ ,  $\mu$ ,  $e$  denote the error term for equations (10), (11) and (12), respectively.

Proceeding with the econometric method, the Random Effect (RE) and Fixed Effect (FE) models were estimated and are represented in the following Eq. (13) and Eq. (14), respectively.

$$y_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} + \dots + \beta_k X_{kit} + (v_i - \varepsilon_{it}) \tag{13}$$

$$y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \dots + \beta_k X_{kit} + \varepsilon_{it} \tag{14}$$

where y represents the dependent variable, X is a set of independent variables,  $\alpha$  is the constant,  $\beta$  is the slope and  $v_i$  is a zero mean standard random variable. In order to assess the most appropriate estimator between the random effects model and the fixed effect models, the Hausman test was performed and is represented in the following Eq. (15)

$$Hausman = (\beta_{1,RE} - \beta_{1,FE})' [cov(\beta_{1,RE} - \beta_{1,FE})]^{-1} (\beta_{1,RE} - \beta_{1,FE}) \quad (15)$$

where  $\beta_{1,RE}$  and  $\beta_{1,FE}$  denote the coefficients estimated from the Random Effect and Fixed Effect models, respectively, and cov represents the covariance matrix. The null hypothesis for the Hausman test is that the random effect model is the appropriate one.

Based on the results of the Hausman test, specification tests for, heteroskedasticity, the contemporaneous correlation among cross-sections and autocorrelation were computed to obtain the most suitable estimator. The specification tests are performed in the residuals of fixed effects regression. The modified Wald test was performed to check heteroscedasticity. This specification test is estimated following Eq. (16)

$$W = \sum_{i=1}^N \frac{(\hat{\sigma}_i^2 - \hat{\sigma}^2)^2}{V_i} \quad (16)$$

where the error variance was calculated as  $\hat{\sigma}_i^2 = T^{-1} \sum_{t=1}^T e_{it}^2$  and  $V_i = T_i^{-1} (T_i - 1)^{-1} \sum_{t=1}^T (e_{it}^2 - \hat{\sigma}_i^2)^2$ . The null hypothesis of the modified Wald test is homoskedasticity (or constant variance), as  $H_0: \sigma_i^2 = \sigma^2$ . In regards to the cross-sectional correlation, the CD-Pesaran test was again applied under the null hypothesis that residuals are not correlated. For the serial correlation, the Wooldridge (2002) test was applied under the null hypothesis of no serial correlation. To test the presence of the first-order autocorrelation in the panel, the Wooldridge test is represented in the following first-differentiated Eq. (17)

$$\Delta y_{it} = \Delta X'_{it} \beta_1 + \Delta \varepsilon_{it} \quad (17)$$

Considering the specification tests, the estimator Driscoll and Kraay (1998) was performed. This estimator is represented in the following Eq. (18)

$$y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \dots + \beta_k X_{kit} + \varepsilon_{it} \quad (18)$$

where, according to Hoechle (2007), standard errors estimate that the covariance matrix estimator is consistent, independently of the cross-sectional dimension N (i.e. also for  $N \rightarrow \infty$ ). The estimator Driscoll and Kraay is more suitable than other large T estimators such as

Parks-Kmenta or Panel-Corrected Standard Errors (PCSE). The reason for this is that the estimators become inappropriate when the cross-sectional dimension  $N$  is also large.

## 4. Results

Firstly, it is important to analyse the descriptive statistics of the variables. Additionally, considering that the sample is based on countries with similarities, Cross-Sectional Dependence is expected. In Table 1, it can be seen the descriptive statistics of the variables and the eventual presence of cross-sectional dependence, through the Pesaran CD-test.

**Table 1**  
Descriptive statistics and cross-sectional dependence.

Variables	Descriptive statistics					Cross-sectional dependence (CSD)		
	Obs.	Mean	Std. dev.	Min.	Max.	CD-test	corr	abs(corr)
<i>LPR</i>	616	1.9262	0.4127	1.1412	3.9400	16.81***	0.184	0.436
<i>LTTR</i>	616	1.9698	0.4688	1.0303	4.1256	13.31***	0.146	0.388
<i>LGC</i>	616	3.3713	0.1640	2.9957	3.8459	8.88***	0.097	0.549
<i>LT</i>	616	4.4145	0.5035	2.9979	5.9733	64.75***	0.727	0.735
<i>LEDUC</i>	616	4.6447	0.1438	4.0595	5.0894	14.47***	0.162	0.469
<i>LCO2</i>	616	2.0598	0.4334	0.9868	3.3011	30.65***	0.344	0.581
<i>LCPI</i>	616	4.3629	0.4858	-1.0908	4.9102	85.78***	0.963	0.963
<i>DLPR</i>	588	0.0083	0.0654	-0.7877	0.2392	5.95***	0.067	0.194
<i>DLTR</i>	588	0.0082	0.0809	-1.1021	0.3341	3.31***	0.037	0.175
<i>DLGC</i>	588	0.0031	0.0121	-0.0348	0.0637	2.22**	0.025	0.310
<i>DLT</i>	588	0.0232	0.0685	-0.3111	0.3281	47.90***	0.538	0.540
<i>DLEDUC</i>	588	0.0066	0.0377	-0.2826	0.3016	16.63***	0.187	0.269
<i>DLCO2</i>	588	-0.0088	0.0612	-0.2981	0.2275	21.09***	0.237	0.305
<i>DLCPI</i>	588	-0.0437	0.0805	-0.0458	0.7189	33.76***	0.379	0.419

Notes: The prefix 'L' stands for natural logarithmic and 'D' stands for the first difference. The CD-test has N (0,1) distribution, under H<sub>0</sub>: *cross-sectional independence*. \*\*\*, \*\*, \* significance at 1%, 5% and 10%, respectively.

By observing the results from Table 1, cross-sectional dependence was detected, which could be related to the dependency of countries sharing common shocks. Due to the presence of cross-sectional dependence, second-generation unit root tests were applied in order to verify the integration orders of the variables. The CIPS test was performed, and the results can be seen in Table 2.

**Table 2**  
Second generation unit root tests.

<b>2<sup>nd</sup> generation panel unit root test CIPS</b>		
Variables	Without trend	With trend
<i>LPR</i>	-4.566***	-3.938***
<i>LTTR</i>	-2.903***	-1.910**
<i>LGC</i>	-2.228**	-1.811**
<i>LT</i>	-1.848**	0.809
<i>LEDUC</i>	-0.555	0.407
<i>LCO2</i>	1.307	-0.166
<i>LCPI</i>	-8.332***	-1.016
<i>DLPR</i>	-16.195***	-13.915***
<i>DLTTR</i>	-15.815***	-13.482***
<i>DLGC</i>	-3.270***	-0.103
<i>DLT</i>	-5.964***	-3.570***
<i>DLEDUC</i>	-6.429***	-5.664***
<i>DLCO2</i>	-8.996***	-8.630***
<i>DLCPI</i>	-8.083***	-5.666***

Note: \*\*\*, \*\*, \* significance at 1%, 5% and 10%, respectively. H<sub>0</sub>: series is I (1).

Considering the null hypothesis for CIPS test is, series is I(1), by analysing the results, we can conclude that all variables are either I(1) or I(0). As the variables are not I(2), the posterior use of the ARDL model is shown to be appropriate. Due to the existence of cross-sectional dependence in the variables, the Westerlund test of cointegration was also computed for each model with constant. This test can only be performed with variables in the same order of cointegration I(1). Using bootstrapping to obtain robust critical values, the null hypothesis for this test is the non-existence of cointegration. The test results can be seen in Table 3.

**Table 3**  
Westerlund cointegration test.

Statistic	Value			Z-value			Robust P-value		
	<i>LPR</i>	<i>LTTR</i>	<i>LGC</i>	<i>LPR</i>	<i>LTTR</i>	<i>LGC</i>	<i>LPR</i>	<i>LTTR</i>	<i>LGC</i>
Gt	-1.837	-2.035	-0.815	-0.662	-1.685	4.618	0.071	0.020	0.884
Ga	-2.067	-2.620	-1.057	4.866	4.398	5.721	0.510	0.124	0.958
Pt	-6.339	-7.665	-4.509	0.480	-0.532	1.876	0.210	0.096	0.475
Pa	-1.636	-1.851	-0.865	2.207	2.027	2.853	0.304	0.235	0.681

Note: the bootstrapping regression with 800 reps was performed; Gt and Ga test the cointegration of each country individually, and PT and Pa test the cointegration of the panel as a whole; the null hypothesis of the Westerlund cointegration test is no cointegration.

By analysing the results, we can conclude that the null hypothesis was not rejected. This demonstrates the absence of cointegration between variables. In order to test the adequacy of RE against FE estimators, the Hausman test was performed. The Hausman test results, as well as specification tests, can be observed in Table 4.

**Table 4**  
Hausman and Specification tests.

Models	<i>DLPR</i>	<i>DLTTR</i>	<i>DLGC</i>
Hausman test	102.05***	114.43***	77.82***
Modified Wald test	4049.25***	1344.60***	1250.34***
Pesaran test	1.631	2.619***	0.288
Wooldridge test	57.746***	76.141***	64.222***

Note: \*\*\*, denote significance at 1%; The Hausman test tests null hypothesis as RE model is the preferred model; Modified Wald test, Pesaran test and Wooldridge test tests the null hypothesis of homoscedasticity, cross-sectional independence and no first-order autocorrelation, respectively.

The results confirm that the Fixed Effects model is the most suitable model for the three measures of income inequality. The specification tests results show the rejection of the null hypothesis for the modified Wald Test, demonstrating the presence of heteroscedasticity. The presence of contemporaneous correlation for the 20/20 ratio model and absence for Palma and Gini models. Finally, the results also show the rejection of the null hypothesis for the Wooldridge test, proving that the data has first-order autocorrelation.

Succeeding the specification test results, the Driscoll and Kraay estimator was applied for each model. The error structure for this estimator is assumed to be heteroskedastic, autocorrelated and cross-sectional dependent. The OLS model, RE model, FE model and FE model with robust standard errors were also estimated to control the heteroscedasticity. The results for the Palma, 20/20 and Gini models can be observed and compared in Table 5, Table 6 and Table 7, respectively.

**Table 5**  
Estimation Results for Palma model.

Dependent Variable <i>LPR</i>	OLS	RE	FE	FE_robust	FE D.K.
<i>DLT</i>	0.1874***	0.1874***	0.2242***	0.2242**	0.2242**
<i>DLEDUC</i>	-0.0005	-0.0005	-0.0117	-0.0117	-0.0117
<i>DLCO2</i>	-0.0222	-0.0222	-0.0383	-0.0383	-0.0383
<i>DLCPI</i>	-0.1419*	-0.1419*	-0.2787***	-0.2787**	-0.2787**
<i>LPR</i>	-0.0347***	-0.0347***	-0.2915***	-0.2915***	-0.2915***
<i>LT</i>	-0.0133**	-0.0133**	0.1275***	0.1275***	0.1275***
<i>LEDUC</i>	-0.0181	-0.0181	-0.0283	-0.0283	-0.0283
<i>LCO2</i>	0.0054	0.0054	-0.0425	-0.0425*	-0.0425*
<i>LCPI</i>	-0.0112	-0.0112	-0.0759***	-0.0759***	-0.0759***
Constant	0.2568**	0.2568**	0.5628**	0.5628**	0.5628**

Note: \*\*\*, \*\*, \* represent a significance level of 1%, 5% and 10%, respectively.

The results revealed that, in the short run, an increase of 1% in the *DLCPI*, decreases income inequality by almost 27%. Meanwhile, in the long run, *LCO2* is statistically significant, where an increase of 1%, causes a decrease in income inequality by almost 4%. A higher decrease of almost 7% on income inequality is caused by the 1% increase of *LCPI*. Additionally, high levels of trade openness, in the short- or long-run, means higher levels of

inequality. In fact, the increase of trade openness by 1% in a short and long run, causes an increase in inequality of almost 22% and 12%, respectively. Besides the high significance of the Error Correction Mechanism, the coefficient varies between -1 and 0. Thus demonstrating that the model adjusts itself into equilibrium and confirms the existence of a long-run relation statistically significant between the variables.

**Table 6**  
Estimation Results for 20/20 model.

Dependent Variable <i>LTTR</i>	OLS	RE	FE	FE_robust	FE D.K.
<i>DLT</i>	0.2457***	0.2457***	0.3111***	0.3111**	0.3111**
<i>DLEDUC</i>	-0.0197	-0.0197	-0.0201	-0.0201	-0.0201
<i>DLCO2</i>	-0.0625	-0.0625	-0.0809	-0.0809*	-0.0809**
<i>DLCPI</i>	-0.1250	-0.1250	-0.3503***	-0.3503	-0.3503**
<i>LTTR</i>	-0.0382***	-0.0382***	-0.3211***	-0.3211***	-0.3211***
<i>LT</i>	-0.0178**	-0.0178**	0.1664***	0.1664***	0.1664***
<i>LEDUC</i>	-0.0219	-0.0219	-0.0557	-0.0557	-0.0557
<i>LCO2</i>	0.0086	0.0086	-0.0503	-0.0503	-0.0503
<i>LCPI</i>	-0.0023	-0.0023	-0.0971***	-0.0971*	-0.0971***
Constant	0.2548*	0.2548*	0.6991**	0.6991**	0.6991***

Note: \*\*\*, \*\*, \* represent a significance level of 1%, 5% and 10%, respectively.

By analysing the results seen in Table 6, similarly to the Palma model, in the short- and long-run, an increase of trade openness and consumer price causes an increase and decrease of inequality, respectively. However, in this model, the results show that CO2 is statistically significant in the short-run instead of a long run. In fact, an increase of 1% of *DLCO2* causes an increase of almost 8% in income inequality. The model also adjusts itself into equilibrium with the coefficient of ECM highly significant and varying between -1 and 0.

**Table 7**  
Estimation Results for Gini model.

Dependent Variable <i>LGC</i>	OLS	RE	FE	FE_robust	FE D.K.
<i>DLT</i>	0.0008	-0.0021	0.0001	0.0001	0.0001
<i>DLEDUC</i>	0.0106	0.0097	0.0093	0.0093	0.0093
<i>DLCO2</i>	-0.0143*	-0.0129*	-0.0139*	-0.0139	-0.0139*
<i>DLCPI</i>	-0.0111	-0.0021	0.0078	0.0078	0.0078
<i>LGC</i>	-0.0268***	-0.0398***	-0.1239***	-0.1239***	-0.1239***
<i>LT</i>	-0.0015	-0.0033**	0.0017	0.0017	0.0017
<i>LEDUC</i>	-0.0084**	-0.0081	0.0022	0.0022	0.0022
<i>LCO2</i>	0.0000	-0.0012	-0.0111**	-0.0111	-0.0111
<i>LCPI</i>	-0.0051**	-0.0043*	-0.0039*	-0.0039	-0.0039*
Constant	0.1614***	0.2105***	0.4426***	0.4426***	0.4426***

Note: \*\*\*, \*\*, \* represent a significance level of 1%, 5% and 10%, respectively.

The results shown in the models across the three tables demonstrate some similarities such as consistency in signals and highly significant coefficient of the Error Correction Mechanism. However, the results for the Gini model revealed less significance. In the short run, an increase of 1% in the *DLCO2* causes a decrease of almost 1% in income inequality.

While in the long run, an increase of 1% in the *LCPI* causes a decrease of less than 1% in inequality. The main reason for this may be the lack of variation on the Gini variable. The semi-elasticities and elasticities were also performed in order to assess the magnitude of the effects. The results for the income inequality measures, Palma ratio, 20/20 ratio and Gini coefficient are displayed in Table 8.

**Table 8**  
Short-run impacts and elasticities.

Models	<i>DLPR</i>		<i>DLTTR</i>		<i>DLGC</i>	
Short run-impactss	(I)	(II)	(III)	(IV)	(V)	(VI)
<i>DLT</i>	0.2242**	0.2280***	0.3111**	0.3197**	0.0001	
<i>DLEDUC</i>	-0.0117		-0.0201		0.0093	
<i>DLCO2</i>	-0.0383		-0.0809**	-0.0684**	-0.0139*	-0.0153**
<i>DLCPI</i>	-0.2787**	-0.2796***	-0.3503**	-0.3556**	0.0078	
Elasticities						
<i>LT</i>	0.4374***	0.4786***	0.5180***	0.5578***	0.0134	
<i>LEDUC</i>	-0.0969		-0.1735		0.0177	
<i>LCO2</i>	-0.1459		-0.1567		-0.0897*	-0.1002***
<i>LCPI</i>	-0.2602***	-0.2773***	-0.3024***	-0.3287***	-0.0318*	-0.0366***

Note: \*\*\*, \*\*, \* represent a significance level of 1%, 5% and 10%, respectively.

One result deserves attention, the variable *CPI* have a negative effect in the short- and long-run for all inequality models except on Gini in the short-run, where the variable is not significant. The results also reveal that although the variable *EDUC* is not significant in any model, trade has a positive effect in both the short- and long-run for the Palma and 20/20 ratios. Regarding the environmental variable, CO2 emissions, it has a negative effect in both the short- and long-run on Gini approach. This negative effect is only seen also in the short-run for the 20/20 ratio. This outcome will be discussed in the next section.

## 5. Discussion

As the results display trade openness coefficient positive in a short and long run, this research supports the branch of the literature, which states that income inequality increases with an increase in globalisation. Consistently with this branch of literature, such as Kanbur (2015), when analysing the estimation results for Palma model, an increase of 1% in trade openness causes an increase in income inequality of almost 22% in the short run and 12% in the long run. Supporting this branch of literature, the estimation results for 20/20 model suggest that an increase of 1% in trade openness in a short and long run, causes an increase in inequality of almost 31% and 16%, respectively. Against the evidence shown in the work of Kraay (2006), where openness to international trade is negatively correlated with the Gini coefficient, the estimation results for the Gini model in this research display trade openness as not significant in a short and long run. However, considering the other estimation models such as Palma and 20/20 ratios, the results support trade openness as a proxy of globalisation, a driver of income inequality for the OECD countries. To Stiglitz (1998), a reason for this may be due to disparities in returns to education and skills. The results shown in this research contradict the work of Asteriou et al. (2014), where evidence suggests a reduction in inequality from trade openness in the 27 countries in the European Union. This contradiction might be due to factors related to the methodology and time span used or even variables chosen as globalisation proxies. Whereas the previous study defends that policies to mitigate inequality should be in regards to foreign direct investment, our research suggests that should be in regards to trade openness.

Regarding the impact of the climate change on income inequality, the results show that an increase of 1% in carbon dioxide emissions causes a decrease in the inequality of almost 8% in a short run and 4% in the long run. This result is shown in the 20/20 and Palma estimation models, respectively. Supporting the decrease in inequality by the increase of 1% in carbon dioxide emissions in the short run, the estimation results for the Gini model, display a decrease in inequality by almost 1%. This research contradicts the evidence shown in the work of Grunewald et al. (2017), which the main findings reveal that reduction in income inequality for upper-middle-income and high-income economies will simultaneously cause carbon dioxide emissions to decrease. The reason for this contradiction might be due to the data set used, covering 158 countries with annual measurements from 1980 to 2008, being associated with one of the most extensive data sets in the existing literature on the relationship between income inequality and carbon emissions. Overall, this research finds that an increase in carbon dioxide emissions per capita causes a decrease in income inequality in a short and long run, for the OECD countries. Supporting the work of Ravallion et al. (2000), this outcome implies that there is

a trade-off between inequality and emissions. In order to decrease income inequality, there is a need to increase carbon dioxide emissions per capita. Then policymakers will be challenged to find effective policies.

Considering the estimation results for the income inequality measures models, the results reveal the importance of fiscal and monetary policies such as consumer price index. Through cross-validation, the results suggest that an increase in the consumer price index causes a decrease in income inequality in the short and long run for the OECD countries. When analysing the estimation results for the Palma, 20/20 and Gini model in a short and long run, the consumer price index coefficient displays as negative with the exception of Gini model in the long run, which does not display statistical significance. This outcome contradicts the work of Cysne et al. (2005), which demonstrates a formal link between inflation and income inequality, as an increase in inflation leads to a deterioration of the income distribution.

As stated before, there still is a lack of consensus on determining measures for inequality. This lack of consensus is due to limitations in the models in which should be taken into account when interpreting conclusions or making decisions based on inequality measures. For instance, inequalities with distinct meanings may correspond to the same index value in the Gini coefficient (Pascoal and Rocha, 2018). The main limitation for the Palma and 20/20 ratios is that, as partial measures, the ratios do not account for full distribution. Therefore, although the Gini coefficient is the standard measure of income inequality, the study of other measures simultaneously, allows for more robustness and consistency in the results. The battery of tests performed in this study reveals that of the three income inequality measures analysed, the 20/20 ratio is the most suitable for the data set used. However, the study of the Palma ratio and Gini coefficient allowed consistency and validation in the results and revealed relevant findings such as the increase of carbon dioxide emissions causes a decrease in income inequality in the long run for the OECD countries.

Overall, the results in this study suggest that for the Organisation for Economic co-operation and development, policymakers should take in consideration policies to decrease trade openness to mitigate inequality. Additionally, in order to achieve growth equality in upper-middle-income and high-income economies, policies should be considered regarding the gradual increase of carbon dioxide emissions and inflation for the observed countries.

## 6. Conclusion

The main objective of this study is to estimate the degree of globalisation impact on income inequality in the short and long run for the countries members of the Organisation for Economic Co-operation and Development, covering the time span from 1993 to 2014. Additionally, inequality measures and other drivers in the short and long run were also studied.

This study contributes to the literature describing which factors have an impact on income inequality using an econometric approach. The data set was subjected to an exhaustive battery of tests to analyse the properties of the data series and guarantee that the most suitable estimator was used. Through the Driscoll-Kraay with fixed effects estimator and the Autoregressive Distributed Lag approach to determine the effects in the short and long run, the overall results of this investigation reveal high consistency with both the literature and the economic theory. The main findings suggest important policy implications to reduce income inequality. For instance, as the results suggest that an increase of trade openness causes an increase of income inequality, it might indicate that greater mobility of goods, capital and labour, pressures the freedom of governments to mitigate inequality through redistributive instruments. Therefore, trade policies should consider the implementation of redistributive systems, such as Conditional Cash Transfers. As the increase of consumer price index causes a decrease in income inequality, the countries members of OECD should maintain the control of inflation levels, through central banks. In regards to climate change, policies should consider the trade-off between income inequality and dioxide carbon emissions. A policy that could successfully address this trade-off is a revenue-neutral redistributive carbon tax that would encourage the reduction of emissions while the revenues could be redistributed to improve public services used by low-income households.

For future research, besides trade openness, it can be considered the multidimensional globalisation characteristic and study social and political characteristics. The study of low and middle-income economies should also be considered when increasing the sample size in order to compare disparities in income levels. For more consistency and robustness, future investigations should include several inequality measures and not only the standard measure of income inequality, the Gini Coefficient.

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