How changes in income inequality affects growth in developed countries?

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How changes in income inequality affects growth in developed countries?

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Executive Summary

As the academic field continues to be divided upon the direction of the relationship between growth and income inequality - some even finding no significant one at all - this research Thesis tries to contribute to the literature by estimating the effect on a set of 36 developed countries over a long time horizon of 53 years. The dynamic model set up is derived from a Human Capital Augmented Solow model with further variables added in line of the existing literature. The effect is estimated by both Pooled OLS, Least Squares Dummy Variables and with the Anderson-Hsiao first-differenced instrumental variable estimator. The first two estimation suffers from biases while the latter one corrects for them. The effect estimated by the Anderson-Hsiao estimator turns out to be positive and significant between income inequality and growth when the first is measured by the Gini Index - even if the effect is very small. To check for robustness, the model is re-estimated by different measures for income inequality - namely the top 1 and 10 percent pre-tax national income shares. The result of this new estimation shows the connection to be also significant, but negative and even smaller. From this we can only conclude that the measurement we choose for inequality matters a lot to its possible relationship to growth.

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1 Introduction

In the past half century the developed world has gone through a lot of change from a socio-economic standpoint: unprecedented technological and social progress, rising (than stagnating) level of globalisation, coupled with stable but mostly slowing-down economic growth. While these changes can be seen as mostly favourable, there is a quite general consensus that there is one trend besides these that may show us an appalling picture of the future: the changes in inequality.

Now inequality can be approached from many different point of views - are we talking about social inequality (racial and gender for example) or economic. Even the economic inequality is usually divided into two categories: income and wealth inequality. It is important to point out here at the beginning, that the main point of focus of the thesis is on income inequality (and its effects on growth). The idea behind the decision is that although it is true that the relationship of income generating wealth is also true backwards (wealth can generate income too), for wealth to grow, income needs to grow first. From this standpoint, choosing income inequality helps us to better understand the underlying trends that drive wealth inequality too. Also worth to mention that wealth generated income is only relevant in the top 10-20 percent of the income distribution and by focusing on wealth inequality, we would capture less from the struggles of the middle and lower classes.

So with the focus on income inequality, what we can in terms of trends is that in the past few decades the developed world experienced a sharp jump in the metric. (Cingano, 2014) - in close relation with the also drastic growth of top income shares (Förster et al., 2014; Alvaredo et al., 2013) (more on the general dynamics is discussed later in Chapter 5).

Now the question may arises - why is growing inequality important? Besides the possible moralistic point of view that rising inequality is unjust (without saying that total equality should be desirable), there are actual social and economic drawbacks that indirectly and directly can affect economic growth. Looking at the trends in growth, the dynamics of GDP per capita in developed countries are clearly showing a slowdown since the 1980's (more on the trends in Chapter 5), but it would be too easy to jump to the conclusion that this is caused by growing inequality itself.

As we will see more in depth in Chapter 2. the academic field is highly divided on how income inequality affects growth. On one side of the debate some research finds that income inequality is actually beneficial to growth. There are papers in the scientific literature that finds a positive relationship between the two even when they examine developed and developing countries together, but the most prominent finding from this side of the question is that while inequality may hinder growth for still developing countries, it is actually beneficial on the top. One of the prominent argument to support this finding is that some growth in inequality helps the top 10 or 1 percent of the society and businesses to accumulate capital more (since a growth in income inequality is stemming from weaker redistribution systems) which they then reinvest into the economy further supporting growth. In the face of growing inequality (in the developed world) this may sound wrong, but - as we will see in Chapter 5. - most of the growth in inequality in rich countries took place during the 1990's and then started to plateau with the beginning of the 21st century (while significant growth still occurred, although at a lower rate).

The other side of the argument (if we don't count the articles finding no significant relationship - which is not necessary unreasonable considering the low amount of such findings) states that growing income inequality does indeed slows down growth. Initial findings supporting the negative effect from the 1990's and 2000's were quickly critiqued as the core of the discussion shifted to the positive relationship. Prominent findings emerged again in the 2010's - most probably due to a paradigm shift in economics after the 2008 financial crisis. Nowadays, growing inequality and its possible negative effects are highly dominant in not just the economic field but on political sciences and sociology too.

What we can see in this short brief of literature of findings is that the topic - still to this day - is highly divisive (besides showing that there is some element of periodicity in the reported effects, which is touched upon in the literature review). This level of heterogeneity in research makes room for new approaches to estimate the relationship, let this new approach be only a different set of countries, different estimation methods, different variables used or just different time horizon examined - all of which can change the significance of the estimation.

The methodologies used in mentioned researches are also highly differing with some setting up the model in a static panel or in a dynamic one (the one the Thesis will utilise). To estimate the latter classic Least Squares Dummy Variables, simpler IV estimations or Generalised Method of Moments estimation are usually used. As it was shown, the methodology chosen can affect the significance of the estimated effects - something that is reproduced in this Thesis.

This research thesis dives deep into the topic, hoping to find an estimation that can contribute to either side of the discussion. For this we estimate the relationship in a dynamic panel model (the lag of the dependent variable is used as an independent one) between the household disposable income Gini coefficient (using the SWIID data set) and real growth in GDP per capita in a set of developed countries. Other control variables are included in line of the existing literature. Later we also re-estimate the model substituting the Gini index for top income share as a measure of inequality for robustness. The model set up closely follows the Human Capital Augmented Solow model derived by Mankiw et al. (1992) from the neoclassic Solow growth model. The effect is estimated with three different estimation techniques: basic Pooled Ordinary Least Squares (Pooled OLS), Least Squares Dummy Variables and the Anderson-Hsiao IV estimation (with only the latter proving to find robust results for the panel data in use). From this point on, the paper is built up as follows: the second chapter serves as the literature review, followed by the presentation of the data used and the model with the methodology chosen. Then after a short detour to explore the trends in growth and inequality (with possible channels existing between them) we present the estimation and draw our conclusions.

2 Literature Review

As mentioned previously, the literature on the relationship between income inequality and growth is highly divided. One of the main source of this heterogeneity comes from the inherent constrains of this field of research: namely, available data for income distribution is highly heterogeneous (Cignano, 2014), while Dominicis et al. (2008) states that different estimation methods and the quality of the data used also influence the results. Since the literature is so heterogeneous in the matter, taking a look behind the possible reasons for it would be beneficial for the thesis.

Here it is important to note that some meta-analytical article differentiates between theoretical and empirical research. In our case, we do not take this distinction and we focus our attention to the empirical part of the field. The theoretical part - focusing on the channels through which inequality can affect growth - is already partly covered in the previous chapter. Regarding the empirical literature, it is also worth noting that the published articles in the topic seem to follow a pattern over time with positive and negative results being reported cyclically (Neves et al., 2016) - this points to some sort of recency-bias in the literature. Neves et al. (2016) also shows an invested U-curve with reported results on the y-axis and time on the x-axis (beginning in 1990).

With that in mind, the literature review is divided into 2 parts: first we review the papers based on their results (are they estimating the relationship to be negative, positive or not significant), then we take a brief methodological overview of the literature to find out what kind of estimation methods are usually used in the field (and what results they produce).

2.1 Negative relationship

Earlier researches on the matter mainly in the 1990's (reaching into the 2000's of course) focused mostly on cross-country and cross-sectional analysis like Alesina and Rodrik (1994); Clarke (1995) or a bit later Panizza (2002) - although he measures the effect only in the US comparing states as cross-sectional individuals. These studies are not only common in their nature but in their results too estimating the effect to be mostly negative. There is however a common critic against these studies, namely that they are highly prone to omitted-variable bias since there are a lot of factors that can have a significant (but unobservable) effect on growth (like technological advancement, cultural differences, institutional systems, etc.) - these critics however can be applied to any research in this field.

Later as more data became available thanks to the data set of Deininger and Squire (1996), this initial quasi-consensus on the negative nature of the relationship was called into question. Knowles (2005) for example argues that the comparability of income distribution data between countries is still a source of concern, since the definition of income - either gross income or expenditures - differs across countries. In light if this, he initially finds that "the significant negative correlation between income inequality and growth across countries may not be robust when income inequality is measured in a consistent manner". In spite if this, the article still belongs to this subsection since he also adds that when we estimate the effect of consistently measured inequality of expenditure data on economic growth, we find a significant negative relationship - although he finds this on a set of developing countries (while our focus is on developed countries).

Around the tun of the millennium some papers also called into question the linear nature of the relationship. Banerjee and Duflo (2003) for example brings back the inverted U-curve into the debate (rhyming with Kuznets) but with a twist: the paper states that a change in income inequality - in any direction - results in reduced growth in the next period (with showing the change in Gini on the x-axis and the growth on the y-axis, we can see a bell-curve taking shape - or an inverted U-curve with respect to Kuznets).

After a period during the 2000's when most research papers published argued for a positive relationship between inequality and growth (especially in affluent countries - more on this later), with the beginning of the 2010's the rhetoric shifted back to argue for the negative relationship. This new shift may be attributed to the 2008 financial crisis which caused a paradigm shift in the field of economics - most notably by ending the dominance of the neoliberal school of thought and halting the expansion of globalisation (two phenomenons that heavily attributed to the growth of inequality). The re-ignition of the debate around income inequality and growth can be partly attributed to Piketty (2014) - who showed new perspectives on the prospects of growing inequality (inverting the Kuznets-curve and stating, that inequality is growing when the returns to capital are higher than the growth rate of the economy) -, or the works of Stiglitz (2015a,b). Another influential book in the topic - may it be more on the theoretical side - was the once already mentioned book of Milanovic (2016), who (besides else) proposed the idea of the Kuznets waves.

With this renewed interest in the topic, came along more empirical evidence on the possible negative relationship. One of the most cited papers supporting this comes from Cignano (2014), who showed that in OECD countries a 1 point decrease in Gini "would translate to an increase in cumulative growth of GDP of 0.8 percentage points in the following 5 years (or 0.15 points per year)". Another OECD (2014) publication of the same year showed that a 3 point rise in the Gini index would hinder economic growth by 0.35 percentage point per year for the next 25 years - resulting in a cumulative loss of 8.5 percent in GDP in developed countries.

Other highly cited papers from non-institutional researchers also argued for the negative relationship from various perspective. Berg and Ostry (2017), Berg et al. (2018) and Royuela et al. (2019) states that higher (income) inequality hinders growth, although the first two examines a more broader set of countries (the latter one focuses on advanced countries) while agreeing that redistribution alone won't solve the problem. In this regard the first study claims that it is insignificant, the second states that while "redistribution has a benign effect on growth, except when its extensive". Halter et al. (2014) argues that growing income inequality fosters growth on the short-term but hinders it on the long-term (with a net total effect being slightly negative). Using panel cointegration, Herzer and Vollmer (2012) also finds the effect to be negative on the long-run - both on the whole sample and in important sub-groups, even in developed countries.

This distinction between country-groups is quite important when we examine the relationship of inequality and growth. Several studies that take a wide cross-sectional sample with both developed, emerging and developing countries find that while the effect may be negative on the whole sample, it vanishes or turns positive when regional dummies are added as argued by for example Perotti (1996). In line of this, we now go over the literature that supports the finding that growing inequality is beneficial to growth.

2.2 Positive relationship

As mentioned before, with the beginning 21st century, the scientific consensus surrounding the negative nature of the relationship began to be challenged - mainly as new methods got adapted. Similarly to Perotti (1996), the highly cited works of Barro (1999, 2000) reaches the concluding remarks that, when taking a broad set of countries into consideration, while the effect may be negative or insignificant on the whole sample, it turns positive in rich countries - both utilises new data and new techniques of estimation compared to earlier studies. A bit later but relevantly here, Voitchovsky (2005) finds (on a set of mostly developed countries) that the shape of the income distribution matters a lot and that inequality is beneficial to growth at the top of the distribution, while also hinders it at the bottom.

Besides these another important paper in the topic from this time period comes from Forbes (2000), who shows a positive effect across the whole sample when country specific effects are taken into account (with a sample including both developed and developing countries) on both short and medium term. Castelló-Climent (2004) estimates the effect in a dynamic panel model with human capital inequality also included, finding a positive effect for income inequality (while pointing out that human capital inequality is actually related to lower subsequent growth rates - both on the long and short-term).

Notwithstanding the recent resurgence of research finding more and more evidence on the negative effect, the literature around the positive effect has not dried up. Castelló-Climent (2010) for example shows similar results as previously discussed: taking into account country-specific effects and the persistency of the inequality indicators across countries with different level of development, the paper finds that that while both income and human capital inequality has a negative effect on the whole sample, this effect disappears or turns into a positive effect when only looking at richer countries. Shen and Zhao (2023) estimates similar effects and Grigoli et al. (2016) finds that the effect is positive for one quarter of the countries in his sample (and negative on the whole - as usual).

2.3 No significant relationship

Now that we see the positive and negative estimates in a somewhat cyclical form (the border between them is naturally not clear-cut), we have to mention that that there are studies across the cycles that show no significant relationship between income inequality and growth. This topic is not widely touched upon and that may not come as a surprise - both Neves et al. (2016) and Dominicis et al. (2008) finds traces of publication bias (besides the time pattern of reported results) in a sense that statistically significant results get published more as both authors and journals prefer to publish these results. The latter also adds, that negative results are also usually overrepresented [1] while results deemed ”more interesting” also gets to be published more often.

In light of this, finding literature that estimates statistically no significant results is quite a challenge - but they exist. Perotti (1996) for example finds that once the regional dummies are added to the regression, the relationship becomes insignificant while Barro (2000) estimates that when both developed and developing countries are examined at the same time, the effect is similarly insignificant. From the same time period Kenworthy (2003) also finds no significant trade-off examining 15 rich countries - the same is true when only looking at the states of the US. From a more recent time Ogus Binatli (2012) also finds no significant relationship when looking at the trends of the 1970’s and 1990’s separately.

[1] Now while this is because the effect is in fact more negative than positive, or just a publication bias influenced by current social trends is hard to answer.

2.4 Methodologies used

As we can see, the academic literature is highly divided on the matter with differing results following each other in kind of a timely manner. An explanation for this kind of heterogeneity can be that most of it is a product of the different measurement types, data used, the quality of the data and the countries (or group of countries examined). In this regard, even the meta-analytical findings of the literature contradict each other - while Neves et al. (2016) states that the above listed factors do not influence the estimated effect size, Dominicis et al. (2008) arrives to the opposite conclusion that estimation methods, quality of data and coverage does influence results. Bleaney and Nishiyama (2004) examine how different growth model specifications affect the estimated relationship (testing three types of specifications and different independent variables). They find that while the estimated effect may be similar in high- and middle-income countries, the coefficient differs significantly between models, suggesting that the growth specifications are not really robust. If we look at how the different methodological approaches followed each other, we can see this heterogeneous effect more clearly.

As highlighted in the previous section, early literature in the topic from the mid-1990's mainly centred around cross-sectional (cross-country or cross-state in case of the US) estimations. These studies from Alesina and Rodrik (1994); Clarke (1995) and Panizza (2002) have mostly used a reduced-form growth regression in a similar manner as below:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \delta INEQ_{it} + u \tag{1}$$

Where Y_{it} is the growth, usually measured taking the natural log of the GDP per capita (or just the GDP itself) then subtracting the first and last value of the examined growth period (for example $lnY_{it} - lnY_{it-\pi}$). This growth rate is then regressed on a set of explanatory variables. $INEQ_{it}$ is inequality (measured by either Gini or income-shares usually) and X_{it} is a set of other control variables that are usually used in growth-regressions (u is the error term). The mentioned studies usually estimate the regression with OLS (the latter one also estimates it with standard fixed effects and GMM) in order to estimate the δ. To avoid reverse causality, the inequality is measured at the beginning of the examined growth period. One common critic against these kind of regressions is that cross-sectional estimates are prone to omitted variable bias - other Unobservable factors like culture, institutions, technology and other country-specific variables can influence growth rates and be correlated to the other explanatory variables too (Dominicis et al., 2008).

One solution to this problem is to assume that these country-specific characteristics are not changing over time (some of them may change slow enough to consider it stable - like climate or culture) and using longitudial data instead of cross-sectional. By doing so, we can estimate the relationship with a fixed or random effects model that allows us to control for these unobservable variables. In the case of growth regressions using panel data, random effects is rarely used since it requires the country-specific effects to be independently distributed of the explanatory variables - this requirement is hard to meet since growth is partly influenced by these unobserved effects.

Problems with fixed effects start to arise too when we start to examine the effect in a dynamic panel model (where the lagged value of the dependent variable is also a regressor). Dynamic panel models are widely used in growth-theory based on the simple intuition that past level of development affects the current growth rate. When we incorporate the lagged values of the dependent variable as an independent one however, serious endogeneity issues arise since the lagged dependent variable is, by design, correlated with the error term (since Y_{it} is a function of the error term, it follows that $Y_{it-\pi}$ is also a function of the error, creating endgeneity bias). The problem with this is that the fixed effects estimation method does not necesarrily control against this problem - although Nickell (1981) finds that with T approaching infinity, the bias tends to zero.

Nevertheless, in the 1990's a new estimation method was developed by Arellano and Bond (1991) to properly estimate dynamic panel models (even with smaller T) with the name of Generalised Method of Moments (GMM). GMM is a form of an instrumental variable estimation where the instruments are the lagged values of the variables while utilising the orthogonality conditions that exist between lagged values of the dependent variable and the disturbance term. GMM exists in two forms: the first-difference GMM (which just as the regular first-differencing method, takes away the unobservable heterogeneity by taking the first difference of the model), and the system-GMM method - extending upon the original Arellano-Bond estimator by Arellano and Bover (1995). The main point of system-GMM is that it uses moment conditions based on the level equations together with the usual Arellano and Bond type orthogonality conditions. Since the introduction of the GMM, it has been one of the most widely used estimation method in growth models - not only for its high efficiency but also because it requires less strict assumptions on the data.

As it turns out however, GMM still has some drawbacks that limits its applicability. Most importantly, GMM is especially useful for so-called "short panels" where we have a relatively large set of cross-sectional units with over a small time-period ("large N, small T" setting). The main idea of GMM is to minimise the Nickell-bias which, over a short time-period, can be very large (the metric of the bias can be seen in Chapter 4.). On long panels however with smaller N cross-sectional individuals (as in our case), the GMM suffers from instrument proliferation and becomes inconsistent. Judson and Owen (1999) for example only recommends GMM or the Anderson-Hsiao estimator for panels with $T \leq 10$ or with $T = 20$. At $T = 30$ for unbalanced panels (again, as in our case) they recommend the use of LSDV.

As we can see from the literature review, the findings on the relationship between growth and income inequality is very heterogeneous. Besides this, we can also see a pattern in the estimation results with the positive or negative relationship being more popular in different time periods during the last three decades - while insignificant findings are more rare (thanks to in part of the publication bias affecting hiding them).

With this solid understanding of the previous literature we can begin our own investigation. First we take a look at the data used to build the model.

3 Data

To describe the data set we begin with the time-horizon and the cross-sectional units. In the Thesis, we examine a group of 36 developed countries ($N = 36$) from all over the world. The original idea was to only include the countries in Western-Europe and North America which are fairly similar with each other, but to allow some level of heterogeneity in the data, more developed European post-socialist and East-Asian countries also got included with Australia and New-Zealand added too (the full list of countries can be seen in the Appendix Table A1.). After the original data collection, a few countries were dropped from the data set because of no proper data coverage (from the macro-data). The dropped countries included small ones like Andorra or San Marino or Israel.

There are many other statistically rich countries that could have been included in the data set like Singapore, or the rich oil-countries of the Middle East. These countries were left out of consideration because of the highly different economic profiles and market structures compared to the included countries. The Middle Eastern countries also do not have the best data coverage for our purposes. Besides these, including these countries would have just increased the unobserved heterogeneity even more and would have made the estimates less consistent.

As for the time-horizon, the main idea was to examine the relationship on as long of a time horizon as possible. The original data set was collected from the year 1960 (where the SWIID Gini data starts) until 2022 but because of the lot of missing values in most countries between 1960 and 1970, the examined time horizon was reduced to 1970-2022. The Gini data for inequality was available for the longest term but for most countries, the macro-data starts at around 1970 (for post-socialist countries, the macro-data usually starts at around 1990).

For the regressions, secondary, macro-level data are utilised - all of them collected from the World Bank's Databank (from different data sets). The dependent variable in the model is the five year cumulative growth of the countries' log-transformed (natural) GDP per capita. This data was retrieved from the organisation's World Development Indicators (WDI) data set. Data are in constant 2015 U.S. dollars.

The question may arise that wouldn't it be better to use the PPP GDP Per capita for better comparability, but there are reasons why it is not used here. First of all the main reason for using 2015 constant dollars is that the PPP data are not available for as long time horizon. Most of the PPP GDP data - not just at the World Bank - starts only in 1990, while the one measured on 2015 USD prices reaches far more back in time (until 1970 or even 1960 in some cases). This is very important for the thesis since the main goal here is to estimate the effect on an as long time-horizon as possible. The loss of better comparability between the countries' income level is also not a big problem since we are less interested in how the countries development relate to each other, we are interested in the trends in their development (and the effect of inequality on it).

As we can see in the summary table (Table 1.) below, the cumulative 5-year growth (calculated simply as $Growth_{it} - Growth_{it-5}$) has a mean of 11.27 percent with a high standard deviation of 10.41. The lowest value is at -29.61 percent (this high fall in GDP per capita happened in Greece n 2012) while the highest one is at 62.62 percent (produced by Malta in the 1970's). Besides the growth rate, all the data in the summary table are presented in their raw, untransformed form.

Table 1. Summary Statistics

		Mean	Std. Dev.	Min	Max	N/n/T-bar
Growth	overall	.1127	.1041	-.2961	.6262	1390
	between	.	.0615	.0442	.2774	36
	within	.	.0862	-.2275	.5180	38.61
Gini Index	overall	28.784	3.9683	16.8	38.6	1421
	between	.	3.421	23.19583	35.35	36
	within	.	1.9868	20.3875	35.3757	39.47
Top 1pc share	overall	0.0971	0.030	0.0251	0.1948	1388
	between		0.0193	0.0616	0.1454	36
	within		0.0230	0.0273	0.1730	38.56
Top 10pc share	overall	0.324	0.0498	0.1669	0.4559	1388
	between		0.0346	0.2631	0.4053	36
	within		0.0359	0.2065	0.4319	38.55
HC	overall	9.3770	1.7652	2.93	13.18	1476
	between	.	1.2806	5.7659	12.2239	36
	within	.	1.2331	6.0482	12.8943	41
Public Expenditures	overall	18.707	3.7038	8.88	30.32	1481
	between	.	3.0905	11.0029	25.0871	36
	within	.	1.9849	11.5459	27.9088	41.14
Gross Capital Formation	overall	24.743	4.8923	11.89	48.28	1481
	between	.	2.8243	20.3973	32.5523	36
	within	.	4.0083	10.4652	46.8552	41.14
Inflation	overall	13.406	78.4149	-4.48	1500	1565
	between	.	28.8767	2.3829	146.4513	36
	within	.	74.3418	-134.175	1366.955	43.47
Trade Openness	overall	83.488	52.4218	10.76	353.79	1481
	between	.	45.9681	21.3842	227.1158	36
	within	.	22.9666	-7.6425	210.1623	41.14

Source of data: World Bank Databank, SWIID v.9.4, World Inequality database

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In the model the Inequality is measured by three different statistics for robustness. First and foremost in the baseline regressions inequality is measured by the household disposable income Gini index. The data for this is collected from the Standardized World Income Inequality Database (SWIID) of Solt (2020) - the latest version was updated in 2022. There are numerous databases for different measures of income inequality but if we want to examine the relationship of growth and income inequality on the longest time horizon possible, it would be ideal to have a database that collects the different estimations for the Gini-index. Collecting them is not enough however because different institutions use different techniques to measure the index. In order to make the different databases comparable, the data needs to be standardised (and fill out for missing data with further imputation). For this purposes, the SWIID serves as the best available option.

The Standardized World Income Inequality Database (SWIID) uses a Bayesian approach to standardise the Gini Index observations from the OECD Income Distribution Database, the Socioeconomic Database for Latin America and the Caribbean produced by CEDLAS and the World Bank, Eurostat, the World Bank's PovcalNet, the UN Economic Commission for Latin

America and the Caribbean, and from various national statistical offices besides other sources. The Luxembourg Income Survey data serve as a standard.

As described by Solt (2020), the database tries to maximise the comparability of available data for the broadest possible selection of countries and years. Despite of this, incomparabilities are still present which sometimes can be substantial - these are reflected in the standard errors of SWIID estimates. As the author states, it is often critical to account for this uncertainty when making comparisons across countries or over time (Solt, 2020). Originally, the inequality estimates and their associated uncertainty are represented by 100 draws from the posterior distribution: for any given observation, the differences across these imputations capture the uncertainty in the estimate. While ideally any model should be estimated with the 100 imputation of a variable used, unfortunately Stata (the program used for the Thesis), does not allow this for every command and problem arises with the estimation used in this Thesis. To solve this issue, the summary statistics (Mean-plus-standard-error Summary Format) of the SWIID database was utilised for the estimation. As the name suggests, this contains the means and standard errors of the 100 imputation of the different inequality estimates.

Now while this may cast some doubt on the applicability of the data set when conducting analysis, but there are a few explanation on why using only the means is sufficient for the purpose of the current analysis. The estimated statistics uncertainty heavily depends on the country for which it was imputed for. For countries (mostly poorer or developing ones) with less general coverage in data (regarding inequality) we can expect higher level of standard errors in the imputed statistics since there are more gaps in the collected data and estimates from different institutions can differ at a higher level. In developed countries the data coverage is higher with different institutions more likely to estimate similar levels of Gini. This can be seen in the data set too: when we only look at the summary statistics of the countries examined in this Thesis, the average standard error of the mean Gini Indexes is only 0.99 (while the average household disposable income Gini is at 28.78 - as can be seen in the summary table. With this in mind, we can be more assured that the summary statistics of the data set is representative of the actual dynamics.

After the Gini, the relationship between growth and inequality is re-estimated by the top 1 and 10 percent income shares (share of the pre-tax national income) retrieved from the World Inequality Database (WID). Pre-tax national income is the sum of all pre-tax personal income flows accruing to the owners of the production factors, labour and capital, before taking into account the operation of the tax/transfer system, but after taking into account the operation of pension system. The central difference between personal factor income and pre-tax income is the treatment of pensions, which are counted on a contribution basis by factor income and on a distribution basis by pre-tax income. The population is comprised of individuals over age 20. The base unit is the individual (rather than the household) but resources are split equally within couples.

As we can see in Table 1. both the top 1 and top 10 income share data have a relatively low standard deviation. The top 1 percent share ranges from 0.0251 to 0.1948 (which is an extraordinary high value if we think about it), while the top 10 percent share ranges from 0.1669 to 0.4559 (a quite high number again).

The second important independent variable in the model is the Human Capital. To measure Human Capital, the average years of schooling among the population older than 15-years was used. The data was extracted from the World Bank's Databank. This statistic also posed some problems since the data is only reported with 5-year intervals between 1970 and 2010 (meaning that there is no data between 2010 and 2022 like with the other macro data). This many missing data in a panel regression (later estimated) causes the estimates to be highly inconsistent and biased (a lot of observation would be omitted from the regressions because the missing data between the 5-year intervals is causing collinearity).

To solve this problem, the missing data between the existing observations were filled out by calculating a simple linear interpolation between the already existing data points. While this may cause further concerns regarding the accuracy of the calculated estimations, the clear linear trends and low variance in the schooling data shows that this is not a high concern - if anything, this just makes the estimations more accurate and consistent. This can be visually confirmed too below in Figure 2.

Figure 1: Actual and Imputed Average Years of Schooling (population above 15-years)
Source: Own calculation. Data from: World Bank Databank

This imputation does not solve the problem of the missing values after 2010 since that kind of extrapolation would indeed make the estimations a bit more inaccurate and inconsistent. Besides this, the last 5 years of observation will get dropped from the regressions (by design - as we will see later), so the missing values from this time period only exist between 2010 and 2017. When we measure the effect with a T of 53, a few years of missing value from the is not a reason for concern.

Regarding the rest of the control variables, Public Expenditures is measured by the general government final consumption expenditure (percentage of GDP). The data was collected from the World Bank's Databank - like the rest of the remaining variables. The general government final consumption expenditure (formerly officially general government consumption) includes all government current expenditures for purchases of goods and services (including compensation of employees). It also includes most expenditures on national defence and security, but excludes government military expenditures that are part of government capital formation. As we can see in Table 1. of the summary statistics, there are quite some variability in government expenditure between the examined rich countries. The lowest observation comes in at 8.88 percent while the highest one is 30.32 percent. The higher level of overall and between standard deviation also points to this phenomenon.

The Gross Cpital Formation variable is pretty straightforward in a sense. Gross capital formation (formerly called gross domestic investment by the World Bank) consists of outlays on additions to the fixed assets of the economy plus net changes in the level of inventories. Fixed assets include land improvements (fences, ditches, drains, and so on); plant, machinery, and equipment purchases; and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings. Inventories are stocks of goods held by firms to meet temporary or unexpected fluctuations in production or sales, and ”work in progress.” According to the 1993 System of National Accounts, net acquisitions of valuables are also considered capital formation.

Another control variable in the model is the inflation percentage in annual form. Inflation as measured by the consumer price index (CPI) reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly. The Laspeyres formula is generally used by the World Bank to estimate the statistic.

This variable has by far the highest level of variation and standard deviation (which is six times higher at 78.4 than the statistics mean value of 13.4 percent value) which points to an abnormal distribution of data. When we look at the maximum value of 1500 percent in Table 1, that is not a measurement or a typographical error. There are more than 20 observation for inflation above 100 percent (and many more above 40 percent even) and there are four more around or above 1000 percent. These extraordinary jumps in inflation almost all come from former socialist countries in our sample from the early 1990’s, as with the fall of socialism, severe economic downturn occurred in most of these countries (for inflation, the turn to a market economy and the consequent phasing out of price controls and fixed exchange rates resulted in hyper-inflationary situations).

Although these outlier observations in the inflation may be a cause of concern again for the accuracy of the estimations, it is worth noting that since the dependent variable is the 5-year cumulative growth, one year shocks have a way lower effect on the overall results (they also fizzle out with the long time-period used).

Last but not least, trade openness is also taken into account for growth. Trade in this case - as measured by the World Bank - is the sum of exports and imports of goods and services measured as a share of gross domestic product. Trade openness also have a high variance with the standard deviation being more than half of the mean value. We can see on the summary table that the minimum value is at 10.76 percent (of GDP) while the maximum is at 353.79 percent.

4 Model and Methodology

4.1 The Model

The relationship between growth and inequality will be explored on a set of developed countries from Western, Middle and Southern Europe, North America, East-Asia and including Australia and New-Zealand.

To examine the relationship, we set up a dynamic panel data model, derived from the neoclassical Solow growth model similarly to Cingano (2014), Castelló-Climent (2010), and Halter et al. (2014). To be more precise, we employ the Human Capital Augmented Solow Model developed by Mankiw et al. (1992) to account for human capital accumulation - the main channel that is disrupted in theory by growing inequality. Mankiw et al. (1992) showed that empirical growth equations similar to the one analysed in the Thesis can be derived from a neoclassical Solow growth mode. To derive the model, Mankiw et al. (1992) starts with a classic Cobb-Douglas production function takes the following form at time t:

$$Y(t) = K(t)^{\alpha}(A(t)L(t))^{1-\alpha} \qquad 0 < \alpha < 1 \tag{2}$$

In this equation, we can input human capital too as a factor of production. In this case we get the following formula:

$$Y(t) = K(t)^{\alpha}H(t)^{\beta}(A(t)L(t))^{1-\alpha-\beta} \tag{3}$$

where Y, K and H are output, physical and human capital respectively, L is labour, A is labour augmenting technology and α and β are the partial elasticities of output with respect to physical and human capital. Just as it is set in the Solow model, L and A are growing at the rate of n and g respectively. This also means that the effective units of labour $A(t)L(t)$ is growing at the rate of $n + g$, while physical capital is depreciating at rate of δ.

If we assume a savings rate of s_k and s_h (fraction of income invested) for physical and human capital respectively, and define the quantities in the above equation 2. in terms of unit of effective labour input $A(t)L(t)$ (thus obtaining $y = Y/AL$, $k = K/AL$, and $h = H/AL$) the evolution of the economy is then determined by the below equations:

$$k(t) = s_k y(t)(n + g + \delta)k(t) \tag{4}$$

$$h(t) = s_h y(t)(n + g + \delta)h(t) \tag{5}$$

We can solve the above equations for k^* and h^* to obtain their steady-state values (or steady-state stocks) of physical and human capital - if we assume a decreasing returns to reproducible factors. These newly solved equations expressing the steady state can be substituted back into the original equation (and taking logs) to arrive to the expression for the steady-state output in intensive form. This intensive form of output can be expressed either with s_k (which stands for the investment into human capital - expressed for example government spending on education) or with $h*$ (the steady-state stock of human capital - expressed for example by mean years of education of diploma attainment ratios). In the context of the Thesis, the second option was chosen as investment into human capital in a current year would only take effect on a very long term (and we are already taking into account the delayed effect of income inequality) while steady-state stock can effect contemporaneous growth rates. So with taking human capital stock into account (and investments to physical capital s_k - proxied by for example gross capital formation as in the Thesis, we arrive to the below steady steady-sate output:

$$lny = lnA(0) + gt + \frac{\alpha}{1-\alpha-\beta} lns_k + \frac{\beta}{1-\alpha-\beta} lnh^* - \frac{\alpha+\beta}{1-\alpha-\beta} ln(n+g+\delta) \quad (6)$$

Where (just to reiterate) lny is the log of the output in efficiency units, $lnA(0)$ is the log of the labour augmenting technology at time 0, gt is the growth in time t, lns_k is the log of investment into physical capital, lnh^* is the steady-state stock of human capital and $ln(n+g+\delta)$ is the growth rate of effective units of labour plus the depreciation of physical capital.

If we for this equation into a dynamic one to express the growth rate of the output, we arrive to the following equation which serves as the final one before we substitute with and add to our variables at hand:

$$\begin{aligned} &lny(t) - lny(t-s) = \\ &\phi(\lambda) lny(t-s) + \phi(\lambda)\frac{\alpha}{1-\alpha-\beta} lns_k + \phi(\lambda)\frac{\beta}{1-\alpha-\beta} lnh^* - \phi(\lambda)\frac{\alpha+\beta}{1-\alpha-\beta} ln(n+g+\delta) \end{aligned} \quad (7)$$

Where the new elements of λ stands for $(n+g+\delta)(1-\alpha-\beta)$ and $\phi(\lambda)$ equals $(1-e)^{-\lambda s}$.

The baseline regression model extends upon the above equation with further variables added and substituting in for the physical capital formation and the stock of human capital. Thus, the equation to estimate the effect looks like this:

$$Y_{it} = \beta_0 + \beta_1 Y_{it-1} + \beta_2 Ineq_{it-5} + \beta_3 HC_{it-5} + \beta_4 X_{it-5} + \delta_t + \alpha_i + \epsilon_{it} \quad (8)$$

The left hand side of the equation, Y_{it} is the 5-year cumulative growth of GDP per capita at time t for country i (or mathematically $Y_{it} = lny_{it} - lny_{it-5}$). On the right hand side, the lny_{it-5} stands for the lagged dependent variable which makes the model dynamic. Besides this, the main independent variable is $Ineq_{it-5}$, which is the initial level of income inequality. HC_{it-5} is the initial level of stock of human capital. X_{it-5} denotes a set of control variables that include investment share, government expenditures, trade openness (all measured in percentage of GDP) and inflation to control for economic stability. These variables were included based on Shen and Zhao (2023) and Gründler and Scheuermeyer (2015) - the latter highlighting that similar variables are proven to explain empirical growth patterns quite accurately. β_0 is the constant term while the other β's stand for the parameters for the variables. δ_t is the unobserved time-invariant effect, α_i is the unobserved heterogeneity across countries and ϵ_{it} is the idiosyncratic error term.

4.2 Methodology

Looking back at the final model in Equation 8. we can see that the lagged dependent variable is only lagged by one year, while the rest of the explanatory variables are lagged by 5 years. The explanation behind this is that since we are estimating growth over a 5-year period, including the lag of 5-years would result is severe measurement error ending up in unavoidable autocorrelation in the error terms. This is caused by the fact that the dependent variable Y_{it} already contains the lagged term of lny_{it-5} which would just show up twice again in the 5-year lag of the dependent variable. To avoid this, we are lagging the dependent variable by only 1-year. This also makes sense theoretically, since as opposed to the other independent variables, the cumulative growth 5-years ago is less impactful on the current growth (if not for the measurement error).

The parameters in the model - deviating from the original idea and proposal - will be estimated with various regressions. Originally, the parameters of the model would have been estimated by the System GMM estimation technique, but after careful testing and investigation, the estimation method was dropped - supported by the academic literature too (more on this later after we discussed the used methods).

The first question that may arise with regards to the model, is why choose a dynamic model to estimate the relationship instead of a static one. First reason behind the choice is the nature of the data and the variables. Dynamic panel data models are widely used in macroeconomics, development economics, and labour economics to analyse relationships usually across countries that involve dynamic adjustment processes. These models can account for unobserved heterogeneity (fixed country-differences or time-invariant effects) and endogeneity issues by including lagged values of the dependent variable and other covariates in the specification. Besides this, a dynamic model can capture important information that a static one may miss out on resulting in omitted variable bias.

When it comes to growth (the main topic if this Thesis), most empirical growth models are based on the hypothesis of conditional convergence, thus equations estimating it usually contain a lagged level of output too. Besides the conditional convergence, it is indeed a highly reasonable assumption to say that last years growths (and maybe even the previous ones) have an effect on the current growth rates. Not calculating in past growth rates when estimating other variables' effect on growth could produce a significant omitted variable bias. Taking all these into account, and looking at our data at hand, it is only reasonable to estimate the relationship of income inequality and growth in a dynamic setting.

This dynamic setting however poses major challenges when it comes to choosing the right estimation technique since the presence of the lagged dependent variable causes problems that are hardly circumventable with a simple Ordinary Least Squares (OLS) estimate. The problem with applying OLS to dynamic panels is that it fails to account for the correlation between the lagged dependent variable and the fixed effect in the error term, which can arise due to the presence of unobserved individual-specific effects. For example, in our context, an external shock to growth in one of the countries (like how Greece was hit harder by the Euro debt-crisis than most other countries), if not accounted for, will show up in the error term. Thanks to this, the fixed effect for that country will appear lower. In the year following the shock, the lagged growth rate will also be lower for that country - together with the fixed effect creating a correlation (endogeneity).

In spite of this, a pooled OLS model might still be an appropriate first step when estimating the result to see the general direction of the relationship - even if the estimation results are highly biased.

The first attempt to solve this issue is to introduce a fixed effects or first differencing estimation that through demeaning, would get rid of unobserved heterogeneity in the model. The problem with these procedures is that both the demeaning and first differencing creates further biases in the estimation. The most important issue with estimating dynamic panels with fixed effects or first differencing is called the Nickell-bias, discovered by Nickell (1981). It occurs because the within transformation used in fixed effects estimation creates a correlation between the lagged dependent variable and the error term. The mean of the lagged dependent variable contains observations 0 through $(T$−$1)$ on y, while the mean error — which is being conceptually subtracted from each ϵ_{it} — contains contemporaneous values of ϵ for $t = 1...T$. This correlation results in a bias that won't disappear if the cross-sectional units (N) are increasing either. In terms of first differencing the case is very similar but with the previous values getting subtracted to get rid of the fixed effect. This can be shown by the below equation:

$$y_{it} - y_{it-1} = \beta_0 + \beta_1(y_{it-1} - y_{it-2}) + \beta_2(x_{it-1} - x_{it-2}) + (u_{it} - u_{it-1}) \quad (9)$$

What the first differencing here does is that it creates a correlation between the terms $\beta_1(y_{it-1} - y_{it-2})$ and $(u_{it} - u_{it} - 1)$ since y_{it-1} is correlated to $u_{it} - 1$.

In theory, there is an important remedy however for both model's applicability for dynamic panel. Nickell states that the bias in the coefficient of the lagged dependent variable (let it be called ρ)is that of an order $1/T$, meaning that as T gets higher, the bias will be lower. In theory, this Nickell-bias is really only a cause for concern in "large N, short T" panels where the shocks to the dependent variable in a year can have a huge effect on the fixed effect in the error term. As T approaches infinity, this effect fizzles out. As Nickell shows, for relatively large $T's$ the limit of $(\hat{\rho} - \rho)$ can be calculated as −$(1 + \rho)/(T$−$1)$. We can put this equation to use with our own estimates to see how much of a bias we are dealing with. As our fixed effects estimation estimates a ρ of 0.8623 (a relatively high number - although statistically not significant, as we will see it later in Chapter 6.), and with a $T = 53$, our bias is -0.0358 - which is only 4.1 percent of the actual value. This result is in line of the existing literature on how to estimate dynamic panels. Judson and Owen (1999) for example finds that for long, unbalanced panels (as in our case) LSDV proves to be an efficient estimator - the possible bias at $T = 30$ (their highest T estimated) heavily depends on the ρ value. The higher the estimated coefficient, as T approaches infinity, the bias will fall too.

Considering this, LSDV has a room for itself in estimating the model since the main source of the bias is tackled by design - although other problems arise when we apply for it on our data. As we will see in Chapter 6. at the results, the fixed effect estimation still shows the lagged dependent variable as endogenous - although its bias, as shown above, is negligible. That said, there is no harm in estimating the model correcting for this endogeneity. Even so, since as we will see the LSDV estimation suffers from heteroskedasticity and serious serial correlation - both of which render the model as biased, especially the latter.

Another approach that can be taken to tackle the Nickell-bias and to solve for existing heteroskedasticity and serial correlation is to instrument the suspect endogenous lagged dependent variable. It is worth pointing out here that the models in question and the ones we use all require the other variables to be exogenous. This requirement however can be eased as we turn to our final estimation method. When using fixed effects, the strict exogeneity assumption is weaker in a dynamic panel setting. To solve this we can turn to the weaker assumption of sequential exogeneity which assumes that the present errors are only uncorrelated with the past values of the other regressors.

With that said, we can try to estimate the parameters in our model with an Instrumental Variable (IV) estimation. There are two short problems with a regular IV estimation: first, a simple IV estimation would still not get rid of the unobserved heterogeneity in the fixed effect so a transformation of the equation is still required first, and secondly, an outside instrument is sometimes quite challenging to find, especially for a lagged dependent variable - for this reason, the instrumental variable has to come from "within" the model, in form of a further lag for example. These two problem (transformation needed and drawing instrument from the model within) was first solved at the same time by Anderson and Hsiao (1981) who introduced a first-differencing IV estimation (which is now named after them as Anderson-Hsiao estimator).

The point of the Anderson-Hsiao estimator is that we first take the first difference of the model, then we use the second lag of the transformed lagged dependent variable to avoid the issue of endogeneity. To draw an instrument from the model in form of a lag is not inherently a bad idea - it is based upon the aforementioned sequential exogeneity assumption which states that past values are inherently orthogonal to future error terms. The lagged dependent variable y_{it-1} can be either y_{it-2} or in the transformed form Δy_{it-1} - both of these are mathematically related to $\Delta y_{it} = y_{it-1} - y_{it-2}$, but not to the also transformed error term. In theory, the choice between the transformed or the untransformed instrument is up to the user - in our case we choose the transformed instrument since the untransformed one was just weakly correlated to the lagged independent variable, resulting in a significant drop in the R-squared of the regression. This first-differencing IV estimation solves for both the unobserved heterogeneity and for the possible endogeneity of the lagged dependent variable. The only drawback of the Anderson-Hsiao estimation is that it is not the most efficient estimator, although it is consistent, because it does not utilise all the existing moment conditions in the model.

Later studies have tried to maximise the the efficiency of the estimator by including more lags and more moment condition. The Generalised Method of Moment introduced by Arellano and Bond (1991), as discussed briefly in the literature review, is a form of an instrumental variable estimation where the instruments are the lagged values of the variables (and not necessarily just the lagged dependent variables') while utilising the orthogonality conditions that exist between lagged values of the dependent variable and the disturbance term. GMM exists in two forms: the first-difference GMM and the system-GMM method - extending upon the original Arellano-Bond estimator by Arellano and Bover (1995) and Blundell and Bond (1998). The main point of system-GMM is that it uses moment conditions both on the level equations together with the usual Arellano and Bond type orthogonality conditions on the first-differenced one, thus creating an even more efficient estimator. Since the introduction of the GMM, it has been one of the most widely used estimation method for dynamic models.

Unfortunately for us, we cannot really implement either of them for our use - although that would have been the original intention. As it is pointed out mainly by Roodman (2009), GMM is really only useful for dynamic panel data that have "large N and small T". The problem with long panels in this case is that GMM ideally would try to use all the existing lags of a variable as an instrument to estimate it - in our case with a $T = 53$, that would end up in so called instrument proliferation. This on paper can be solved by collapsing the instrument matrix into a one column vector, but the levels equation would still utilise all the year dummies as instrument.

So to sum up the methodology implemented in this Thesis, we first start the estimation of the model with a simple Pooled OLS, which while is highly biased and inconsistent, can show us the general direction of the trends. After this, we run the regression with a fixed effects (LSDV) estimator that while is theoretically more sound, still suffers from heteroskedasticity and serial correlation - a huge problem for dynamic panels. To correct for these effects and to get rid of any bias regarding the lagged dependent variables endogeneity, we estimate the parameters of the model with the Anderson-Hsiao estimator, a first-differenced IV estimation that solves for endogeneity, heteroskedasticity and serial correlation at the same time. This however will come with a price of less efficiency as the standard errors grow and the R-squared falls back to a still high, but much lower percentile.

To check for the robustness of the findings, we will re-estimate the relationship between inequality and growth with a different measure of inequality - the top income shares. For this we will use the Anderson-Hsiao estimation only which already proved to be the least biased to any possible misspecification. The relationship is measured on both top 1 and top percent income shares (share of national income, pre-tax).

In the next short chapter, we take a look at the evolution of inequality and growth with some possible theoretical channels that exist between the two. The description of the trends can help us better understand our estimation in the following chapter with the results.

5 Trends in Inequality and Growth

As part of the descriptive analysis, it is worth shortly go through the general trends in both income inequality and growth. Lets first begin with the trends in the first.

5.1 Rising inequality

In terms of income inequality (in terms of household disposable income) measured by the Gini coefficient, the OECD average of 0.29 in the mid 1980's has increased to 0.32 by 2011/12 - with some countries experiencing sharper, some experiencing lower increases or even decreases in some cases. In total, the Gini coefficient has increased in 19 out of the 22 OECD countries over the time period (Cingano, 2014).

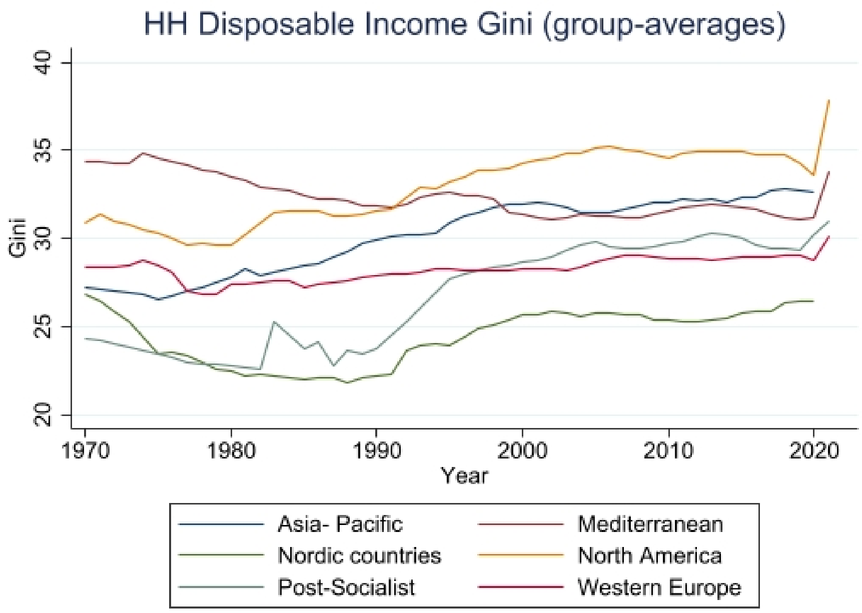

Figure 2: Evolution of household disposable income Gini in different developed country-groups
Source: Own calculation. Data from: World Bank Databank

If we look at the data collected from the SWIID by Solt (2020), we see that the Gini index in Western Europe rose from a decade average of 27.8 in the 1970's to 28.9 for the 2010's (an estimated average of Western European countries for the corresponding decades). Similar statistics show an even more drastic rise in the US and Canada (the Gini went from a decade-average of 30.3 to 34.64 in the same time period), in the Asia-Pacific region (from 27.06 to 32.37) and in the more developed post-socialist countries of Central and Eastern-Europe (from 23.46 to 29.82 - although, for most countries in the region, the data starts at the end of the 1980's). If we plot the regional averages for every year we have data for, we can see on Figure 1., how the Gini index started to rise at around the 1980's - following a generally downward trend. Note that from the previously not mentioned groups, only the Mediterranean countries show a decrease in inequality.

This increase in the Gini coefficient is partially rooted in the dynamics of top income shares which have also risen considerably over the past few decades. As Alvaredo et al. (2013) pointed out in their study, between 1980 and 2007, the top 1 percent income share rose by around

135 percent in the United States and the United Kingdom, while in Australia and Canada it rose by 105 and 76 percent respectively - they also point out that the top income share rose considerably less (if any) in continental Europe. Worth noting that the OECD arrives to similar conclusions regarding the difference in trajectory of continental Europe and English-speaking countries (Förster et al., 2014). A similar graph to Figure 2. can be shown for the top 1 and top 10 percent income shares (by the means of the different group of countries) - for which the data was collected from the World Inequality Database (WID).

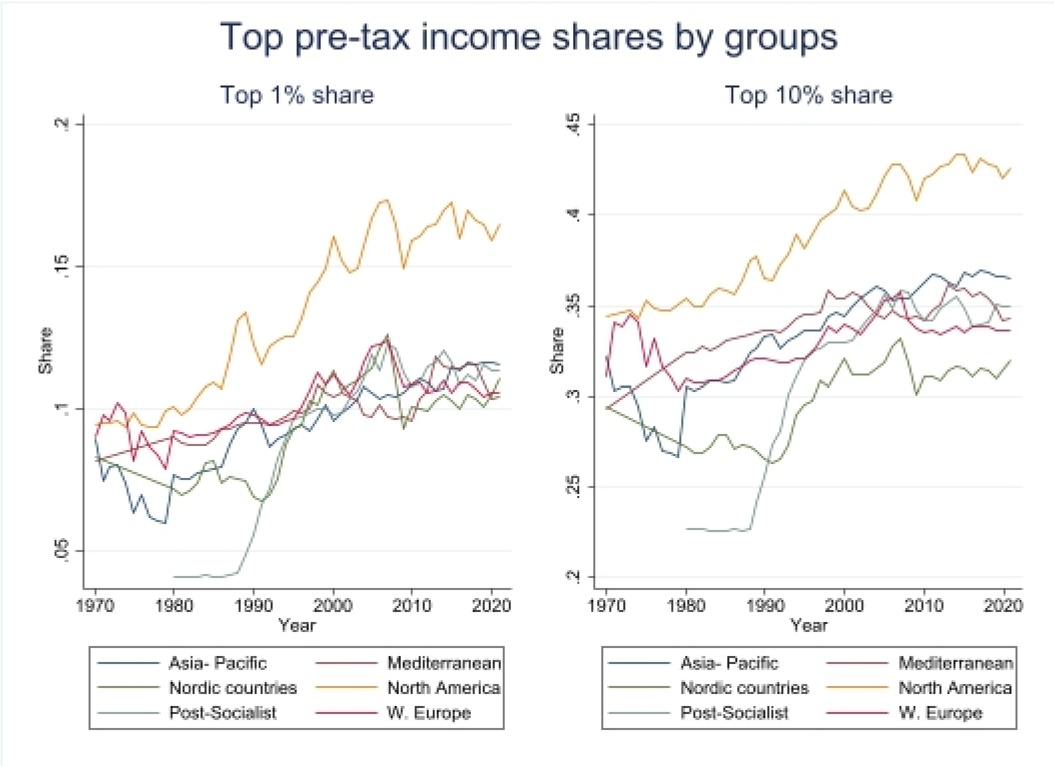

Figure 3: Pre-tax national income shares of the top 1 and 10 percent
Source: Own calculation. Data from: World Inequality Database

Figure 3. above shows us the sharp jump in top income shares since 1970. The increase in inequality captured by these graphs are way more dramatic then the one measured by the Gini Index. We can see an almost continuous rise in top income shares with the beginning of the 1980's which only comes to a halt after the 2008 recession. In line of the previous findings mentioned, we can see that the growth in top income shares is lead by the United States and Canada, while the other country-groups show a similar level of rise. It is worth highlighting the trends in the European post-socialist countries that had a very low level of top income shares that quickly started to catch up with other developed countries after the fall of socialism.

The difference between the rate of change in Gini and top income shares is an important indicator on what to expect from the results of the estimation in the next chapter. As we will see, the fall of the growth rates are also substantial, which means that a measure that captures a stronger growth in inequality (the income shares) might gives us a stronger and different level of relationship between growth and inequality.

As we can see there is a general trend in rising inequality since the 1980's and 1990's while before it in the 1970's we see the opposite trend taking place. This kind of change in trend is important for the research as to capture its possible effect on growth rates.

5.2 Decreasing growth rates

As mentioned before in the introduction, while inequality is rising, growth rates in the developed world are following a decreasing trend. As it can be seen on Figure 3. below. The 5-year cumulative growth are averaged on the different groups examined.

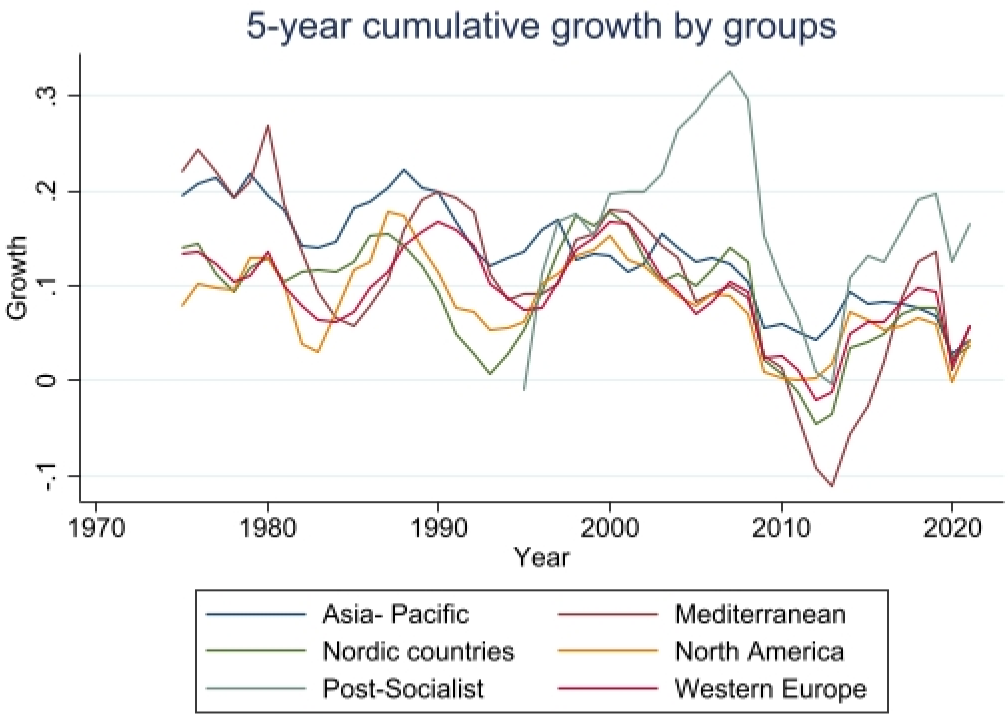

Figure 4: 5-year cumulative growth averaged in the examined groups
Source: Own calculation. Data from: World Bank Databank

As we can see almost all of the groups that we have available data for from 1970 onward are showing a clear slowdown. From the general levels of 10-25 percent growth in GDP per capita before 1980, this fell below 20 percent at around 1990 and fell even lower after the turn of the millennia (with a clear downward shock from the 2008 recession. In this context, the growth rates of the 2010's were also heavily affected by the crisis - especially in Europe where the long lasting Euro-crisis prolonged the recovery. The only group that went against the grain is the group of post-socialist countries (for which the data begins only at around 1990 with the fall of socialism). We can see a very sharp jump in growth rates in this particular group right from the beginning which only rose higher until the 2008 recession pushed them back too. This level of growth was mainly driven by the Baltic countries and Romania which experienced a 5-year growth of 40-50 percent in the lead-up to the recession.

It would be easy to point out that the relationship is clear - inequality is increasing, growth is decreasing, the two must be connected. However, as we know, correlation does not mean causation. Even on a theoretical level, the connection between the two - the channels through which inequality would decrease or increase growth is not set in stone and is highly divided

5.3 Channels Between Inequality and Growth

One side of the argument states that inequality affects growth directly and indirectly through socio-economic drawbacks. These drawbacks possibly hindering growth are stemming in the fact that the above discussed rise of the top 1 percent income share is accompanied by a decreasing wage share in developed countries: between OECD countries the Wage share has shrank from 73.4 percent in 1980 to 64.9 percent in 2007 (Stockhammer, 2017) and the OECD also finds that this wage share decrease has been accompanied by a significant decoupling from labour productivity (OECD, 2018) in advanced economies. The falling wage share with the decoupling from productivity results in a stagnating middle and poorer class. This phenomenon is illustrated on a wider scale by Milanovic (2016) with his famous ”elephant-curve” (showing that at the 80th percentile of the global income distribution - mainly the middle class of advanced counties - have experienced a near 0 percent cumulative gain of income between 1988 and 2008). The problem is more prevalent in the United States where the average hourly compensation - in a cumulative basis - has only risen by 9.3 percent between 1973 and 2013 (while productivity is up by 74.7 percent - for a reference, before 1973 they were growing in sync) (Mishel et al., 2015). The described phenomenons can negatively affect growth through different channels. On one hand, the widening gap between the the top percent of the income distribution and the rest can result in higher social unrest and political tensions (Perotti, 1996; Alesina and Perotti, 1996) (which we may already see around us), which can indirectly put a downward pressure on growth through increasing political instability (which results in decreasing business confidence for example). Another source of downward pressure on the long-term growth can the financial instability caused by the rising household debt around the developed world (Stiglitz, 2015a). In contrast the low growth of household income of the middle class, consumption has been increasing in a much faster pace (OECD, 2019) which is a result of debt substituting for the missing growth of income. This substitution can is hardly sustainable if it continues to grow (Barba and Pivetti, 2009).

Despite all these possible channels through which growing income inequality can hinder economic growth, there is still no clear consensus on how the first affects the latter. A substantial amount of research (beginning with Simon Kuznets (1955)) states that income inequality is actually beneficial to growth in developed countries (Barro, 1999; Grigoli et al., 2016; Castelló-Climent, 2010). A potential channel through which inequality can help growth is that since the top 1 (or 10 for that matter) percent saves most of its income which then re-enters the economy in the form of investment, a higher level of inequality is thus supporting growth with faster capital accumulation (Stiglitz, 2015a). In connection to this, the supply-side of economics often points out that a higher level of income-share going to the elite is beneficial to growth since it is the elite who is the most responsible for creating jobs (Stiglitz, 2015a) (which is basically a side-effect of higher level of investments). Another explanation for the positive relationship can be that by reducing redistribution (which raises inequality) the incentive to work more and earn more money increases. This increased motivation translates to higher level of competition on the labour market and in the SME sector which only helps growth.

Now that we have a better understanding of the trends in income inequality and growth, we can investigate our regression results so see if they are in line of the expected trends and theory.

6 Results

6.1 Main Results

We begin the presentation of the results in the small-form of the regressions where only the lagged dependent variable and the inequality (measured in Gini) are estimated with year dummies included to control for trends in time (the year dummies are included in every regression estimated, but dropped from the output tables). It is important to point out again, that the 5-year growth is only lagged by 1-year as opposed to the rest of the control variables which are lagged by 5-years (as described already in the methodology part).

Table 2. presents the small-form of the results. Column 1 contains the estimation results obtained by Pooled OLS, column 2 shows the results from the LSDV estimation and the third column is the AH estimation. The point of the small-form is to see the general direction of the relationship between only the inequality, the lagged dependent variable and growth.

Table 2. Estimation Results (No controls)

	(1)	(2)	(3)
VARIABLES	Pooled OLS	LSDV	Anderson-Hsiao
Lagged 5-year growth	0.9312***	0.8623	0.2007***
	(0.0140)	(0.0157)	(0.0826)
Inequality	0.0012	-0.0035	0.0767
	(0.0065)	(0.0196)	(0.0566)
Constant	0.0116	-0.0393	0.0513***
	(0.0229)	(0.0632)	(0.0085)
Observations	1,260	1,260	1,198
R-squared	0.9026	0.8614	0.5321
Number of country_id		36	36
Estimator	OLS	FE	FD/IV
Standard Error	Robust	Robust	Robust
Instrumented			D.l5_gr5
Instrument			LD.l5_gr5
Underid. test			0
Weak Instruments test			98.52
Overid. test			0

Source: Own calc. Data from: World Bank Databank, SWIID v.9.4

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The interpretation of the coefficient for the lagged growth variable is the rate of adjustment, in other words, how persistent is the variable. The value should be between 0 and 1 in absolute terms which is achieved here, however the very high value estimated by both POLS and LSDV is already a sign for concern (tests for heteroskedasticity and serial correlation are carried out on the full models later). The AH estimator offers a more reasonable value although it is relatively low. The concrete interpretation of the significant values is that (since all variables are log-transformed) a one percent rise in last years growth will result, on average, in a 0.93 percent rise in current years data for POLS and in a 0.86 percent rise in case of LSDV.

When it comes to inequality, what we see in Table 2. is that if we don't control for other effects that may impact growth, none of the estimation shows inequality as significant. The general direction of the relationship is also questionable since we see the sign changing when we estimate it in small-form with LSDV, then it turns positive again when estimated by the Anderson-Hsiao estimator. This however can be the result of the values being very close to 0 with a high standard deviation - which in the case of POLS and LSDV are higher than the actual estimates. The bias in the POLS and problems in the LSDV are clearly showing in this small-form since we can see the drop of R-squared (centered R-squared in case of AH) when we estimate it with a more consistent and unbiased estimator. This also indicates that the model in this form is underidentified. To obtain a more defined model, we have to add new variables (selected in line of the existing literature) which helps us to further understand the model.

Table 3. Estimation Results (With controls)

	(1)	(2)	(3)
VARIABLES	Pooled OLS	LSDV	Anderson-Hsiao
Lagged 5-year growth	0.945***	0.848***	0.278***
	(0.0159)	(0.0209)	(0.0795)
Inequality	-0.0115	0.0597**	0.110*
	(0.0112)	(0.0280)	(0.0564)
Human Capital	0.0116*	-0.0101	-0.0581
	(0.00615)	(0.0183)	(0.0837)
Public Expenditures	-0.0118*	0.0372**	0.115***
	(0.00717)	(0.0158)	(0.0303)
Gross Capital Formation	-0.0493***	-0.0996***	-0.146***
	(0.00815)	(0.0122)	(0.0143)
Inflation	0.00608***	0.00632**	0.00006
	(0.00171)	(0.00234)	(0.00190)
Trade	-0.00243	-0.00199	-0.00169
	(0.00226)	(0.0144)	(0.0177)
Constant	0.223***	0.0742	-0.000929
	(0.0776)	(0.130)	(0.00746)
Observations	1,015	1,015	939
R-squared	0.917	0.894	0.613
RMSE	0.030	0.028	0.025
Number of country_id		36	36
Estimator	OLS	FE	FD/ID
Year dummies	YES	YES	YES
Standard Error	Robust	Robust	Robust
Instrumented			D.l_gr5
Instrument			LD.l_gr5
Underid. test			0.000
Weak Instruments test			75.67
Overid. test			0.000

Source of data: World Bank Databank, SWIID v.9.4

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

After adding the control variables of Human Capital (measured in mean years of schooling in the working age population), Public Expenditures , Gross Capital Formation, Trade (all three in in GDP percentage) and inflation, we see that the models become a bit better defined (also, as we just added the variables, it is worth taking a look at the preliminary graphs on the partial relationships between the different independent variable and growth to get a scope on what to expect from their relationship. This graph can be seen in the Appendinx).

The first column again shows the result for the Pooled OLS estimation which gives a very similar - and statistically significant at 1 percent level - estimate for the lagged dependent variable at 0.945 (meaning that a 1 percent change in last years 5-year cumulative growth would result in a 0.945 percent increase in growth today). Besides this, the main independent variable of Inequality is still not significant, thus the change of the sign compared to the small-form does not really tell us anything (also considering that the value is very close to 0 again with a high standard deviation). Human Capital is significant at 10 percent with a positive value (a 1 percent increase in average years of schooling would result in a 0.0116 percent higher growth rates 5-years later). The other variables of the model are also statistically significant, expect Trade but all of them have a very low value close to zero with also very high standard deviations (which are robust to heteroskedasticity). The R-squared in the model is is still very high - a bit even higher then in the Table 2. Although the model seems to be a bit more better defined now, the results are not really representative due to the theoretical drawbacks of estimating POLS on a dynamic model.

Compared to this, LSDV seems to also improve with the introduction of the added variables. Although the (clustered) standard errors are a bit higher now then in the smaller estimation, the estimated parameters are mostly statistically significant. In the meantime, the R-squared (within) are a bit higher then compared to the small model, it is a bit lower than in the POLS estimation - the Root Mean Squared Errors (RMSE) on the other hand are a bit lower, indicating a better fit (as RMSE measures how close are the estimated fitted values to the real ones).

Looking at the coefficients, we can see that most of them are significant - including the Inequality. Firstly, the estimated coefficient for the lagged dependent variable is 0.848 (a similar value to the small-form model), indicating that a 1 percent increase in the lagged dependent variable is associated with a 0.848 percent increase in growth rate (on average), holding all other variables constant. For inequality, we can see that a 1 percent change in the Gini index 5-years ago would result in a 0.0597 percent change in the growth rate today (as indicated, this result is significant at a 5 percent level). Now while this estimate is very low compared to what we could have expected, the more interesting point is that the relationship seems to be positive between inequality and growth - even if just slightly.

The other variables in the model estimated with LSDV show a varying significance level with Human Capital, besides Trade this time not being one while Government expenditures. Gross Capital Formation (GCF) and inflation both having a significant relationship (as a 1 percent increase in GCF would result in a 0.1 percent lower growth rates while inflation seems to support it by 0.006 percent). What is interesting is that GCF is having a negative sign, while inflation is positive, although its value is very low - both of which are slightly unexpected.

If we go a bit deeper into regression diagnostics, we quickly discover that the LSDV regression still suffers from several biases. The most important test that we have to run after LSDV is to check for autocorrelation since that would make the model highly biased and would lead to inconsistent estimates. In the same take, we test for heteroskedasticity too since for LSDV to work, we need errors that are independently distributed from the variables. When we run the tests for LSDV and the Anderson-Hsiao estimation, we can clearly see in Table 4. below how the latter improves the biases.

Table 4. Tests for regressions

	LSDV	Anderson-Hsiao
Test for Homoskedasticity	Modified Wald test	Pagan-Hall (with fitted values)
Result	0.0000	0.5947
Test for no autocorr.	Wooldridge test	Arellano-Bond
(AR1)	0.0000	0.1045
(AR2)		0.952

Source: Own calculation

Note: Test for AR(2) for LSDV not reported, suspect AR is shown in Appendix.

As we can see in the above table, the LSDV estimator suffers from both serious heteroskedasticity and first-order serial correlation. For homoskedasticity, the modified Wald test was taken with the nullhypothesis of homoskedastic distribution of error over the independent variable - the test was confidently rejected meaning the presence of heteroskedasticity. For serial correlation, the Wooldridge test was utilised for which the null of no first-order autocorrelation was strongly rejected. These error processes are graphically presented too in the appendix.

Another problem that we may face is that even though we showed that the Nickell-bias (or dynamic panel bias) is very low in our case, the possibly endogenous lagged dependent variable still can disturb our estimation (and based on the above test statistics, the model estimated by LSDV is not quite right). Theoretically, there is no clear-cut test for the possible endogeneity of a variable when we do not run an IV regression. What we can do in this case is that we run a fixed-effects IV regression in which we treat the lagged dependent variable as possibly endogenous one (and instrumenting it with its second lag - just as in the Anderson-Hsiao estimation). As it is reported in the respective Stata command documentation by Baum et al. (2023), the result of this estimation can be found in the Appendix (under Table A2.) with the test for endogeneity included. The test carried out is defined as the difference of two Sargan-Hansen statistics: one for the equation with the smaller set of instruments, where the suspect regressor(s) are treated as endogenous, and one for the equation with the larger set of instruments, where the suspect regressors are treated as exogenous. The null hypothesis of the test is that the specified endogenous regressor can actually be treated as exogenous - this hypothesis is clearly rejected so the variable should be treated as endogenous.

If we do so, we can re-estimate our model with the Anderson-Hsiao estimator (Anderson and Hsiao, 1981). This - as described before - deals with the fixed effects by first-differencing, then estimates the differenced equation by a simple Instrumental Variable estimation. In their original paper, the instrument was also differenced (in our case, an instrument in levels produces heavily inefficient and inconsistent estimation). A first concern regarding instrumenting with lags, is that we may not be sure about the exogeneity of the lagged value of the variable. In out case, the use of the second lag as an instrument is not a problem for two reason: the first reason is purely theoretical in a sense that based on the already mentioned sequential endogeneity assumption, past values cannot be correlated with the present error term (or simply put, Y_{it-2} is uncorrelated to ϵ_{it}). Nevertheless, the two terms can still be correlated if the residuals from the regression are showing a strong AR process (like the one estimated by LSDV). In connection to this, as we saw in Table 4. of the test statistics, autocorrelation is not present - neither on the AR(1) level, nor at AR(2) (this is also shown visually in the Appendix with the residual plots of the full AH regression). If we were to detect autocorrelation, we could not have used the further lag as an excluded instrument.

Now that we determined that the Anderson-Hsiao estimator can correct for the biases present in the previous two estimations, we can begin to interpret the results in Table 3. Generally speaking, the more robust estimate of Anderson-Hsiao indeed came with the price of lower efficiency compared to the estimates obtained by LSDV - the standard deviations are higher while the R-squared is also lower then what we can see in column 1 and column 2 (the latter is probably the effect of lessening the effect of serial correlation). In spite of these, the RMSE is lower even if by very little. Other test-diagnostics are also presented in Table 3. to confirm the validity of the estimation technique. Below the instrumented variable (that is the differenced, lagged dependent variable) and the excluded instrument, we can see the test result of the underidentification test (which is calculated - in case of robust standard errors - by the LM and Wald versions of the Kleibergen-Paap rk statistic. The rejection of the test means that the model is not underidentified). For possible weak identification (which arises when when the excluded instruments are correlated with the endogenous regressors, but only weakly) the also robust Kleibergen-Paap Wald rk F-statistic is calculated. Here, as a general rule of thumb, we can reject the hypothesis of weak instruments if $F \geq 10$ - in our case the F-statistic is quite large at 75.67. Last but not least, the overidentification test is also reported which calculates the Hanshen or J-statistic for possible overidentification. In our case, since the model uses only one instrument for one endogenous variable, the model is exactly defined (resulting in the rejection of the test).

When looking at the coefficient of the lagged dependent variable is still strongly significant, but its value is way lower - for every 1 percent growth in the previous year, the current years 5-year cumulative growth rate will be 0.278 percent higher. The drop in the value is most probably caused by the disappearing autocorrelation from the error, which causes the (now instrumented) lagged dependent variable to have a lower effect. This would also partially explain the drop in the R-squared (centred) metric

Regarding inequality, we see that while the estimated coefficient is less significant (it is only significant at 10 percent level), the effect is way stronger than as it was calculated by LSDV (or by with POLS) - for every 1 percent growth in the Gini Index, the 5-year cumulative growth will be 0.11 percent higher. In other words, if a country with a Gini of 25 experiences a growth of 10 percent in the statistic (which is not unreasonable based on the trends in Gini in the examined countries), the subsequent 5-year growth period will produce a 1 percent higher growth rate. While this effect is still not too large, the positive relationship is not exactly in line of what was expected but also not unsupported by theory and literature. As it was pointed out in the literature review, there are a number of research that finds the effect to be negative on the whole sample, but positive when only developed countries are examined, while some publications found the effect to be entirely positive. Nevertheless, since the size of the effect is not quite big while it is also only significant at 10 percent level, it may worth it to further examnin the relationship with a different measurement for inequality.

If we take a look at the rest of the variables, we can see that the mean years of schooling is still not significant (thus the interpretation of the negative sign is redundant) together with Trade Openness and in this case, Inflation also became insignificant (the estimated coefficient for the variable is basically 0 either way - which sounds logical if we consider that inflation 5-years ago would have little effect on the economy today). In the meantime, Government

Expenditures still prove to be significant with a higher (than estimated in column 2) value of 0.115 (meaning that ceteris paribus, a 1 percent rise in government expenditure in terms of GDP percentage, would result in a 0.115 percent rise in growth in a 5-year span) and the same goes for Gross Capital Formation

So as it turns out, for our model constructed, the least biased (and more theoretically sound) estimation method was the Anderson-Hsiao estimation. To further check the robustness of the model, alternative measurements are introduced for Inequality to see if the effects are changing.

6.2 Checking for Robustness

To see if the model still stands its ground in the face of different measurements for inequality, we re-estimate the model with the top 1 and top 10 percents pre-tax national income shares. Refitting the model with different measurements is not without a merit, especially in our case when the independent variable of inequality is not a clear-cut defined statistics. While the Gini Index is the most widely used statistic to measure inequality, the top income shares also give important insight into its development. Besides this, as we saw in the previous chapters, compared to the Gini, the trends in top income shares are showing a much more drastic rise over the examined time-horizon. This may already signal us that the relationship between growth and income shares may be different - and we would not be wrong.

When we revisit the model with the same AH-estimator but with top income shares as a measure for inequality, we can see that the general predictive power of the model hasn't changed much - let it be estimated by substituting in with the top 1 or the top 10 income share. The centred R-squared in both cases are identical (standing at 62.29 percent) and the standard errors also have not changed much. Looking at post-estimate test-statistics of the models we see that in both cases the model is nether under- or overidentified while the weak instrument hypothesis can also be rejected in face of the large F statistic for it. The Pagan-Hall p-value for heteroskedasticity is also reported (failing to reject the null means that we are dealing with homoskedastic data) besides the p-values for the Arellano-Bond test for AR(1) and AR(2) - both of which are confidently not rejected (meaning no serial correlation at neither level).

As the model seems to be correctly defined, we can turn our attention to the coefficients. In terms of the control variables, we do not observe any significant change in the coefficient of the same significant variables (namely, Government Expenditures, GCF and the lagged term which is slightly bigger in this case - the first two has almost the same coefficient estimated), while Inflation and Trade are still not significant and very close to being 0.

The more important thing is what is happening with the main explanatory variable. When we estimate the relationship between the same cumulative 5-year growth and the top 1 percent national income share (in column 1), we can see that the estimate for inequality has changed sign (and became more significant reaching below 1 percent significance) and is now negative. The effect itself is quite small, standing at only -0.0267 (meaning that ceteris paribus, a 1 percent growth in the top income share would incur, on average, a 0.0267 percent decrease in the subsequent 5-year growth period). The effect is also negative - and slightly higher - when we substitute in with the top 10 percent income share (although it is "only" significant at 5 percent significance level). In that case we see that for every 1 percent growth in the top 10 percents income share, the subsequent 5-year cumulative growth is hindered by 0.07 percent.

The change of the sign is an interesting phenomenon not entirely expected in the beginning of the research. One would expect that the estimate would be consistent over different measurement types (since the effectively capture the same effect) but that is clearly not the case. It is also not entirely surprising if we think back to the trends we saw in top income shares in the previous chapter. Since the top income shares exhibited a way stronger increase in the backdrop of substantial slowdown of growth, it could have been expected that the relationship would be different - although not the change of sign.

Table 5. Anderson-Hsiao Estimation with Top Income Shares

	(1)	(2)
VARIABLES	Top 1% share	Top 10% share
Lagged 5-year growth	0.315***	0.316***
	(0.0760)	(0.0760)
Inequality	-0.0267**	-0.0701**
	(0.0113)	(0.0299)
Human Capital	-0.0777	-0.0800
	(0.0805)	(0.0803)
Public Expenditures	0.115***	0.116***
	(0.0316)	(0.0314)
Gross Capital Formation	-0.144***	-0.145***
	(0.0153)	(0.0154)
Inflation	0.000314	0.000246
	(0.00193)	(0.00192)
Trade	0.0163	0.0158
	(0.0204)	(0.0203)
Constant	-0.00486	-0.00480
	(0.00715)	(0.00716)
Observations	869	869
R-squared	0.629	0.629
Number of country_id	36	36
Estimator	FD/IV	FD/IV
Standard Error	Robust	Robust
Instrumented	LD.gr5	LD.gr5
Instrument	L2D.gr5	L2D.gr5
Underid. test	0.000	0.000
Weak Instruments test	71.11	71.14
Overid. test	0.000	0.000
Pagan-Hall p-val.	0.3322	0.3444
A-B test (1) p-val.	0.1395	0.1422
A-B test (2) p-val.	0.6685	0.8090

Source of data: World Bank Databank, World Inequality database

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Based on these opposing result, the only thing that we can confidently state, is that the measurement of inequality is an important determinant to the existing relationship between the variable and growth.

7 Conclusion

As we saw it throughout the Thesis, the academic sphere is still highly divided on the question of how income inequality affects growth. As a lot of research estimate the effect on different set of countries, over different time horizons, with different variables added, the estimated effects vary accordingly. Some paper finds the effect to be positive across a whole sample of countries with different level of development, some find it negative on the whole, and some find it negative for developing and positive for developed countries only - of course, lot of estimate find it negative on developed countries alone too. These latter parts are what is in the interest of the Thesis - how income inequality affects growth in a sample of developed countries only.

Since the topic is far from being settled, there is always room to add a new finding, a new approach to the discussion - and this was the goal of the current Thesis. The main idea of the research was to collect a set of countries that are homogeneous enough to reduce the possibility of omitted variable bias, but also offers some level of heterogeneity for a consistent estimate, and then estimate the relationship over a time horizon as long as possible (which was reduced from the initial 63 years to 53 between 1970 and 2022). The point of the long time horizon is to capture the trends in inequality that are changing more slowly as some other macro-level statistic (especially in the case of the Gini Index). This decision for the time-horizon however proved to incur difficulties when estimating the effect.

The model set up was derived from the Human Capital Augmented Solow growth model with further added control variables that were in line of the existing literature - these included (besides Human Capital) Government Expenditure, Gross Capital Formation, Inflation and Trade openness. The model became a dynamic panel model after adding the lagged dependent variable as a regressor too.

The parameters of the model were estimated by three methods: simple Pooled OLS (POLS), Least Squares Dummy Variables (LSDV) and by the Anderson-Hsiao (AH) estimator. Initially, the relationship was intended to be estimated by the Generalized Method of Moments estimation too, but as it turned out, it is not fitting for models with a long time-horizons (as the initial point of the method is to instrument the endogenous and predetermined variables with all of their possible lags. This in our case would result in instrument proliferation and even if we collapse the instrument matrix, the presence of long time horizon make the estimator very inconsistent).

First, the regressions were run in a small-form including only the lagged dependent variable, inequality (measured by Gini only for the small-form) and the time trends (with year dummy variables). While these initial regressions showed inequality to be insignificant, they were quite underdefined in that form. After adding further the further variables, the estimations returned better results - although after running tests for heteroskedasticity and serial correlation (which if present, the dynamic model is highly biased), LSDV turned out to be biased (POLS theoretically cannot estimate unbiased dynamic panel model). After running the regression with the Anderson-Hsiao estimator, both of these problems were eliminated while it also took care of the endogeneity issue of the lagged dependent variable. To check for robustness, the latter estimator was run again but this time inequality was measured by both top 1 and top 10 percent pre-tax national income share.

The results were consistent in some sense: the lagged dependent variable in both cases showed similar and significant value which is also true to Public expenditures and GCF. Inflation and Trade was insignificant in all of the AH estimations. What was not consistent is the effect of Inequality on the cumulative 5-year growth. When we estimated the effect with Inequality being measured by the Gini coefficient, the effect shows a positive value of 0.11 (meaning that for every 1 percent rise in Gini, ceteris paribus, the subsequent 5-year growth will be 0.11 percent higher on average). When we estimated the effect with top 1 and 10 percent share, the effect turned negative with the value of -0.026 and -0.0701 respectively (the first being significant at 1 percent, the latter at 5 percent significance level).

What we can conclude from this result - and may serve as a contribution for the literature too - is that under the circumstances we examined the relationship of growth and inequality, the measurement of the latter matters a lot for the outcome. Since top income shares showed a stronger increasing trend over time, it is logical to assume a stronger relationship - but the sign of this should be interpreted with care. A further topic of discussion could be to determine which measurement is better reflecting the trends in terms of income inequality - but that is a topic for another research.

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Appendix

A Country-groups

Besides the selected developed countries, we could have also include other affluent countries such as the UAE, Saud-Arabia or Singapore, but the structure of their market economy is markedly different. Although all of these countries have adopted some form of capitalism, Singapore's heavy state-control and involvement, the UAE's and Saud-Arabia's oil-dependency makes them hard to compare it with the considered developed countries - the different trends in growth and changes in inequality can be a result of how their different institutional system reacts to changes in the global economy.

Table A.1. Countries by group

North America	Asia- Pacific	Nordic countries	Mediterranean	Western Europe	Post-Socialist
Canada	Australia	Denmark	Cyprus	Austria	Croatia
United States	Japan	Finland	Greece	Belgium	Czechia
	New-Zealand	Iceland	Italy	France	Estonia
	South-Korea	Norway	Malta	Germany	Hungary
		Sweden	Portugal	Great-Brittain	Lithuania
			Spain	Ireland	Latvia
				Luxembourg	Poland
				Netherlands	Romania
				Switzerland	Slovakia
					Slovenia

B Estimations

B.1 Growth against the independent variables

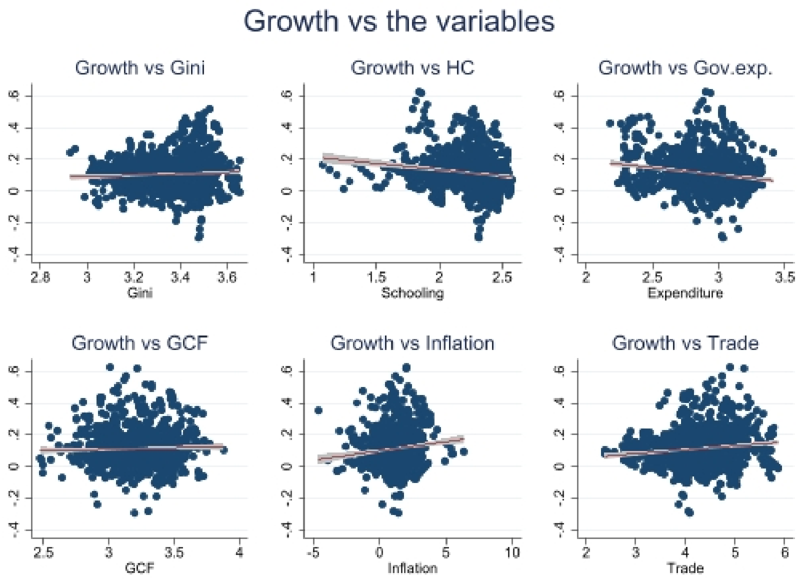

Figure B.1: Relationship between the different variables and growth.

B.2 AR processes

Below we can see the AR(1) and AR(2) processes for the LSDV estimation (with the control variables included). As we can see, the model suffers from heavy autocorrelation.

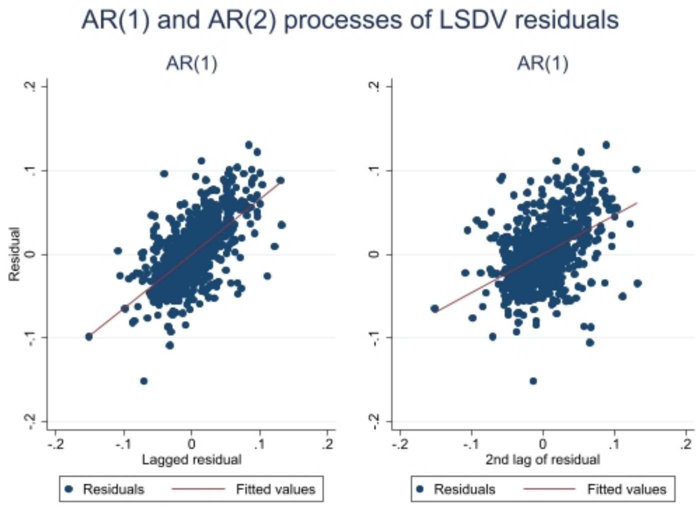

Figure B.2: AR processes of the LSDV estimation

As it was referred, the AR processess of the Anderson-Hsiao estimation are also shown below (although the test resulted in acceptin the null hypothesis of no serial correlation - the value of the AR(1) however was close to 10 percent, so it may be worth it visually inspect too).

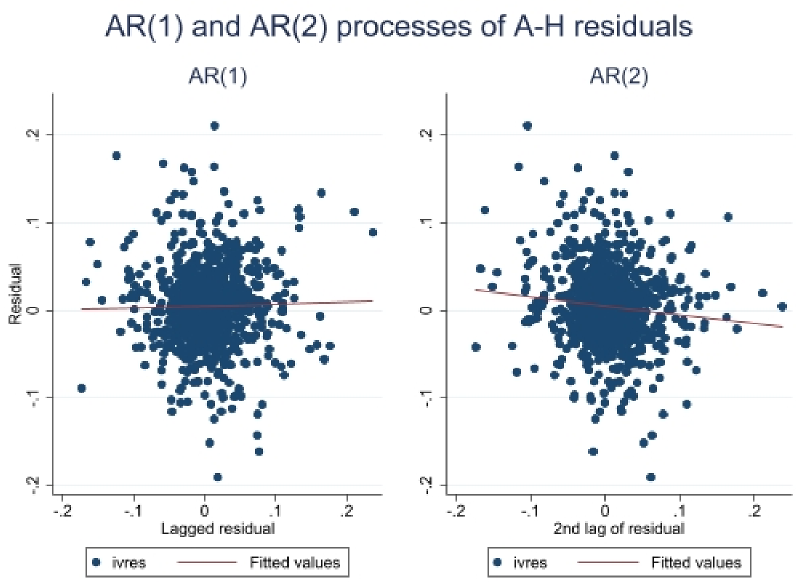

Figure B.3: AR processes of the AH estimation

B.3 Fixed Effects IV for Endogeneity test

To find out whether we face an endogenous regressor in the lagged dependent variable we can run an FE IV estimation after which we can test for endogeneity. The results of the full estimation can be seen below on Table A2. with the endogeneity test result also reported. The 0.000 p-value of the test means that the regressor is indeed endogenous and thus, should be treated as such.

Table B.2. Fixed-effects IV estimation

	(1)
VARIABLES	Fixed effects IV
Lagged 5-year growth	0.727***
	(0.0199)
Inequality	0.0932***
	(0.0197)
Human Capital	-0.0316*
	(0.0172)
Public expenditures	0.0419***
	(0.0126)
Gross Capital Formation	-0.115***
	(0.00887)
Inflation	0.00305*
	(0.00178)
Trade	0.0187*
	(0.00954)
Observations	991
Number of country_id	36
R-squared	0.889
Estimator	FE/IV
Endogeneity test	0.000
Underid. test	0.000
Weak Instruments test	2478
Overid. test	0.000

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$