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Inequality and Economic Growth:

An overview of how income inequalities have affected economic growth in the OECD countries from 1993 to 2018

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Master in Economics

Supervisor: Associate Prof. Sofia Vale, Economics Department

March, 2024

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Resumo

Esta dissertação estuda o impacto da desigualdade de rendimento sobre o crescimento económico num grupo de 37 países da OCDE entre 1993 e 2018 utilizando médias de 5 anos. Foram consideradas diferentes medidas de desigualdade como o coeficiente de Gini do rendimento disponível e percentis da distribuição do rendimento nacional. As estimações foram feitas utlilizando *two-step system General Method of Moments*, seguindo a literatura. O conjunto de variáveis de controlo tem em consideração características como os níveis de saúde, o capital físico, o capital humano, entre outras. Os resultados demonstram que a desigualdade tem um impacto negativo, embora pequeno, sobre o crescimento económico, confirmado em todas as estimações, utlilizando diferentes medidas de desigualdade e diferentes instrumentos.

Palavras-chave: Rendimento, Desigualdade, Crescimento económico, Método dos momentos generalizados

Códigos JEL: C33, E24, O15, O47, P44

Abstract

This paper assesses the role that income inequality plays in economic growth among a group of 37 OECD countries between 1993 and 2018, using 5-year averages. Different inequality measures were considered such as the Gini coefficient of disposable income and shares of income on different percentiles of the pre-tax national income distribution. Following the literature, the estimations were performed using the two-step system GMM for controlling endogeneity and bi-causality in this relationship. The set of control variables comprises features such as health, human capital, and physical capital, among others. The main results show that inequality has a small but negative impact on economic growth regardless of the inequality measure used and across different instruments.

Keywords: Income, Inequality, Economic growth, System-GMM

JEL codes: C33, E24, O15, O47, P44

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Abbreviation Index

FE: Fixed-Effects

GMM: General Method of Moments

GDP: Gross Domestic Product

LSDV: Least Squares Dummy Variables

OECD: Organisation for Economic Co-operation and Development

Chapter 1

Introduction

Since the 1980s, inequality has been increasing (Piketty, 2014) while GDP growth has slowed down. This has brought up the discussion on the relationship between economic growth and inequality, leading to the question many authors have been trying to answer over the years, "is income inequality a driver of economic growth?". This study attempts to answer this question.

The 1980s were the turning point in the dynamics of income inequality (Alvaredo et al., 2018). In the year of 1979, Margaret Thatcher started serving Britain as prime minister. She claimed she would turn around the high inflation and the ongoing recession by deregulation of the financial sector, selling state-owned companies, and taking power from trade unions. Two years later, following the same liberal ideas, Ronald Reagan was elected president of the United States of America. The most influential countries in the world shifted their approach to the market, revolutionising the Western world. Other factors not related to the above helped the liberalisation of the market, such as India, which started deregulating and China and Russia initiated the transition away from communism. These events led to a substantial increase in the GDP growth rates of the countries mentioned, with some exceptions such as China in 1984 (data from WDI) reaching as high as 15% annually. At the time this led to the association of further market deregulation with economic growth. On the other hand, it has shaped the income inequality dynamics until today.

The world economy changed in such a way that today, the top 1 per cent of the income distribution captures twice as much income as all the bottom 50 per cent combined (Alvaredo et al., 2018). The authors analyzed the inequality trends in each country starting in the referred turning point (1980) until 2016. They designed projections for how global inequality will behave until 2050 under three different scenarios, for both the top 1% and the bottom 50%. Using the United States inequality trend of the new liberal era, their results showed that the top 1% share will increase by almost 28% until 2050, while the global share of the bottom 50% decreases to values below the ones registered in 1980. In the second scenario, every country follows its trend. With this projection, the share of the bottom 50 stays almost at the same level while the share of the top 1% increases but at a slower pace when compared to the US trend. Finally, in the last scenario, all countries follow the trend displayed by the European countries. This scenario is the only one where the income percentages are converging as the global share of the top 1% decreases while the bottom 50% increases its share. This demonstrates the different inequality paths brought up by the new economic organization that started in 1980.

Regarding the relationship between inequality and economic growth, no consensus has been reached over the years. When early theories questioned the existence of a trade-off between income and inequality, they found this trade-off to be positive (Kuznets,1955; Kaldor, 1957). This is explained by the fact that inequality at an early stage of development positively affects economic growth, but only up to a certain point of inequality, the inverted U-curve. Later literature found this trade-off to be negative the unequal distribution of income takes resources away from productive activities, lowering the efficiency at the economic level and consequently reducing incentives to invest (Alesina and Perotti, 1996; Barro, 2000). Nowadays, the impact of inequality on growth is non-existent. The movements of GDP are related to external factors (Kolev, 2016).

This paper studies the relationship between income inequality and economic growth, answering two main questions. First, whether inequality is related to economic growth. Secondly, knowing what is the impact of different inequality measures on economic growth. In order to answer these questions, the model was built relating the GDP per capita growth rate from Penn World Tables (PWT) with two different inequality measures. Inequality is initially measured through the Gini coefficient, retrieved from SWIID, where we find a negative trade-off between inequality and economic growth. Then, inequality is captured through percentiles of pre-tax national income taken from WID. The use of percentiles makes it possible to detect specific groups of the income distribution that affect economic growth.

The model is based on panel data for a total of 37 OECD countries from 1993 to 2018, the most recent reliable data available, where these 25 years are converted into five equal periods of 5 years each. In line with most of the literature, this paper uses a two-step system GMM as an estimator for the estimations. This choice was made to avoid the problem presented by the second most used method in the literature, the LSDV. This problem is related to the correlation of the fixed effect with both future and current GDP.

The findings reveal that in the group of OECD countries, inequalities are harmful to economic growth. Overall the estimations showed that economic growth and inequality share a negative relationship during the period under consideration, with growth being more sensitive to changes at the extreme points of the income distribution.

The remainder of this work is organized as follows: In Chapter 2, we present the literature that studied the relationship between income inequality and growth, highlighting the channels through which inequality affects growth; Chapter 3 presents the methodology, starting by discussing the pros and cons of different inequality measures and presents the econometric model; Chapter 4 shows and discusses the results from the estimations; finally, the last chapter (5) has the conclusion of this study answering the questions of this dissertation.

Chapter 2

Literature Review

2.1. Review

Rising inequality has attracted considerable interest among academics, policymakers, and the public in recent years, as shown by the attention received by an academic book recently published, "Capital in the Twenty-First Century" (Piketty, 2014).

Understanding the relationship between income inequality and economic growth is one of the most significant challenges of the twenty-first century. Both theoretical and empirical literature is inconclusive as to whether the effect of inequality on growth is predominantly positive or negative. There is also no conclusion on the channels through which inequality impacts growth or the correct estimations to use.

In the realm of social sciences, the discourse surrounding this theme has endured over an extensive period. Simon Kuznets (1955) delivered the inaugural and pivotal contribution to this discussion, proposing the existence of a trade-off between economic growth and inequality. His hypothesis, illustrated by the inverted U-curve, marked the genesis of the discourse on the examination of inequalities and their implications for policymakers. According to the inverted U-curve theory, as economic forces commence in developing countries, inequalities escalate, positively influencing economic growth. This phenomenon persists until a specific developmental threshold, the turning point, situated at the apex of the inverted U. Beyond this juncture, on the right side of the inverted U-curve, inequalities begin to diminish. Consequently, one can argue that economies are deemed developed at this juncture. It is therefore deduced that economies in the early stages of development tend to exhibit higher levels of inequality compared to their developed counterparts.

Kuznets' ideas seem to elucidate and rationalise instances where economic or political transitions result in social costs, such as the transient surge in inequality as an aftermath of economic growth, aligning with the long-term projections of the 'inverted U-curve' (Korzeniewicz and Moran, 2005). Early theoretical literature propagated the notion that inequality could stimulate growth, positing that the affluent possess a higher propensity to save, and these savings would subsequently fund investment in the economy (Kuznets, 1955; Kaldor, 1957). Subsequent literature emphasised the pathways through which inequality could foster growth, particularly by encouraging incentives for innovation and entrepreneurship. This is due to redistribution diminishing the rewards for innovation (Lazear and Rosen 1981).

Galor and Zeira (1993) disrupt this initial consensus on the positive correlation between inequalities and economic growth. They highlight the constraints imposed by credit market imperfections on the poor and those subject to credit constraints, resulting in missed investment opportunities in physical and human capital and, consequently, foregone economic growth and fixed costs of investment in education. Inequality can induce under-investment in human capital, thereby hindering growth, as households with low initial wealth levels cannot access high-return investments, perpetuating a cycle of poverty, they refer to as a poverty “trap”.

An alternative perspective posits that unequal income distribution instigates disruption and diverts resources away from productive activities. This engenders coordination failures, diminishes efficiency-enhancing cooperation, and introduces uncertainty into both the political and economic environments. Consequently, such conditions create disincentives for investment, contributing to instability. The diminished investment, in turn, leads to lower growth rates (Alesina & Perotti, 1996). The greater the disparity between mean income and the median voter's income, the more pronounced the social and political instability. This triggers the median vote preference for redistribution through taxation, thereby reducing incentives and impeding economic growth (Bertola, 1993). In a similar vein, Meltzer and Richard (1981) assert that higher income inequality encourages a majority coalition in the electorate to demand more redistribution, which is detrimental to growth.

Inequality exerts a negative impact on economic freedom, as the elite enhances its control over economic freedom and the ability to shape institutions, akin to a form of 'political capitalism' (Krieger and Meierrieks, 2016). This elite power is wielded to curtail economic freedom further in alignment with Acemoglu et al. (2005). Within this framework, redistributive efforts may impede economic growth by introducing inefficiencies, crowding out private economic activity, and adversely affecting saving and investment decisions (Scully, 2002). Unequal income distribution can also hinder growth as the elite finds it easier to capture institutions, extract resources from the economy, or move their capital abroad to countries with lower capital taxation (Glaeser, Scheinkman & Shleifer, 2003). Differences in capital taxation mainly underpin the relationship between income inequality and economic growth. Countries characterized by high financial disparities potentially create a vicious cycle by relying more heavily on capital taxation, thereby decreasing growth rates and lowering income, especially for the groups that ultimately need redistribution – the poor (Adam et al., 2015).

On the contrary, there is scant evidence supporting the 'leaky bucket' hypothesis (Okun, 1975). This hypothesis, operating at a macroeconomic level, posits that the negative effects of fiscal redistribution on growth (unless extreme) might represent a win-win policy due to its equality-inducing effects. More equal societies exhibit faster and more sustainable growth than less equal ones, as inequality correlates with lower investment in human and physical capital, higher fertility, and weaker political institutions (Berg et al., 2018). Greater inequality motivates more fiscal redistributive policy, leading to lower work effort and investment, resulting in diminished economic growth (Barro, 2000).

Banerjee and Duflo (2003) assert that the growth rate follows an inverted U-shaped function of net changes in inequality, challenging the functional form assumptions made by previous studies. However, their paper provides limited insight into the fundamental question of how inequality directly affects growth. Numerous cross-national studies fail to observe a U-shaped curve in the relationship between income levels or subsequent growth and changes in income inequality (Bruno, Ravallion & Squire 1998; Deininger and Squire 1996, 1998; Li, Squire & Zau 1998; Ravallion, 1995). Ferreira, Lakner, Lugo, and Ozler (2014) introduce the distinction between "good" and "bad" inequality, where 'good' inequality rewards effort and leads to better performance, while 'bad' inequality wastes human potential, akin to inequality of opportunity.

To assess the impact of inequality on growth, authors commonly employ pre-tax income, yet the primary effects hinge on net inequality, influencing prospects for social stability, consensus, and incentives (Berg, 2018). Challenges persist in measuring the changing distribution of income and wealth, both within and between countries globally (Alvaredo et al., 2017). While the Gini coefficient is widely used to measure income equality, Forbes (2000) and Malinen (2013) argue that it is inaccurate in its measurements.

Knowles (2005) contends that much evidence from cross-sectional studies on the relationship between growth and inequality is derived from inequality data that are not fully comparable. Once accounting for the heterogeneity in underlying income concepts, he concludes that no remaining relationship between income inequality and economic growth exists, although inequality in expenditure is still negatively correlated with growth. The diverse results of this study may also stem from different time frames considered. However, despite continuous improvement in inequality data, reduced-form panel data studies yield heterogeneous results, with ongoing concerns about functional form and appropriate estimation techniques raised in the literature.

Substantial evidence supports the idea that financial development and liberalization enhance growth (Arestis, Chortareas & Magkonis 2015; Valickova, Havranek & Horvath 2015). Van Velthoven, De Haan, and Sturm (2018) posit that the inequality-raising effects of finance contribute to economic growth, likely in a non-linear manner, with overall welfare effects expected to be positive.

2.2 Channels

In theory, it is conceivable to discover work that posits inequality having a positive impact on growth (Kuznets, 1955; Kaldor, 1957; Lazear & Rosen, 1981) or a negative effect on economic growth (Perotti, 1996; Bertola, 1993; Banerjee & Newman, 1993). However, the empirical literature on these attempts has been largely inconclusive. This section provides an overview of the different channels through which inequality may affect growth.

Kaldor (1957) demonstrated that inequality could enhance growth by facilitating capital accumulation, given that the affluent have a higher propensity to save. The higher saving rates of the wealthy make it possible for them to undertake significant investments and enable at least a few individuals to accumulate the minimum needed to start businesses and obtain a good education (Barro 2000). High inequality creates incentives to take risks and work harder, leading to high levels of innovation and entrepreneurship (Lazear & Rosen 1981).

Subsequent literature seems to highlight the detrimental channels of inequality for GDP growth rates. At a certain point, inequality becomes untenable for the majority of voters. This occurs because the majority of the electorate are either worse off to the detriment of the affluent, or their income is increasing at a slower rate than those at the top. In response, the voter turns their back on political power while demanding change, knowing they have the numbers to elect the government. These changes begin by pressing the government for more taxation and higher redistribution. This pressure generates economic uncertainty and leads to political instability. This instability leaves doubt in investors, reducing incentives to invest and, consequently, lowering investment and growth rates (Bertolla, 1993; Meltzer & Richard, 1981; Alesina & Perotti, 1996).

The second channel is related to the "human capital theory." Inequality leads to under-investment by the poor caused by financial market imperfections. People in the lower-income percentiles depend on their low levels of income and wealth to make worthwhile investments (higher return investment). Education is a worthwhile investment and an engine for economic growth. Still, a large part of the population, the poor, are not allowed to make this type of investment due to financial market imperfections. They are creating a poverty trap for generations to come. In conclusion, financial market imperfections create under-investment in human capital, lowering aggregate output (Galor & Zeira 1993).

Daniel Markovits has recently put forward a new channel in his book "The Meritocracy Trap" (2020). Meritocracy transformed economic inequality and corrupted politics because the affluent will organise and protect their wealth in every manner possible, even at the expense of the majority, destroying middle-class jobs either by increasing the requirements, only accepting super-skilled workers, or by increasing a ridiculous number of hours in the working schedule.

Chapter 3

Methodology

3.1. Inequality measures

One crucial aspect in the examination of inequality involves selecting the appropriate methods for its measurement. "An inequality measure is often a function that ascribes a value to a specific distribution of income in a way that allows direct and objective comparisons across different distributions." (United Nations, 2015, p. 1)

This paper commences by exploring the most prevalent method found in the literature for assessing income inequality: the Gini coefficient. This method's prevalence within the literature often overshadows other alternatives, such as the Atkinson inequality measurement or income percentiles. The Gini coefficient, named after Corrado Gini, was developed in 1912 as a groundbreaking index for measuring inequality, building upon earlier work by Max Lorenz in 1905.

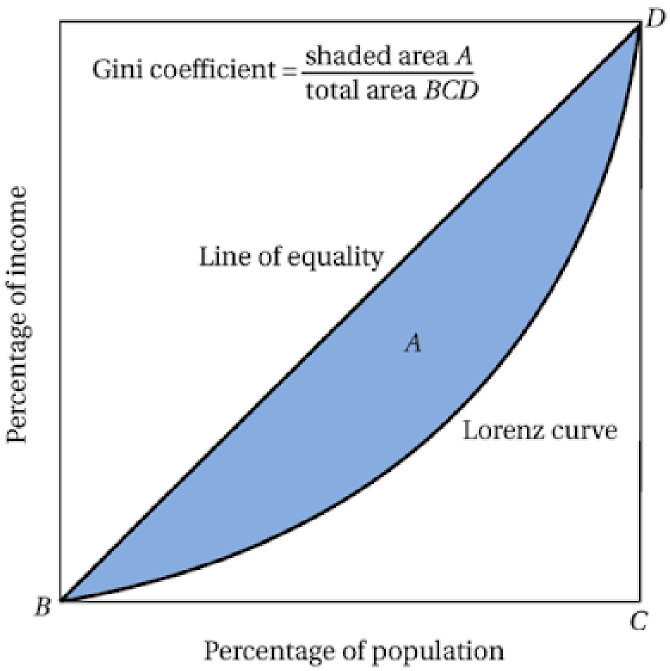

Figure 1 Gini coefficient explained. Source: Investopedia

Figure 1 contains a visual presentation of the Gini, represented as the blue area with the letter "A". As we can see, the Gini is calculated based on the line of equality, where incomes would be equally distributed across the sample, and the Lorenz curve, which effectively represents the level of income distribution in the sample. The Gini results from dividing the difference between these two, resulting in the blue area, by the total area between the points B, C, and D.

The Atkinson measure emerges as the most viable alternative to the Gini index, particularly prevalent among welfare-based indicators. This measure signifies the proportion of income within the studied group that would need to be relinquished to achieve a more equitable distribution of wealth. The primary limitation of the Gini coefficient lies in its uniform weighting of the entire distribution by design. Conversely, the Atkinson inequality measure assigns greater weight to the lower end and better accommodates factors relevant to inequality, such as child mortality, illiteracy, income poverty, and other similar considerations

Delving deeper into the limitations of the Gini coefficient, there exist concerns regarding its calculations, especially concerning sample size, suggesting a downward bias, as demonstrated by Deltas (2003). It is observable that smaller countries tend to display lower coefficients, while larger, economically diverse nations typically exhibit higher coefficients.

In certain scenarios, the Gini coefficient may yield identical results for countries with disparate income distributions but similar income levels. This limitation arises due to factors such as younger working-age populations earning relatively less compared to older individuals. Notably, the Gini coefficient does not provide insights into the configuration of the Lorenz curve. Consequently, it is plausible that a country's relative income dynamics (between the affluent and the impoverished) change while the aggregated Gini coefficient indicates no discrepancies, as exemplified by Osberg (2017) using the hypothetical country "Adanac."

Despite the aforementioned limitations, the frequent use of the Gini coefficient suggests that many scholars perceive it as the most effective measure of inequality available, albeit imperfectly so. The Gini coefficient demonstrates greater sensitivity to income changes around the median income. Moreover, its continued prevalence in assessing inequality can be attributed to two primary reasons: the availability of more extensive data compared to other measures and its better compatibility with existing literature.

Cingano (2014) and Piketty (2014) have raised objections to relying solely on single summary indices, like the Gini index, to gauge inequality. They argue that it is challenging to encapsulate inequality for all nations using a singular average, as it merely presents the sometimes insignificant impact of an average on growth. Consequently, they advocate for employing composite measurements, such as the ratio of income percentiles on either side of the median (Cingano's suggestion) or percentiles share ratios (as proposed by Piketty). Utilising percentiles to measure inequality offers the advantage of discerning how income changes within each percentile contribute to economic growth and how alterations in the gap between percentiles may impact growth.

As a complement to the Gini coefficient, this study incorporates recently compiled data from the World Inequality Database (WID), encompassing national income shares. Thus, this paper aims to investigate the influence of income inequalities on economic growth by utilising two distinct inequality measurements: firstly, the Gini coefficient derived from the Standardized World Income Inequality Database (SWIID), followed by pre-tax national income shares extracted from WID.

In summary, this section outlines the intention to explore the effects of income disparities on economic growth through the use of two diverse measures of inequality. The initial measure utilises the Gini coefficient derived from disposable income data in SWIID, while the subsequent measurement involves pre-tax national income shares sourced from the WID dataset.

3.2. Countries and Time Span

This thesis aims to examine the impact of income inequality on economic growth within OECD countries from 1994 to 2018. This timeframe was selected due to the availability of the most recent and reliable data for the chosen variables. Throughout this period, significant economic and social events unfolded, including a global economic crisis, which will be thoroughly discussed in the "Descriptive Statistics" section (Section 3.4).

The chosen countries constitute members of the Organisation for Economic Co-operation and Development (OECD), encompassing a total of 37 countries at the time of this work's composition (with Costa Rica becoming the 38th country to join the OECD in May 2021). This cohort of nations displays a diverse array of differences, ranging from demographic to geographical distinctions.

Regarding geographical differences, a noticeable concentration of OECD countries resides in Europe. More than half of the current 37 members are situated in Europe, specifically 26, including Turkey, which geographically straddles both Europe and Asia. This European concentration offers an intriguing prospect for drawing significant conclusions about the relationship between inequality and economic growth, given the similarities shared by some of these countries. For instance, many of them utilise the euro as their currency and are subject to the regulations of the European Union. Nonetheless, it's essential to acknowledge that these nations are governed by distinct national laws and other variables that set them apart.

Moreover, demographic variations among these countries are substantial. The sampled countries exhibit a wide range of population disparities. On one end of the spectrum, the United States of America boasts a population exceeding 300 million, while on the other hand, Iceland's population stands at just under 350 thousand as of 2018, as per data retrieved from PWT 10.0. These demographic distinctions illustrate the considerable diversity within the sample, signifying a crucial aspect for the study's considerations.

3.3. Variables and Data Source

In this paper, the dependent variable used is the growth rate. To derive this variable, we manipulate data from two sources: the Expenditure-Side real Gross Domestic Product (GDP) expressed in 2017 U.S. dollars at Purchasing Power Parity and population data. Initially, we convert the GDP to per capita levels by dividing the GDP by the population—a variable used as the dependent variable, as will be elaborated upon later. Subsequently, we apply a lag to the variable and logarithmically transform both variables. Finally, to compute the growth rate, we subtract the value of the logarithmically lagged GDP from the current logarithmically transformed GDP (all transformations were executed using Stata).

Both sets of data for the aforementioned variables were obtained from the same source—the latest update of Penn World Tables version 10.0 provided by the University of Groningen.

Initially, we utilize the Gini Coefficient of disposable income as the explanatory variable. This is made possible through the use of the recently compiled SWIID version 9.0 by Frederick Solt (2020). Solt's dataset is constructed through a meticulous three-step process: Firstly, it involves the integration of databases such as the WIID (World Income Inequality Database), LIS (Luxembourg Income Study), and Statistics New Zealand sources. Secondly, it includes the exclusion of observations that do not cover the entire population. Finally, the dataset undergoes a complex imputation procedure, extensively elucidated by Jenkins (2015) in "World Income Inequality Databases: An Assessment of WIID and SWIID."

Regarding the scope of coverage concerning income distribution measures across countries, two well-known databases are the WIID and SWIID. However, the WIID has been critiqued in the literature for being unbalanced and heterogeneous. The SWIID's construction addresses some of these shortcomings. While the WIID is provided by the United Nations University-WIDER, the SWIID utilizes and transforms the WIID data, resulting in a dataset with fewer gaps. This enables higher-quality cross-country and longitudinal analyses.

The second explanatory variable comprises different income percentiles of national income derived from the latest WID update (World Inequality Database). This database is constructed by an international consortium of scholars, including notable figures such as Thomas Piketty, Facundo Alvaredo, Emmanuel Saez, Gabriel Zucman, and others.

The most recent data from the World Inequality Database (WID) offers an invaluable tool for assessing inequality across nations. It diverges from prior literature by basing its distribution analysis on National Income instead of Gross Domestic Product (GDP), which has been frequently employed in earlier studies. This variance is justified because National Income accounts for GDP minus consumption of fixed capital (capital depreciation) while also incorporating net foreign income.

The rationale behind this deviation is twofold. First, the depreciation of the capital stock, a component of GDP, does not represent income for any individual or entity. Second, in certain scenarios, a portion of domestic output is directed towards foreign capital holders, such as in the case of offshore wealth. This phenomenon significantly impacts GDP due to the substantial sums involved. Thus, in a country with a substantial GDP but substantial foreign outflows and capital, the resulting income available for distribution to its population is considerably limited by capital depreciation. Conversely, National Income captures these aspects, rendering it an excellent and distinct alternative to GDP (WID.WORLD).

The percentiles provided by WID differ from those used by Cingano (2014) in terms of both source and specific percentile categorization. WID presents four distinct percentiles for all indicators in its database. In this analysis, we focus on pre-tax national income and consider the following percentiles: the bottom 50%, the Mid 40%, the top 10%, and the top 1%. These percentile groupings offer a comprehensive view of income distribution, enabling a nuanced examination of inequality across different segments of the population.

The set of control variables encompasses a Human Capital Index sourced from the Penn World Tables version 10.0, derived from average years of schooling. In assessing the health levels of each country, we consider either life expectancy in years or Age Dependency—a ratio reflecting the percentage of the elderly population in relation to the working-age population. These health metrics are obtained from the World Bank Open Data. To account for the impact of governmental influence, we incorporate the share of government spending, measured as a percentage, from P.W.T. 10.0. Alternatively, we utilize Trade, calculated as the total of exports and imports of goods and services as a share of gross domestic product, also sourced from the World Bank Open Data. Additionally, we incorporate the Share of gross capital formation from P.W.T. 10.0 to round out the control variables.

The second analytical approach involves different percentiles of national income and GDP per capita serving as explanatory variables. These percentiles include the share of national income held by the top 1% and 10%, the bottom 50%, and the middle 40%, all retrieved from WID. The dependent variable in this model remains the growth rate of the GDP, as previously described.

Regarding variables bearing the "lag" prefix, these signify measurements taken at the outset of each period. For instance, if a period commences in 1994, the lagged values of variables with this prefix pertain to their values at the beginning of the period—specifically, the values from the year 1993. This captures the variable values in the year prior to the commencement of each period, aiding in accounting for their preceding period's data.

3.4. Descriptive Statistics

This section provides a concise overview of the variables under investigation, focusing specifically on growth rates, income percentiles, and the Gini index throughout the period from 1994 to 2018.

Figure 2 illustrates the trend in economic growth over time. Initially, it is evident that the average economic growth was generally positive. However, there exists considerable variation in growth rates among countries annually and from one year to the next. At the onset of the period, the average economic growth slightly surpassed that of recent years and remained positive throughout. The decline observed can be attributed to the global economic crisis that struck the world economy around late 2007 and early 2008. Following this downturn, growth rates have gradually approached values closer to those observed prior to the crisis. Notably, in the last two years, values seem to cluster more tightly around the mean, with no discernible outliers. This concentration contributes to the observed decrease in the mean displayed in the figure.

In contrast, Figure 3 illustrates the Gini coefficient of disposable income across countries over time. It depicts a marginal increase in the average Gini coefficient, indicating a gradual rise in income inequality over the period. Moreover, the disparity among countries in terms of the Gini coefficient is significantly more pronounced compared to GDP per capita growth rates. The range spans from values as high as 54.3 to as low as 20.8, as outlined in Table 1. The presence of numerous outliers at the upper end of the chart results in a considerable deviation of countries with Gini coefficients in the lower concentration band (ranging from 20 to 33) away from the mean.

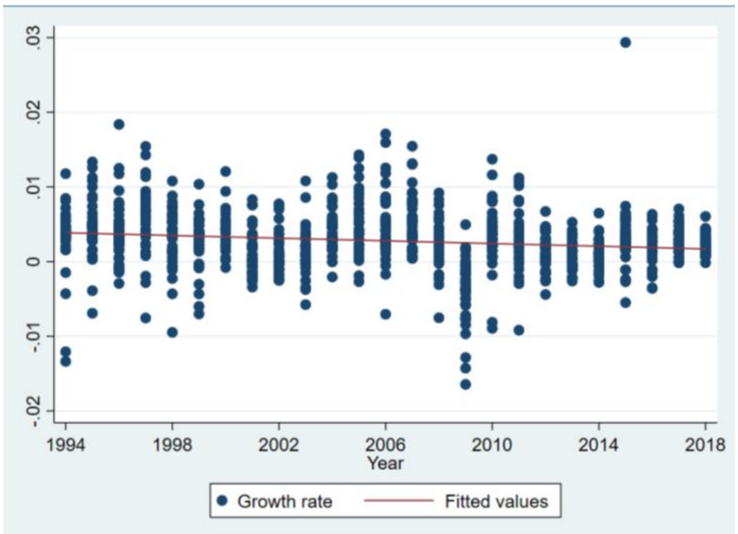

Figure 2- GDP per capita yearly growth rate, 37 OECD countries, 1994-2018

Source: author's calculations using PWT 10.0

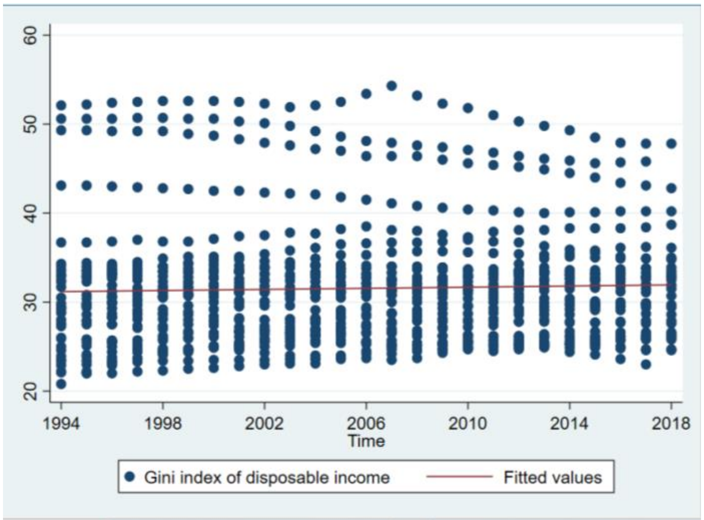

Figure 3- Gini of disposable income, 37 OECD countries, 1994-2018

Source: SWIID v9.0

Figure 4 depicts the correlation between the previously mentioned variables—output per capita and the Gini index. An observable trend emerges on the left side of the graph, coinciding with the range of Gini values between 20 and 40, consistent with the observations in Figure 2. At initial inspection, discerning a clear pattern that links inequality to economic growth appears challenging. The graph presents a scattered distribution without a readily apparent association between income inequality, as measured by the Gini index, and economic growth represented by output per capita.

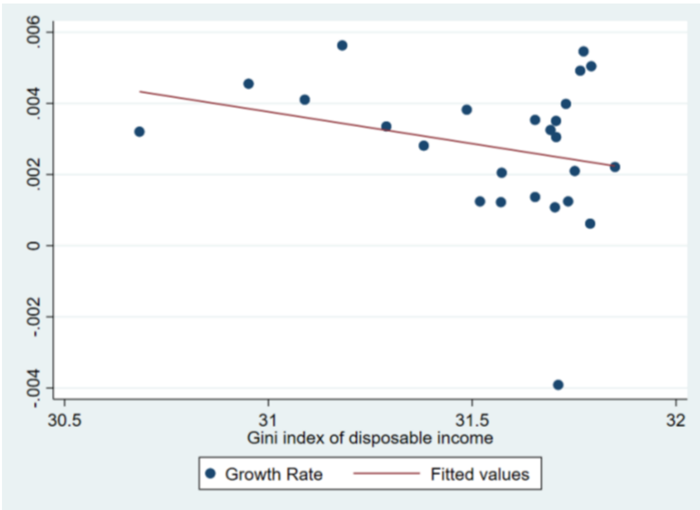

Figure 4- GDP per capita growth rates and Gini coefficient of disposable income, 37 OECD countries, 1994-2018. Source: author's calculations using PWT10.0 and SWIID v9.0

Figure 5 delineates the trajectory of pre-tax national income across percentiles throughout the years. A noticeable trend emerges: a significant shift in income distribution from the lower and middle percentiles toward the upper echelons. At the onset of the period, those within the bottom 50% of the income distribution claimed approximately 22.4% of the total national income. However, by the conclusion of the period, this share had diminished to 20.4%. Similarly, the middle 40% experienced a substantial decline from 45.1% to 42.8% of the total national income. Conversely, the top 10% saw a noteworthy increase in their share from 32.5% to 36.8% (+4.3%). Within this increase, the top 1% notably contributed to over half of this growth, escalating from 10.2% to 12.8% of the total national income—an uptick of 2.6 percentage points.

Table 1 supplements these graphical representations by offering descriptive statistics of the variables utilized in these graphs, as well as those employed in the ensuing econometric estimations. It presents key metrics including the mean, standard deviation, minimum, maximum, and the number of observations for each variable throughout the considered period. These statistics provide a comprehensive overview of the variables, aiding in the subsequent analytical procedures.

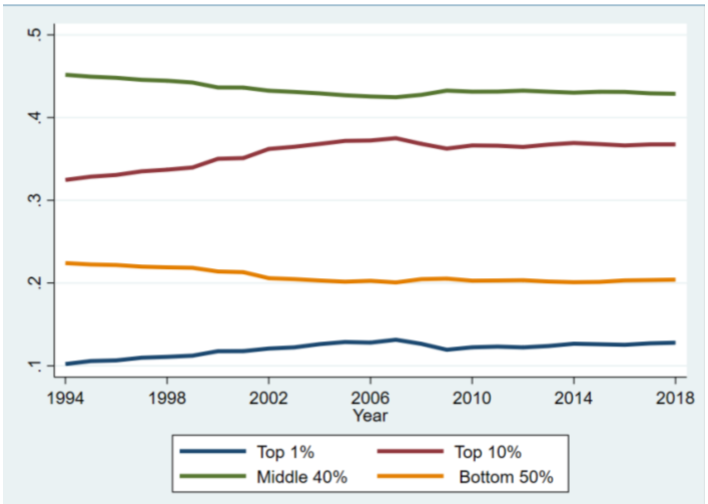

Figure 5 – Pre-tax National income averages, 37 OECD countries, 1994-2018

Source: author's calculations using WID

Table 1. Descriptive Statistics of Control Variables

Variable	Mean	St. Deviation	Minimum	Maximum	Observations
Real GDP per capita growth (%)	.002778 %	.0040431	-.0164441	.029349	925
Gini (index)	31.546	6.630653	20.8	54.3	913
Bottom 50 (%)	.207988 %	.0447502	.0709	.3065	903
Mid 40 (%)	.4342196 %	.0427739	.2776	.5223	903
Top 10 (%)	.3583508 %	.0783511	.2419	.6375	903
Top 1 (%)	.120663 %	.0466897	.0536	.3204	911
Human Capital (years)	3.151685 years	.4062362	1.843728	3.848829	925
Government expenditure (%)	.1854572 %	.0601466	.0670114	.4697913	925
Trade (%)	88.18916 %	53.45235	16.10447	408.362	922
Investment share (%)	.2560867 %	.0549933	.0833712	.5487379	925
Life expectancy (years)	78.03551 years	3.45597	65.66439	84.21098	925
Age Dependency (ratio)	21.84094	6.20936	7.461164	46.17086	925

3.5. Equation

The regressions employed in this study adhere to the Barro-style growth regressions (Barro, 2000). As illustrated in Equation 1, growth is modeled as a function of initial economic output per capita, and inequality, our principal explanatory variable, and a suite of control variables, namely physical capital, human capital, the share of government consumption, and life expectancy—all expounded upon in Z. The estimation of this equation employs panel data methodologies. The baseline regression specification is structured as follows:

$$lnY_{i,\tau} - lnY_{i,\tau-1} = \beta_1 Gdp_{\tau-1} + \beta_2 Z_{\tau-1} + \beta_3 Ineq_{\tau-1} + d_\tau + \varepsilon_{i,\tau} \quad (1)$$

In Equation (1), $lnY_{i,\tau}$ represents the logarithmic value of Expenditure-Side real GDP at chained PPPs (2017 US dollars) at time τ, with "i" denoting a specific country. Consequently, the left-hand side offers an approximation of GDP per capita growth for these countries during the period. $Z_{\tau-1}$ is a vector of regressors comprising a set of control variables. This vector encompasses pre-determined growth drivers that evolve over the study, measured at the period's outset. $Ineq_{\tau-1}$ serves as the measure of inequality, employing either the Gini index or percentiles of pre-tax national income.

The coefficient β_1 measures the impact of initial GDP per capita on growth, β_2 captures the impact of the control variables (e.g., physical capital, human capital, government consumption, life expectancy), and β_3 represents the impact of inequality on growth. The term d_τ accounts for time-specific effects, and $\varepsilon_{i,\tau}$ is the error term.

The entire series is segmented into five-year subperiods, following established literature, from which average values are computed. Therefore, the model relies on five non-overlapping time intervals of five years (t=5). Equation (1) can be rearranged as Equation (2):

$$\frac{lnY_{i,t} - lnY_{i,\tau-1}}{5} = \beta_1 Gdp_{\tau-1} + \beta_2 Z_{\tau-1} + \beta_3 Ineq_{\tau-1} + d_\tau + \varepsilon_{i,\tau} \quad (2)$$

Concerns have been raised in the empirical literature regarding the feedback loop between GDP dynamics and inequality. This dynamic panel form frequently exhibits Nickel bias, named after Stephen Nickel (1981). This well-recognized issue involves fixed-effect correlation with both future and current GDP. While the Nickel bias diminishes as the dimension T approaches infinity in both fixed and random effects models, it persists even if the cross-sectional dimension goes to infinity. The conventional solution involves creating dummies for each entity, employing the least-squares dummy variable estimator to extract the fixed effects from the error term. However, despite this transformation, a correlation between the regressor and the error term persists.

Conversely, simulation studies indicate that a simple least-squares dummy variable (LSDV) estimator produces accurate results when T is approximately 30. El-Shangi and Shao (2017) conducted a simulation comparing the LSDV estimator with the first-step difference general method of moments (GMM) and system GMM (SGMM). This test drew on Moral-Benito's findings (2013), demonstrating that LSDV outperforms GMM in terms of absolute mean and bias. However, the significance of this demonstration by El-Shangi and Shao (2017) diminishes somewhat because even large datasets typically assume small-time dimensions. Instead, datasets often consider periods (a) as the time dimension. Given the use of periods (a), presumed to be much less than 30, the number at which LSDV estimators yield accurate results, it is concluded that LSDV does not outperform GMM due to the smaller time dimension used in this type of study, falling short of the optimum level.

This paper aligns itself with recent literature on the dynamics between GDP and inequality, drawing insights from scholars such as El-Shangi and Shao (2017), Van Velthoven (2018), Berg (2018), and others. The analytical framework employed follows a two-step system GMM, as advocated by Arellano and Bover (1995), subsequently refined by Blundell and Bond (1998). In direct comparison with the one-step system GMM, the two-step approach is found to be more robust, as evidenced by Roodman's (2009) demonstration of its greater efficiency and resilience against heteroscedasticity and autocorrelation.

Despite its merits, it is important to acknowledge the limitations of the system GMM estimators, which rely heavily on mean stationarity assumptions, originally tailored for persistent data. This crucial aspect is occasionally overlooked in the application of these estimators.

Delving into the foundational GMM approach outlined by Arellano and Bond (1991), the methodology initiates with first-difference GMM. This process involves transforming all regressors, typically through differencing, utilizing the generalized method of moments to eliminate country-specific effects and incorporating lagged values of the right-side variables. System GMM (Arellano–Bover/Blundell–Bond) builds upon the difference GMM by assuming that the first differences of instrument variables are uncorrelated with fixed effects. This approach combines the original equation (first-differenced equations) with an additional set of equations in levels, where the lagged first differences of the right-hand side variables serve as instruments. This augmentation leads to a significant enhancement in efficiency and allows for the inclusion of a more extensive set of instruments.

The primary challenge associated with the GMM estimator, as highlighted by Roodman (2009), centers around the issue of the number of instruments. Employing an excessive number of instruments in GMM estimation may potentially undermine the Sargan/Hansen test, a crucial measure we utilize to assess the validity of the instruments in the regression. This overuse could also result in the generation of implausible p-values. However, there exists no unanimous agreement on the threshold for the number of instruments deemed excessive, except that it should not surpass the number of countries (N).

Evidence from Monte Carlo simulations indicates that halving the number of over-identifying instruments can alleviate bias by up to 40%. Specifically, a key limitation of the first-difference GMM lies in its propensity to eliminate much of the variation in data. This implies that past levels offer minimal or no information about future changes, particularly when the variable Y exhibits characteristics akin to a random walk. In such cases, lagged explanatory variables may serve as weak instruments for the variables (Blundell and Bond, 1998). To address this issue, we employ the Sargan/Hansen test as a tool to monitor the problem of instrument validity. This test assesses the joint validity of the instruments in GMM estimation, and we scrutinize Hansen's values, with particular concern for those below 0.1.

To conduct the GMM model estimation, Stata was chosen in adherence to the recommendations outlined by Roodman (2009), as detailed below. The first recommendation emphasizes having a panel with a small number of periods (T) and a large number of countries (N). In accordance with this guidance, this paper adopts a time dimension of 5 (T=5, representing five periods of non-overlapping 5 years each) and N=37 (37 countries).

The second recommendation involves the inclusion of time dummies to address autocorrelation and to ensure robust estimates of the coefficient standard errors, assuming no correlation across individuals in the idiosyncratic disturbances.

The third recommendation advocates for the use of an orthogonal option for panels with gaps. This is applied in all estimations, even when gaps are only present in the series for income shares (percentiles).

The fourth recommendation dictates that every regressor be included in the instrument matrix.

Fifth, pre-determined variables should be designated in the command "gmmstyle(variable)." In all estimates, only one pre-determined variable remains constant throughout the study: the lagged output (lagged expenditure-side real Gross Domestic Product per capita expressed in 2017 U.S. dollars at Purchasing Power Parity) for every regression.

The sixth recommendation endorses the use of the Hansen test to assess the validity of the instruments employed in the regression.

The final recommendation stresses the importance of reporting all specification choices of the models. These specifications are elaborated upon in the Appendix for further discussion.

Chapter 4

Results

4.1. Estimations using Gini

Table 2 presents the results of estimations employing the Gini coefficient as a measure of inequality. All models employ the two-step system General Method of Moments.

The initial column provides estimates using per capita GDP as a predetermined variable. This column includes a single control variable, indicative of external openness (Trade), derived by summing imports and exports and dividing the result by GDP. Subsequent columns gradually introduce additional control variables to assess whether Hansen's test for plausible values experiences an increase. The sequential addition of variables is intended to examine the possibility of bias resulting from an augmented set of instruments.

Column 2 introduces a new set of variables to the control set ($Z_{i,t}$), such as the share of government spending (Government Spending) and the share of gross capital formation (Investment Share). Column 3 differs from Column 2 solely in the instrument panel, featuring a greater number of instruments. In the fourth column, Human Capital is added to the model. Column 5 alters instrumental variables in comparison to Column 4. Column 6 introduces the variable Life Expectancy to Equation 4. In Column 7, the control variable for health is changed, replacing Life Expectancy with Age Dependency. Finally, in Column 8, the number of countries under analysis is adjusted, retaining only those with complete information for all periods and variables in the model.

Columns 3 and 5 are included due to literature suggesting that an increase in the number of instruments may elevate Hansen test values, potentially introducing bias in estimations. Notably, Column 2, with fewer instruments than Column 3, exhibits higher values of the Hansen test. Conversely, in Column 5, the addition of one more variable results in a decrease in Hansen test values, confirming the absence of the issue highlighted by Roodman regarding the use of "too many" instruments.

Table 2. Results of the estimations using GINI as a measure of inequality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	-0.001**	-0.002*	-0.001***	-0.002**	-0.001***	-0.002***	-0.002***	-0.001**
Trade	0.0001*							
Investment Share		0.026	0.019	0.048	0.023	0.076	0.052	0.02
Government Spending		-0.175**	-0.121***	-0.186***	-0.118***	-0.187***	-0.200***	-0.157
Human Capital				0.011*	0.008**	0.013	0.013	0.006
Life Expectancy						0.003		
Age Dependency							0.0003	0.0001
AR1	0.004	0.053	0.044	0.029	0.026	0.048	0.015	0.184
AR2	0.032	0.01	0.01	0.013	0.009	0.021	0.014	0.031
Hansen	0.190	0.222	0.370	0.367	0.362	0.751	0.524	0.349
Instruments	17	13	14	14	15	15	15	15
Observations	182	185	179	185	179	185	185	170
Countries	37	37	37	37	37	37	37	34

Note: All the variables are measured in period $t-1$. We are using 5-year averages and a Robust, 2-step System GMM estimator with Windmeijer-corrected standard errors. All regressions include period dummies.; Hansen denotes the p-value on the Hansen test of over-identifying restrictions. ***, **, * denote significance at the 1, 5, and 10% levels, respectively

In all estimations, the influence of the Gini coefficient of disposable income on GDP per capita growth is statistically significant. Across all models, the coefficient associated with the Gini coefficient is consistently negative, signifying that an escalation in income inequality corresponds to a reduction in economic growth. This observed trade-off aligns with the findings of numerous empirical studies. For instance, in the complete model (Column 7), a 1% increase in inequality is associated with a 0.2 percentage point decrease in the annual growth rate. The remaining estimations demonstrate a more modest impact of inequality on economic growth, with coefficient estimates ranging between -0.2% and -0.1%. The most substantial impact of inequality on economic growth in Table 1 is approximately 0.2 percentage points, observed in Columns 2, 4, 6, and 7.

Turning to the control variables, the trade coefficient is significant at a 10% level in the initial model, while in subsequent models, the share of government consumption proves to be statistically significant at either a 5% or 1% significance level. The human capital index is significant at 10% or 5%, with the exception of Column 6, and all other variables are statistically insignificant. Regarding the sign of the coefficients, the share of government consumption exhibits a negative association, implying a dampening effect on economic growth. In contrast, trade and human capital show positive associations, contributing to an increase in GDP per capita growth.

4.2. Estimation using Percentiles

To delve deeper into the impact of inequality on economic growth and validate the prior findings, we adopt a similar methodology to Cingano (2014), employing percentiles of the income share to gauge inequality.

Table 3 presents the results of Equation (2) using the WID percentiles indicators as a measure of inequality. In all models, all the control variables are included in the instrumental matrix, ensuring alignment between the columns representing instrumental and control variables. The tables are interpreted from left to right, reflecting ascending levels of inequality, specifically, from the Bottom 50 to top inequality, i.e., Bottom 50, Middle 40, Top 10, and Top 1.

Table 3. Results of the estimations using Income Percentiles as a measure of inequality

	(1)	(2)	(3)	(4)
Inequality	0.071*	0.035	-0.050*	-0.142*
Government Spending	-0.104***	-0.082**	-0.109**	-0.162***
Human Capital	0.116***	0.011***	0.010***	0.022***
Age Dependency	0.0003	0.0003	0.0003	0.0007
Investment Share	0.037	0.037	0.034	0.095*
AR1	0.034	0.026	0.034	0.071
AR2	0.029	0.031	0.031	0.043
Hansen	0.177	0.059	0.194	0.512
Instruments	16	16	16	16
Observations	179	179	179	179
Countries	37	37	37	37

Note: All the variables are measured in period $t-1$. We are using 5-year averages. Inequality is measured by percentiles. The percentiles in columns (1), (2), (3), and (4) are respectively the bottom 50, the mid 40, the top 10, and the top 1% of the income distribution.
We use a Robust, 2-step System GMM estimator with Windmeijer-corrected standard errors. All regressions include period dummies.; Hansen denotes the p-value on the Hansen test of over-identifying restrictions. ***, **, * denote significance at the 1, 5, and 10% levels, respectively

The new models corroborate the results of the estimations obtained using the Gini coefficient, although displaying less robust statistical results. Increasing the share of national income from the bottom 50% and middle 40% has a positive impact on economic growth. As shown in columns 1 and 2 of Table 3, along with the literature, reducing inequality increases economic output. In turn, an increase in the national income from the top 10 and top 1% is shown to harm economic growth. A one percentage point increase in the share of national income that belongs to the middle 40 percentile of the distribution contributes to a positive increase of 0.35% in economic growth, 0.71% in the case of a one percentage point increase in the share of the bottom 50 percentile.

In comparison, the top 10 percentile decreases growth by half a percentage point, while the top 1% appears to have an even more damaging impact on growth, around 1.42%. All the deciles prove to be statistically significant at the 10% level except for the middle 40 percentile, which is not significant. There are also concerns about the values presented on the Hansen test for the first three columns.

As expected, inequality proves to harm economic growth. This impact seems to be more sensitive on the extremes of the national income distribution, either the bottom 50 or the top 1 percentile, where we have found the highest coefficients and the highest statistical significance.

4.3. Discussion

Our findings highlight a negative relationship between inequality and economic growth within the selected sample of countries. This contradicts the results presented by Barro (2000), who identified a negative relationship between economic growth and inequality primarily for developing countries. Notably, Barro's findings indicated a positive relationship for the rich countries in his sample.

Kolev (2016) posits a nuanced perspective, suggesting that the correlation between income inequality and economic growth tends to be positive for countries with low Gini coefficient levels, such as those in European countries. However, this correlation shifts towards negative levels as the Gini coefficient increases, particularly when surpassing the levels observed in most European countries, which tend to be comparatively lower on a global scale.

Contrary to the viewpoint presented by School et al. (2016), our results indicate a trade-off between inequality and growth, with a negative impact of inequality on economic growth. School et al. argue that the positive impact of inequality on growth in their study is non-robust and influenced by two main factors. First, during the 1990s, inequality was on the rise simultaneously with a significant output collapse in many countries. Subsequently, in the late 1990s, as economies began to recover, they exhibited reasonable economic growth rates.

The observed association between economic expansion and increasing inequality in the initial periods can be attributed to the methodology employed in constructing regressions for inequality-growth studies, as exemplified in Equation 2. In our study, akin to many others, we follow a Barro-style growth equation (Equation 1), a framework commonly used in empirical studies. This type of equation typically incorporates inequality measures with values from the preceding year or period.

During the period under examination, a significant global crisis unfolded, originating in the US financial market in 2007 and subsequently spreading worldwide. Barro-style growth equations, including ours, have a distinctive feature of utilizing lagged inequality measures to explain current growth. In the early 1990s, the world faced elevated inequality levels coupled with low growth rates. However, towards the end of this period, growth rates witnessed an upturn. When employing lagged inequality to elucidate current growth, the positive values of economic output in the subsequent period might falsely suggest that inequality drives economic growth in the next period.

Despite the complexity introduced by the events of the early 1990s, our study reinforces its results, affirming a negative and significant impact of inequality on growth. To be specific, a 1% increase in inequality is associated with a 0.2 percentage point reduction in the yearly growth rate. This holds true even when considering the episode in the 1990s, which, though influencing the correlation, does not detract from the negative impact of inequality on growth identified in our study.

The results presented in Table 3, where national income percentiles are used to measure inequality, corroborate the previously discussed findings, underscoring the detrimental impact of inequality on economic growth, particularly pronounced in the bottom 50 and top 1 deciles. When comparing our results to those of Cingano (2014), who utilizes the same estimator, the two-step system GMM, we observe a consistent negative trade-off between inequality and growth, albeit with slightly lower values in our study.

The most substantial disparities in results arise when comparing the coefficients' values for our percentiles against those for Cingano's deciles. In our models, inequality appears to have the most pronounced negative impact on the bottom 50 and top 1. While our findings align partially with Cingano's (2014) results, where the third and fourth deciles exhibited the highest coefficients, these deciles are encompassed within our Bottom 50, which also demonstrates the highest coefficients, along with the top 10. However, our values are comparatively lower than those obtained by Cingano.

Conversely, Cingano (2014) couldn't establish significance for the top deciles, whereas we conclude a negative impact of the top decile on economic growth, approximately 0.5%, and 1.42% for the Top 1 percentile.

This prompts a discussion raised by Kolev (2016), suggesting that the system GMM may not effectively control for country-specific effects, and that the GMM coefficient range is more extensive than alternative estimators, such as OLS or fixed effects (LSDV).

Chapter 5

Conclusion

In recent decades, the exploration of the interplay between inequality and economic growth has emerged as a highly delicate and extensively debated subject within both empirical and theoretical realms, shaping dialogues in democratic nations. Despite the extensive discourse, a consensus remains elusive. Divergent perspectives persist, with some arguments asserting a positive correlation between inequality and economic growth, while others emphasize a negative impact.

This paper delves into the intricacies of the inequality-growth relationship by utilizing an enhanced panel data set. Our data, sourced from the Penn World Tables (PWT) for GDP per capita growth, the Standardised World Income Inequalities Database (SWIID), and the World Income Data (WID) for inequality metrics, enables the construction of a comprehensive panel dataset. The sample encompasses 37 countries within the OECD over five distinct periods spanning from 1993 to 2018. We employed the two-step system General Method of Moments as our estimator.

The outcomes of our estimations reveal a discernible negative relationship between economic growth and inequality throughout the considered period. This corroborates the findings of scholars such as Galor and Zeira (1993), Alesina and Perotti (1996), Acemoglu et al. (2005), Alvaredo et al. (2017), Berg et al. (2018), and numerous other contributors to the discourse on this complex relationship.

By employing expenditure-side real GDP per capita at constant prices (2017) and PPP as the dependent variable, our study has illuminated the predominantly positive influences of factors such as the share of capital formation, the human capital index, age dependency, and life expectancy on economic growth. Conversely, a negative impact on growth was identified in relation to the share of government spending. These findings remain consistent across two distinct approaches, utilizing either the Gini coefficient or the percentiles of national income as measures of inequality.

In the case of the Gini Index as the metric for inequality, our analysis revealed a 0.2% negative impact of inequality on economic growth. Turning our attention to Table 3, where inequality was gauged through national income percentiles, we observed that an increase in national income within the Bottom 50 and middle 40% percentiles resulted in growth increments of 0.71% and 0.35%, respectively. Contrarily, the Top 10 and 1%

exhibited a negative impact on growth, with figures of -0.5% and -1.42%. In conclusion, our results converge to a singular insight: a modest yet discernible negative relationship exists between inequality and economic growth.

The utilization of percentiles allows for a nuanced observation of where the impact of inequalities is most pronounced, thereby guiding policymakers on which segment of the income distribution to target. Our findings highlight that the top 1%, representing the wealthiest percentile, exhibits the highest coefficient, closely followed by the bottom 50% percentile. Consequently, national entities should strategically direct policies to redistribute income from the top 1% to the lower echelons of the distribution. This approach is anticipated to yield the most significant economic growth, as indicated by our results.

It's essential to recognize that income inequality is intertwined with various factors, including opportunity inequality, as articulated by Daniel Markovitz (2020), and wealth inequality. These three concepts are interconnected and can collectively exert a detrimental impact on economic growth. Moreover, technological progress has contributed to the displacement of low-skilled jobs, amplifying wage disparities. In response, governments should address inequality of opportunity by providing avenues for skill enhancement among less qualified workers. Unfortunately, public entities may encounter limitations or choose not to furnish this type of qualification, inadvertently perpetuating protection for the wealthier classes. Tackling these dimensions of inequality is crucial for fostering inclusive growth and mitigating the adverse effects on the overall economy.

Countries with a historical trend of elevated unemployment levels may consider implementing measures such as liberalizing the labor market. While labor market rigidities can result in higher wages, they also contribute to increased wage disparity and elevated unemployment rates. Addressing unemployment requires strategic actions, such as reducing social security benefits and implementing more progressive income taxes, with a specific emphasis on relieving the tax burden on lower incomes. These measures aim to incentivize the unemployed and inactive population to actively seek paid employment. However, implementing such measures can be challenging, as governments often face budgetary constraints that limit their flexibility in executing necessary reforms to revive public finances.

In our analysis, the standout indicator for statistical significance is the percentage of Government Consumption. This underscores the importance of national entities adopting a focused approach to capturing income from the higher echelons of the distribution. Simultaneously, governments should exercise caution in direct investments in the economy, as our results indicate a negative impact on economic growth. Instead, the emphasis should be on income redistribution strategies. This nuanced approach acknowledges the constraints posed by budgetary pressures and encourages governments to prioritize actions that maximize the positive impact on economic growth while addressing income disparities.

This study acknowledges certain limitations that warrant consideration. The selection of variables is one area where improvements can be made. For instance, the choice of the PWT measure for Human capital, rather than alternatives such as the percentage of the working-age population completing secondary or tertiary education from WID, could impact the comprehensiveness of our analysis. Another critical variable, government consumption, appears to exhibit exceptionally high statistical significance in Tables 2 and 3, possibly absorbing all the information. In future research, it would be prudent to explore alternative variables, like foreign openness (Trade), in place of government consumption to enhance the robustness of our findings.

Furthermore, the study's scope is somewhat limited by the concentration of countries, primarily in Europe. While some diversity is present, a broader representation of countries from various regions would contribute to a more comprehensive understanding of the global dynamics between inequality and economic growth.

The temporal aspect also poses a limitation, as the study covers a 25-year interval. Given the nuanced nature of inequality and growth dynamics, a more extended time sample could offer a more in-depth exploration of these relationships.

For future investigations, expanding the use of Least Squares Dummy Variables (LSDV) could provide valuable insights. While the prevalence of studies using the two-step GMM system aids comparability, incorporating diverse estimation methods can contribute to a more comprehensive understanding of the subject. Addressing these limitations in future research endeavors will undoubtedly enhance the robustness and applicability of the findings in the realm of inequality and economic growth dynamics.

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Appendix A

As for the GMM model the tool used was Stata therefore this paper was written following "How to do xtabond2: An introduction to difference and system GMM in Stata" by Roodman (2009). The recommendations we follow:

I. Our panel has Small T and Large N as suggested. In this paper T=5 (five periods of 5 years) and N=38 (38 countries)

II. Include Time dummies, to account for autocorrelation test and the robust estimates of the coefficient standard errors assume no correlation across individuals in the idiosyncratic disturbances. Which we use (y1, y2, y3, y4, y5) as seen in figure 5

III. Use orthogonal for panels with gaps, which we used even though our data has no gaps.

IV. Put every regressor into the instrument matrix, with exception of regression presented on the first column from table 2. Where The Gini is a regressor although It is not included on the matrix of instruments. All the other regressions follow the rule of including every regressor on the instrument matrix.

V. If a variable is pre-determined use *gmmstyle(variable),* used for the lagged output in every regression in this paper.

VI. Mind and report the instrument count, using the Hansen test to detect the validity of the instruments.

VII. Report all specification choices, the specifications will be discussed below.

Variables and Source

Variable	*Definition*	*Source*
rgdpe	Expenditure-side real GDP at chained PPPs (in mil. 2017US$)	PWT 10.0
Gini	Gini index of disposable income	SWIID 9.0
Investment share	Share of gross Capital formation at current PPPs	PWT 10.0
Government spending	Share of government consumption at current PPPs	PWT 10.0
Trade	Trade (% of GDP)	World Bank
Unemployment	Unemployment, total (% of total labor force) (national estimate)	World Bank
Human Capital	Human capital index	PWT 10.0
Life Expectancy	Life expectancy at birth, total (years)	World Bank
Age dependency	Age dependency ratio, old (% of working-age population)	World Bank
Top_1	pre-tax national income Top 1%	WID
Top_10	pre-tax national income Top 10%	WID
Mid40	pre-tax national income Middle 40%	WID
B50	pre-tax national income Bottom 50%	WID
Consumer Price Inflation	Inflation, consumer prices (annual %)	World Bank

Variable transformation

The variables with the lag prefix mean they are measured at the beginning of the period, what this means is that the value of the variable is accounting for his value on the year "zero" of each period, so for example if the period starts in 1994 the lagged values of the variables with the lag prefix present the values at the beginning of the period, the values from the year of 1993. It accounts for the values of the variable on the year before the start of each period.

rgdpe_pc is given by a simple division of the rgdpe by the population data from the same database (PWT). logrgdpe_pc is the logarithm of *rgdpe_c.* While *GRlrgdpe_pc* represents the growth rate of *rgdpe_pc,* it is built by subtracting lagged logrgdpe_pc on logrgdpe_pc and then using the command collapse(mean) on stata for the mean of the growth rate of rgdpe_pc on each period. For a better understanding, next I present all the commands used in both tables. Starting with table 2, the following is an example of a stata output.

Table 2

Column 1: xtabond2 gr loglgdp_pc lGini_disp l_TradE y1 y2 y3 y4 y5, gmm(loglgdp_pc,collapse) iv(l_LifeExp l_csh_c l_CPI l_TradE l_hc l_csh_i l_Unemployment y1 y2 y3 y4 y5) nodiffsargan twostep robust orthogonal small

Column 2: xtabond2 gr loglgdp_pc lGini_disp l_csh_i l_csh_g y1 y2 y3 y4 y5, gmm(loglgdp_pc,collapse) iv(lGini_disp l_csh_g l_csh_i y1 y2 y3 y4 y5) nodiffsargan twostep robust orthogonal small

Column 3: xtabond2 gr loglgdp_pc lGini_disp l_csh_i l_csh_g y1 y2 y3 y4 y5, gmm(loglgdp_pc,collapse) iv(lGini_disp l_csh_g l_csh_i l_Top_10 y1 y2 y3 y4 y5) nodiffsargan twostep robust orthogonal small

Column 4: xtabond2 gr loglgdp_pc lGini_disp l_csh_i l_csh_g l_hc y1 y2 y3 y4 y5, gmm(loglgdp_pc,collapse) iv(lGini_disp l_csh_g l_csh_i l_hc y1 y2 y3 y4 y5) nodiffsargan twostep robust orthogonal small

Column 5: xtabond2 gr loglgdp_pc lGini_disp l_csh_i l_csh_g l_hc y1 y2 y3 y4 y5, gmm(loglgdp_pc,collapse) iv(lGini_disp l_csh_g l_csh_i l_Top_10 l_hc y1 y2 y3 y4 y5) nodiffsargan twostep robust orthogonal small

Column 6: xtabond2 gr loglgdp_pc lGini_disp l_csh_i l_csh_g l_hc l_LifeExp y1 y2 y3 y4 y5, gmm(loglgdp_pc,collapse) iv(lGini_disp l_csh_g l_csh_i l_hc l_LifeExp y1 y2 y3 y4 y5) nodiffsargan twostep robust orthogonal small

Column 7: xtabond2 gr loglgdp_pc lGini_disp l_csh_i l_csh_g l_hc l_AgeDep y1 y2 y3 y4 y5, gmm(loglgdp_pc,collapse) iv(lGini_disp l_csh_g l_csh_i l_hc l_AgeDep y1 y2 y3 y4 y5) nodiffsargan twostep robust orthogonal small

Abbreviation	**meaning**	**Note**
gr	Growth rate	Transformed data
loglgdp_pc	Logarithmic and lagged GDP per capita	
lGini_disp	Lagged Gini	
l_TradE	Lagged Trade	
l_csh_i	Lagged Investment share	
l_csh_g	Lagged government spending	
l_hc	Lagged Human Capital	
l_LifeExp	Lagged Life Expectancy	
l_AgeDep	Lagged Age Dependency	
l_Top_10	Lagged Top 10	

Note that y1, y2, y3, y4 and y5 represent time dummies for each one of the 5 periods.

In figure 5 there is a visual representation of the output given by Stata when the commands of column 1 are submitted.

```
. xtabond2 gr loglgdp_pc lGini_disp l_TradE y1 y2 y3 y4 y5, gmm(loglgdp_pc,collapse) iv( l_LifeExp l_csh_c l_CPI l_TradE l_hc l_csh
> _i l_Unemployment y1 y2 y3 y4 y5)  nodiffsargan twostep robust orthogonal small
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed, perm.
y5 dropped due to collinearity
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-step estimation.

Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: Country                         Number of obs      =       182
Time variable : period                          Number of groups   =        37
Number of instruments = 17                      Obs per group: min =         4
F(7, 36)      =     70.26                                      avg =      4.92
Prob > F      =     0.000                                      max =         5
------------------------------------------------------------------------------
             |              Corrected
          gr |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  loglgdp_pc |  -.0143069    .0036625    -3.91   0.000    -.0217349    -.006879
  lGini_disp |  -.0006837    .0003296    -2.07   0.045    -.0013521   -.0000153
     l_TradE |   .0000516    .0000282     1.83   0.076    -5.62e-06    .0001089
          y1 |    .000423    .0028479     0.15   0.883    -.0053528    .0061988
          y2 |   .0030935     .002596     1.19   0.241    -.0021715    .0083585
          y3 |   .0025472    .0022222     1.15   0.259    -.0019597    .0070541
          y4 |    -.00234    .0015428    -1.52   0.138    -.0054689     .000789
       _cons |   .1759157    .0468997     3.75   0.001     .0807988    .2710327
------------------------------------------------------------------------------
Instruments for orthogonal deviations equation
  Standard
    FOD.(l_LifeExp l_csh_c l_CPI l_TradE l_hc l_csh_i l_Unemployment y1 y2 y3
    y4 y5)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(1/4).loglgdp_pc collapsed
Instruments for levels equation
  Standard
    l_LifeExp l_csh_c l_CPI l_TradE l_hc l_csh_i l_Unemployment y1 y2 y3 y4 y5
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.loglgdp_pc collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -2.88  Pr > z =  0.004
Arellano-Bond test for AR(2) in first differences: z =  -2.15  Pr > z =  0.032
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(9)    =  36.92  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(9)    =  12.43  Prob > chi2 =  0.190
  (Robust, but weakened by many instruments.)
```

Figure 5- Stata output of column 1

Table 3

Column 1: xtabond2 gr loglgdp_pc l_B_50 l_csh_g l_hc l_AgeDep l_csh_i y1 y2 y3 y4 y5, gmm(loglgdp_pc,collapse) iv(l_B_50 l_hc l_csh_g l_AgeDep l_csh_i l_CPI y1 y2 y3 y4 y5) nodiffsargan twostep robust orthogonal small

Column 2: xtabond2 gr loglgdp_pc l_M_40 l_csh_g l_hc l_AgeDep l_csh_i y1 y2 y3 y4 y5, gmm(loglgdp_pc,collapse) iv(l_M_40 l_hc l_csh_g l_AgeDep l_csh_i l_CPI y1 y2 y3 y4 y5) nodiffsargan twostep robust orthogonal small

Column 3: xtabond2 gr loglgdp_pc l_Top_10 l_csh_g l_hc l_AgeDep l_csh_i y1 y2 y3 y4 y5, gmm(loglgdp_pc,collapse) iv(l_Top_10 l_hc l_csh_g l_AgeDep l_csh_i l_CPI y1 y2 y3 y4 y5) nodiffsargan twostep robust orthogonal small

Column 4: xtabond2 gr loglgdp_pc l_Top_1 l_csh_g l_hc l_AgeDep l_csh_i y1 y2 y3 y4 y5, gmm(loglgdp_pc,collapse) iv(l_Top_1 l_hc l_csh_g l_AgeDep l_csh_i l_CPI y1 y2 y3 y4 y5) nodiffsargan twostep robust orthogonal small

Abbreviation	**meaning**	**Note**
gr	Growth rate	Transformed data
loglgdp_pc	Logarithmic and lagged GDP per capita	
l_B_50	Lagged Bottom 50	
l_M_40	Lagged Middle 40	
l_Top_10	Lagged Top 10	
l_Top_1	Lagged Top 1	
l_csh_i	Lagged Investment share	
l_csh_g	Lagged government spending	
l_hc	Lagged Human Capital	
l_AgeDep	Lagged Age Dependency	