Inequality, redistribution and growth – interrelations and directions

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Abstract

In this thesis I set out to examine the relationships between growth, inequality and redistribution. It has been difficult to disentangle cause and effect definitively in these relationships. Still, the literature is mainly focusing on the effect of inequality and redistribution on growth, keeping the possible reverse relationship out of the picture. Typically, growth will be treated as the endogenous variable placed on the left hand side of a regression model with inequality and/or redistribution entering as explanatory variables.

Even though most researchers are fully aware of the possible endogeneity problem arising from this approach, to my knowledge few attempts have been made to systematically sort out the directions of how growth, inequality and redistribution interrelate. The historic lack of reliable cross-country time series data on inequality may have been a constraint. Recent developments in data-access allowing for simultaneous analysis of inequality, redistribution and growth have inspired new studies on how inequality and redistribution affects growth. The data innovations also give new opportunities to reach conclusions regarding the directions of the relationships. In this thesis, I investigate these relationships in a dynamic cross-country perspective with Granger causality tests being conducted inside the framework of a system GMM-model.

When treating growth as the dependent variable, testing whether or not the time-series of inequality and redistribution contribute to the explanation of the time-series of growth, the findings are weak. As I flip the coin, however, I find a substantial and highly significant effect of growth on both inequality and redistribution. This challenges the common view that growth is to be treated as the endogenous variable when exploring the relationship between inequality, redistribution and growth.

The analysis suggests that the effect of growth on inequality prior to taxes and transfers is substantially higher than the effect on inequality post taxes and transfers. Thus, the increased inequality appears to be partly offset by a redistributive response. This result can be read as a confirmation of the redistribution hypothesis, predicting that more unequal societies will tend to redistribute more.
Preface

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1 Introduction

The academic and political discussion on inequality, redistribution and growth has moved substantial steps and risen on the global agenda during the last years. Traditionally, economists have placed heavy concern on the alleged trade-off between redistribution and economic growth, with Okun (1975) and his theory of the “leaky bucket” as an important reference point. Equality has been treated as a goal defined by politicians out of some perception of “fairness”, but at the cost of overall efficiency and growth in the economy. The issue of distortive taxation and the disturbance of incentives are central topics in this literature.

The premises of today’s debate are quite the opposite, with the possible negative effect of growing inequality on long-term growth as the main topic of concern. In the aftermath of the financial crisis, the role of inequality and redistribution seems to be at the heart of every political discussion on how to recover and achieve sustained growth. Publications like Joseph E. Stiglitz “The Price of Inequality”, not to mention Thomas Piketty’s “Capital in the 21. Century” and Anthony B. Atkinson’s “Inequality: What can be done”, have contributed substantially to the public conversation on the possible linkages between inequality, redistribution and growth. In 2014, growing inequality was, for the first time, pointed out as the most important global challenge by World Economic Forum.¹

The interest in inequality and redistribution and its impact on growth has also moved its way into the offices of the makers of global policy-recommendations like OECD, The World Bank and IMF. Both OECD and IMF have recently launched studies trying to sum up what we actually know about these interrelationships.² What seems to be a robust conclusion across several studies is that lower inequality is correlated with faster and more durable growth for a given level of redistribution. In other words – for a given level of redistributive efforts, more unequal societies will tend to grow slower.

² Cingano (2014) and Ostry et al. (2014)
Both studies also conclude that there is no empirical evidence suggesting that redistributive policies, such as taxes and social benefits, harm economic growth, provided these policies are well designed, targeted and implemented. This made OECD Secretary-General Angel Gurria state: “This compelling evidence proves that addressing high and growing inequality is critical to promote strong and sustained growth and needs to be at the center of the policy debate”.3

Even though the literature is mainly focusing on the effect of inequality and redistribution on growth, it seems obvious that there exist interrelationships between all three variables. A whole branch of literature is dedicated to the link between initial inequality and redistribution. The median voter theory, first proposed by Anthony Downs (1957) in his book “An Economic Theory of Democracy” has inspired a number of theories all building on the basic idea of the voter in the middle holding decisive power. There also exist some theories and empirical studies on the effect of growth on inequality and redistribution with Kuznets (1955) serving as a theoretical starting point. Still, my experience, when digging deeper into the literature, is that few attempts have been made to go systematically through the interrelationship between all three variables combined, trying to sort out which directions dominate the picture. Thus, this is the ambition of the present paper.

In the IMF-paper, Ostry et al. (2014) maps out what they consider to be the most important relationships at play, see Figure 1. The most compelling about this picture is how all arrows, directly or indirectly are pointing towards growth, while growth is not considered to have any effect of interest on any of the other variables.

Ostry et al. are well aware that such relationships might exist. For instance they write:

*“There are many other arrows one could draw in the picture, such as from growth back to inequality and redistribution. In addition, there are possible channels that relate the levels of income, inequality and redistribution. The paper emphasizes those shown here.”*

And further:

*“It bears emphasizing that the literature has found it difficult to disentangle cause and effect definitively in these relationships... For us, the main concern would be if high growth led to more equality, in which case we would be worried that we were picking up this reverse effect rather than causality from equality to high growth.”*
However, the literature, which has focused on whether a higher level of income is associated with higher or lower inequality, has reached something of a consensus that there is no overall net effect (Dollar and Kraay, 2002; Dollar, Kleinberg and Kraay, 2013).

The arrows of Ostry et al. appear to be representative. It seems to exist a rather common perception among researchers regarding the causal direction of these relations. Studies typically treat growth as the dependent variable, placing various measures of inequality and/or redistributive efforts on the right side of the equation. This is not at all surprising: The question “What do we need to do to achieve sustained growth?” is a natural starting point for most policy discussions. The answer to that question will have huge policy implications, making it a highly relevant and interesting topic to investigate.

Still, there is, in my opinion, a need to conduct more analyses to sort out what causes what – where do it all start? Which variable is the key mover? Cross-national research on the causes and consequences of income inequality has been hindered by the limitations of existing inequality datasets. Firstly there has been a lack of time-series data measuring inequality and redistributive efforts as such, forcing researchers to use a wide range of proxies, such as tax-take, government spending, education levels etc. Secondly, the comparability of observations across countries has often been a challenge due to differences in the way variables are being defined. The recent development of standardized, reliable long time-series data for inequality both prior to and post redistribution through taxes and transfers does not solve all challenges, but makes it possible to investigate these relationships more directly than before. The three major studies on inequality and growth based on such data so far (Ostry et. al (2014), Cingano (2014), Halter et al. (2014)) all aim at describing the effect of inequality on growth. But the data also allows for analysis on how growth affects inequality, and the relationship between inequality and redistribution.

In this thesis, I choose to operate within the same methodological framework as the three studies referred to above, but instead of focusing solely on the effect of redistribution on growth, I investigate the relation between all four variables (market inequality, net inequality, redistribution and growth) using Granger tests for causality. The basic idea of the empirical analysis is to test the time-series of the variables
pairwise in both directions to see if it is possible to get any indication of the directions of the relationships between

a) growth and inequality pre taxes and transfers

b) growth and inequality post taxes and transfers

c) growth and redistribution.

Although clear conclusions are hard to establish based on the methods and analyses conducted in this thesis, the ambition is, nevertheless, to bring a little more clarity into the discussion on how inequality, redistribution and growth are interrelated.
2Existing theories and empirical findings

2.1 Is inequality and redistribution bad for growth?

Great changes have taken place in the discussion on inequality and redistribution and its effect on growth in recent years. From regarding redistributive policy as a pure value-based question of “fairness” or solidarity with the poor, possibly at the cost of overall growth, there now seems to be growing concern about rising inequality and how it might impede economic growth through a variety of mechanisms. The attention has moved to search for the answer to the fundamental question “Is inequality and redistribution bad for growth?”

In the aftermath of the financial crisis, Europe is facing the threat of prolonged low growth. While growth-rates of 3-4 percent used to be normal up until 2008, potential growth in the euro-zone is now estimated to average just 1 percent over the medium term, according to the IMF.\(^4\) The fund warns that this "is well below what is needed to reduce unemployment to acceptable levels in many countries". How to recover and achieve sustained growth is a crucial question to European policy-makers, and the role rising inequality plays in the growth-puzzle is thereby getting a lot of attention.

A vast amount of both theoretical and empirical studies have been conducted, discussing the impact of inequality on growth. Theories suggesting both positive and negative mechanisms have been developed, and empirical studies attempting to test these mechanisms have been largely inconclusive. It is impossible to sum up the whole variety of suggested effects, but there seems to exist some basic hypotheses that researchers return to over and over again in various ways.

“The human capital accumulation theory” is perhaps the most dominating argument used by advocates for more progressive redistributive policy these days. It was first formalized by Galor and Zeira (1993), and the basic idea is how inequality is harmful to growth due to reduced opportunities for the poor. When facing low income,

individuals will have limited opportunities to make reasonable investments, for example to attend higher education or invest in their own health. If financial market imperfections are present such that the poor have limited access to capital, this will be the case even when the rates of return on such investments are high. This will, according to the theory, lower output and thereby growth for the society as a whole over time. Aghion et al. (1999) strongly emphasize the role of credit market imperfections in creating inequality: “Our theoretical framework suggests that, when capital markets are highly imperfect and the production technology exhibits diminishing returns to capital, inequality in the distribution of wealth is bad for growth. Redistribution from the rich to those who are poorly endowed with physical or human capital creates investment opportunities, thus fostering growth. A possible interpretation of the opportunity-enhancing model is in terms of education investments.”

The OECD-report “Trends in Income Inequality and its Impact on Economic Growth” (Cingano, 2014) can be read as a confirmation of the human capital accumulation theory. By using data from 31 OECD-countries for the period 1970-2010, the authors find the single biggest impact on growth to be the widening gap between the lower middle class and poor households compared to the rest of society. The impact of inequality on growth stems from the gap between the bottom 40 percent with the rest of society, not just the poorest 10 percent. Education is the key, due to this study. A lack of investment in education by the poor is the main factor behind inequality harming growth. It is suggested that increased inequality have a negative impact on growth mainly through diminishing investments in education, especially among the lower middle-class. The theory has huge policy implications, and raises some fundamental questions about the magnitude and targeting of redistributive policy.

The human capital theory might be relevant for a wide range of societies, also countries with a relatively compact income distribution. But in more diverse societies, inequality might have a more direct impact on growth due to social instability and general mistrust in political institutions. In extreme cases this might take the form of coups, revolutions and mass violence. In addition to reduced opportunities for the poor, this will generally lead to lower investments, and thereby harm growth. Alesina and Poretti (1996) is one of the studies finding empirical support for this hypothesis.
The theories I have explored so far are both closely linked to the bottom part of the income distribution. If the broad share of the population experience satisfying living conditions making it possible to make reasonable investments and contribute to the society in a productive way, it might be the case that the development in the top deciles should be of less concern to economists and politicians. But there are also theories suggesting that the widening gap between the very richest and the rest of the society, as observed in a number of countries, is affecting growth in a negative way.

Thomas Piketty’s “Capital in the 21th Century” is stressing how accumulation of capital among the few is making the relative value of work and effort less important. The underlying story is related to Piketty’s claim that capital under normal conditions will pay higher interest than the overall growth level in the economy deciding income growth (the well-known g>r-relationship). The individuals accumulating capital will over time get relatively richer than wage earners by doing nothing else than holding capital. When it is getting increasingly more important to be born by the right parents or marry well compared to getting and education and work hard, growth is curbed. The great historical deviation from this trend stems from the rebuilding years after World War II, after an enormous amount of capital was demolished. In this context, the development of a “super-rich” elite of capital holders seems relevant for considerations concerning growth.

Joseph Stiglitz in his book “The Prize of Inequality” (2012) attacks the issue from a different angle, claiming that high levels of inequality is associated with excessive risk-taking and financial instability. Stiglitz points at the ballooning of financial excess preceding the crisis of 2008, and concludes that the influence of the super-rich is creating financial instability.

The traditional demand-side versus supply-side conflict in economics has also implications for how we assess the link between inequality and growth. The view of demand-side defenders would typically be that higher inequality will tend to reduce overall demand in an economy since low-income households are more prone to increase domestic spending rather than saving when income rises. This might be
harmful to growth since the level of demand is of uttermost importance to the general level of activity. On the other hand, supply-side economists will be concerned with issues like how the tax rates influence savings behavior and labor supply. Savings are necessary for capital accumulation and thereby investments. How one emphasize these considerations, will of course influence the view on distributive policy and its effects on growth.

Traditionally, the actual redistributive policies have been seen as the factor harming growth, not that inequality itself is the problem. From there comes the conception that inequality impede growth at least in part because it calls for efforts to redistribute. Or put in another way – the treatment of inequality might be worse for growth than the condition itself. The positive incentive effects of inequality, such as the willingness to work hard and undertake risk will be undermined, and efficiency gets lost due to taxation.

The endogenous fiscal policy-approach with reduced incentives to invest due to lack of pro-business policies is one example of this way of thinking. The main idea is that efforts to redistribute produce policies that tax investments and growth-promoting activities (Alesina and Rodrik 1994; Persson and Tabellini 1994; Perotti 1996).

This discussion is obviously not new. Economists have always been concerned about the distortive effects of redistributive arrangements and how these effects might undercut growth. But the growth-halting effects are not a necessity. Tax arrangements made to offset market imperfections like negative external effects, can perfectly well have a redistributive effect and at the same time increase the efficiency of the economic system. Several studies (as Benabou 2000) point out that some categories of government spending, such as health, education and investment in public infrastructure may both be pro-growth and pro-equality. Still, this remains a vital research issue.

Prescott (2004) is one of the recent studies on the negative distortionary effects of taxation which has received substantial attention. His paper claims that the entire difference between European and US per capita work-hours can be entitled to higher income tax rates in Europe. The analysis builds on the assumption that labor taxes are
entirely redistributed to households as lump-sum transfers that are valued as if they were privately purchased goods and services. In this way Prescott rules out the possible income effect of taxation, and is left with a pure negative substitution effect of higher income taxes on labor supply. The main critique of the study is based on the lack of realism in this assumption. When looking at the European welfare states, tax revenues have for a large part been funneled into public goods and government expenditures that are poor substitutes for private goods. I.e., Ljungqvist and Sargent (2006) find that the negative income effect of taxation has worked in favor of sustaining high employment in the European welfare states.

The Nordic welfare states are interesting cases in this context, and potential outliers in Prescott’s line of reasoning. The Nordic countries have in common a fairly high tax level combined with generous transfer schemes and general access to well-developed public goods. Still labor participation and economic growth is high. This makes Kleven (2014) ask the question: Are the Scandinavians different?

Kleven claims the Scandinavian countries to be economic and social success stories. This could appear as a paradox, considering that the countries operate with a very high “participation tax-rate”5 of around 80 percent, compared to 63 percent in the US. According to standard incentive theory and the hypothesis of Prescott, this should undermine work-participation and thereby overall economic performance. Part of the explanation of why the system works, according to Kleven, is that tax revenue to a large degree is spent on the subsidization of public goods that are complementary to working, such as child care, elderly care and education. This encourages high levels of labor supply. Surprisingly this study finds a negative correlation between the employment rate and the average participation tax-rate across countries. This correlation is even stronger for females.

To broaden the picture, Andersen et al. (2007) suggest that the key factor explaining the economic results of the Nordic model is how the system provides people with basic security and risk-sharing, generating political support for growth enhancing restructuring, free trade and open markets. The economic argument in favor of free trade and open markets, the authors argue, are not that there are no losers, only that the winners gain so much that they can – in principle – compensate the losers.

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5 The combined effect of higher taxes and reduced transfers when entering employment.
“Solidaristic wage setting, active labor market policies, redistribution of income via tax-transfer schemes, comprehensive and generous unemployment insurance schemes and other elements of social protection can all be regarded as ingredients in such compensation mechanisms”, they write.

As already mentioned, Ostry et al. (2014), sum up the attempts made so far to sort out the effects of inequality, redistribution and growth. They claim that inequality has a negative impact on per capita growth. Further they suggest that redistribution is generally benign in terms of its impact on growth: “Only in extreme cases is there some evidence that it may have a direct negative effect.” Or put another way – the available macro-data do not support that there is a big trade-off between redistribution and growth. The level of distortionary effects will of course depend on the both the scope of redistributive efforts, and how these are arranged.

What seems to be a robust conclusion across the more recent studies is that lower inequality is correlated with faster and more durable growth for a given level of redistribution. In other words – for a given level of redistributive efforts, more unequal societies will tend to grow slower. However, it is fair to say that one would still like to see more theoretical and empirical evidence on these relationships.

### 2.2 Does growth affect inequality?

The effect of growth on inequality is a topic who has gained far less attention than the opposite relation, and the empirical studies conducted seem to mainly focus on how growth affects the poor. Is growth pro-poor or not?

A key contribution is the Kuznets curve. Kuznets (1955) suggested that in the long run, modern economic growth would generate an early industrialization phase of rising inequality, followed by a mature industrialization phase of declining inequality. Inequality in both income and wealth should therefore tend to follow an inverted U-shaped path, the so called Kuznets curve, see Figure 2. The motivation of the theory was factor demand effects generated by the transition from traditional agriculture to modern industry that initially would lead to a rural-urban inequality gap. But with

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6 -0.1435*** (0.0444) in the baseline regression. All results reported in Appendix B.1.
industrialization and rising average income-levels, democratization and the development of a modern welfare state would follow, leading to a later inequality decrease.

Figure 2. The Kuznets curve

Kuznets himself was cautious about the strength of the argument, as there was lack of evidence to confirm his hypothesis. The curve still has served as a benchmark in later academic discussions on the effect of growth on inequality. It is worth noting that Kuznets theory was launched in the aftermath of World War II, a time-period characterized by rapid economic growth and falling inequality in the whole western world. There exist World Bank Studies based on limited post-war data, confirming the existence of a Kuznets curve-relationship for most OECD-countries. There appears to be a virtuous circle, where lower inequality fosters growth, which in turn reduces inequality. But this was a trend that turned sharply in the late 70s and beginning of the 80s for several OECD-countries.
The most striking conclusion from existing studies of time-series data is the lack of a universal trend. Atkinson (1997) and Piketty (1996) present surveys of relevant empirical and theoretical literature on the determinants of income inequality. Some countries with a sharp increase in the income inequality, for instance US and the UK, have experienced similar rates of growth as countries where inequality has remained more stable, as Germany. This underlines that even if growth matters in shaping the distribution of income, other determinants, such as redistributive policy, also play a crucial role. All together this suggests that it will be hard to find newer empirical evidence confirming the “downward” side of the Kuznets curve, at least when we are looking at developed countries.

More general critics of the Kuznets curve theory typically argue that it’s U-shape stems from historical differences in inequality between countries - not from progression in the development of individual countries. For instance, many of the middle income countries used in Kuznets' data set were in Latin America, a region with historically high levels of inequality. When controlling for this variable, the U-shape of the curve tends to disappear (see, i.e. Deininger and Squire, 1998).

Palma (2011) is one of the most recent studies to examine the possible existence of a Kuznets curve relationship, using data for a broad set of countries. He concludes that the “upwards” side of the inverted U- curve has evaporated “and with it the statistical support it was for the hypothesis that posits that, for whatever reason, things have to go worse before it can get better”. This follows from the fact that many low and low-middle income countries now have a distribution of income similar to that of most middle-income countries, with some obvious exceptions among Latin-American and Sub-Saharan countries.

The East Asian experience is maybe the most prominent example defying Kuznets’ theory. In the early 90s, the region experienced rapid growth followed by a simultaneous decline in inequality. Stiglitz (1996) highlights how the high growth rate immediately was translated into investments in universal education, land-reform and industrial policies that distributed income more equally through high and increasing
real wages. This increased people’s possibility to consume and invest, leading to a positive feedback-loop to the growth-rate.

As seen so far, there are prominent historical examples of growth being associated with both increased and decreased inequality. It therefore makes sense to assume that the redistributive effects of growth might somehow be linked to the characteristics of the drivers behind growth.

The idea that integration across countries (globalization and free-trade) is associated with economic growth and convergence across countries but increased inequality within countries is a popular one. Openness and trade create a game of winners and losers, and it seems less likely that low-skilled low-productive labor will come out as winners when the economy is exposed to global competition. This is somewhat linked to the theory of cumulative advantage, a well-known concept in the literature of social mobility. It refers to a general mechanism for inequality in which a favorable position becomes a resource that produces further relative gains (i. e. DiPrete and Erich (2005).

Aghion et al. (1999) picks up on this general idea in their study on how new growth theories can contribute to the explanation of the sharp increase in inequality experienced by most of the Western world during the last decades. The study focuses on earnings inequality, mainly because labor income is the main source of personal and household income. In my opinion, this can be seen as an adequate proxy for measuring market inequality (i.e. inequality prior to taxes and transfers). The authors state that economic growth during the past twenty years has been followed by a widening in earnings distribution in a number of the world’s most developed economies, with UK and the US as good examples. Up until the 70s, the high supply of labor led to an overall fall in relative wages in both countries. During the last decades, however, the relative demand for skilled labor has steadily increased, which in turn has increased the skill premium. Two competing explanations have traditionally been proposed to explain this structural change in favor of skilled labor: the impact of trade and skill-biased technological change.
Traditional trade theory (Heckscher-Ohlin) predicts that trade will result in specialization. Developed economies will import labor-intensive goods, and specialize in the production of skill-intensive goods for the export-market. Low-skilled jobs vanish and the demand for high-skilled labor drives up the skill-premium. The predictable result is increasing wage-inequality. Therefore, trade will tend to increase wage inequality between low-skilled and high-skilled industries in developed countries as labor-intensive industry is replaced by more skill-intensive production. There is a shift between industries. Increasing wage inequality within one industry would typically be the result of skill-biased technological change.

When doing empirical tests of the blue-collar/white-collar share of employment in the US, Berman et al. (1994) finds that the within-component accounts for as much as 70 pst of the rise in white-collar employment between 1979 and 1987. Machin (1996) makes a similar finding for the UK. Krugman (1995) concludes, on the basis of several empirical studies, that the effect of East Asia imports on industrial countries’ labor markets has been small, leaving skill-biased technological change to account for most of the increased wage inequality.

Still, Aghion et al. (1999) argue, one cannot interpret the absence of between-industry shifts as refuting the role of trade: “If unskilled labor were more substitutable for intermediate goods than skilled labor, cheap intermediate goods would increase the demand for skilled workers, shifting the within-industry labor demands in all industries that use such inputs, irrespectively of whether they themselves produce traded or untraded goods and of whether they are skill- or unskilled labor intensive”. Falk et al. (1997) and Koebel (1997) both find that unskilled labor is indeed more substitutable for intermediate goods. Access to cheap intermediates on the world-market will then increase the relative demand for skilled workers, making trade contribute to within-group wage inequality. In this way, skill-biased technological change ends up being complementary to trade liberalization.

If technological change contributes to increased wage-inequality, it must be because it is skill-biased. In the neo-classic growth theory-framework, often technology is modelled as a multiplicative factor to the Cobb-Douglas production-function
\[ Y = AK^\alpha L^{1-\alpha}. \]

Production growth that cannot be accounted for by labor- or capital-growth – the Solow residual - is treated as a measure of technological progress.

There are several reasons this being a problematic way of defining the level of technological progress, but the most critical, given the present context, is that the technology parameter \( A \) affects all workers equally. Hence it is an inappropriate measure of biased technological change affecting the productivity of different groups of workers in different ways. The empirical literature on the topic therefore makes use of more direct measures of skilled-biased technological change, with R&D expenditures and computer use is the most common ones. Berman et al. (1994) show that these two factors account for 70 percent of the move away from production labor within manufacturing in the period 1979-1987. This is consistent with the findings of other studies on other OECD-countries investigating the relation between technological progress and share of non-skilled workers in the work-force.

The paper of Aghion et al. also brings in a third element: the organizational change within firms. Certain skills will be firm-specific and rely on the organizational form of the enterprise. This means that wages are not entirely market-determined. There has been a growing literature investigating the role of organizational change in explaining rising wage-inequality. As Aghinon et al. formulates it, “the underlying idea is that, as changes in organization take place, the productivity gap between individuals with different skill levels increases”. Two clear trends are flattening firm structures and a growing segregation of workers by skills, leading to a higher homogeneity of firms regarding the skills of the employees. “Economic activity has shifted away from firms like General Motors which use both high- and low-skilled workers to firms such as Microsoft and Mc Donald’s whose workforces are much more homogenous”. This development goes hand in hand with technological change, and might strengthen the effect of technology on wage inequality as the productivity gap between firms increase.

All these three elements – trade, skill-biased technological change and organizational change - contribute to widening the earnings distribution, and all three phenomena are closely associated with growth over the past decade. In other words, the authors argue that increased inequality in earnings is directly linked to the nature of the forces
driving economic growth in the developed world. A brief summary may point to
technological change as a main driver behind the widening wage gap, as trade
liberalization and organizational changes mainly affect wage inequality insofar as they
are related to technological change.

2.3 Does inequality trigger redistribution?

The level of redistributive efforts varies tremendously across countries. This might
very well be the result of differences in the societies’ preferences for redistribution.
But democratic structures and how well the public’s preferences are translated into
actual redistributive politics is also a central topic in the literature.

On the overall level, it seems reasonable to assume that the demand for redistribution
is somewhat linked to the need for redistribution, in other words that there should exist
a link between inequality prior to taxes/transfer and redistributive efforts. From
standard social welfare theory, maximizing a social utility function with increasing but
diminishing returns, it follows that the most unequal societies should make the
strongest redistributational efforts.

One obvious theoretization of the link between inequality and redistribution is the
median voter theory. The theory is the basis of a whole branch of studies with different
modifications and expansions, but the basic idea is straightforward: With the median
voter as decisive, more unequal societies will choose greater redistribution. Political
competition drives the level of welfare spending towards the ideal point of the median
voter. If the income of the median citizen is an increasing function of the income of
the middle quantile as a whole, then the level of redistribution will decline as the
middle quintile’s income rises.

This theory leans on a set of assumptions that might very well be discussed. For
instance that all voters vote and that their preferences on transfers and taxes are single-
peaked and determined solely by their position in the income distribution. It also
requires that the ratio of benefits from government expenditure to tax payment is
falling in income. It is definitely not obvious that tax and transfer-schemes are arrayed
at along a simple continuum of progressivity. The Nordic welfare states with their
universalistic approach to public transfers and goods are typical examples of societies where this assumption will not necessarily hold.

When trying to test the straightforward application of the median voter hypothesis, most studies find a rather weak support for it, see for example Dalgaard, Hansen and Larsen (2005), Kenworthy and McCall (2008) and Lind (2005).

Milanovic (2000) is a study often referred to, as it tests the median voter theory by using OECD data on pre-tax inequality and the extent of redistribution. This might seem obvious, but due to lack of data, the theory was only tested for inequality in post-tax income and the size of transfers up until Milanovic’s study. This led to a time-sequencing problem since people’s voting decisions are based on their incomes before redistribution. Lind (2005) also points at the possibility of mechanical rejection of the theory when using post-tax data, due to the simple fact that high tax rates reduces post-tax inequality. When post-tax inequality is used as a proxy for pre-tax inequality, there will be a negative bias in the estimate as a result of reverse causality. It is also straightforward that the size of total transfers is irrelevant to the median voter. If most of the transfers are rewarded to other groups, the gain of the median voter will be marginal even though the size of transfers might be substantial.

If the median voter theory were to hold, Milanovic (2000) claimed that the median voter would have to benefit from redistribution, but not necessarily more than anyone else. The hypothesis also implies that the poorer in relative terms is the median voter, the larger is his gain. By placing the median voter in the fifth and sixth decile of factor-income distribution, the author is able to examine each of these corollaries. Using this approach, the theory seems to fail. Typically, the three lowest deciles gain while everybody else, including the median voter, lose. Thus the median voter hypothesis fails when we focus on the truly redistributive transfers only.

One of the main points of Milanovic is the difficulties in testing the median voter theory empirically. It is hard to determine exactly who the median voter is and against whose income the median voter compare his own income. In order to avoid the

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8 A percentage point decrease in the factor-income share of the middle class is associated with a 0.4 point increase in middle-class share gain. When treating pensions as regular income and not part of the transfer scheme, the values of the coefficients are about the same, but their level of significance decreases, and $R^2$ becomes practically zero.
arbitrariness in the search for the median voter, he launches the so-called “redistribution hypothesis” simply predicting that more unequal societies will be associated with greater redistribution. This is easier to test, and Milanovic conduct such tests on LIS data in both his 2000- and 2010-papers by calculating the sharegain realized by different deciles of income distribution when people are ranked by their income prior to taxes and transfers. Milanovic finds, in line with the idea of the redistribution hypothesis that higher initial inequality leads to a higher sharegain of the poor. Remarkably, the gain is almost as great as to make the position of the poor and the very poor independent of their initial shares. These results are in line with the main findings in the literature. According to Ostry et al. (2014), available empirics show almost no overall correlation between net and market inequality. Greater sharegain of the poor through redistribution tend to compensate for higher market income inequality when making across-country comparisons.

An alternative way of explaining the median voter’s preference for redistribution, even though she typically will not benefit directly from it, is the insurance element of redistribution. One might think that some level of transfers to the bottom deciles provides a certain security against income loss. Typically the low-wage earners will be more exposed to the risk of losing income, implying that if the insurance element dominates the demand for redistribution, this demand will decline as the middle quintile’s income decreases. This is certainly not always the case. Basset et al. (1999) suggests that a high income level is positively related to redistribution simply due to high income elasticity of demand for social insurance schemes. Put another way – insurance is a normal good, and when income declines, so will the demand for redistribution due to the income effect. The insurance element of redistribution might then be an explanation of the sometimes observed Robin Hood-paradox.

Moene and Wallerstein (2001) recognize both the median voter approach and the insurance element, and try to demonstrate that the combination of the two leads to different conclusions. The redistributive motive would lead self-interested voters to support welfare policy up to the point at which their gain from income redistribution

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10 Nearly 60% of the difference in inequality is lost through redistribution.

11 Lindert (2004) launched this expression to describe the observed tendency that modern social policy first was developed in more egalitarian societies like Germany and the Scandinavian countries.
matches their share of the cost. The insurance motive, on the other hand would lead the same voters to support welfare policy to obtain protection against risks that the private insurance markets fail to cover. When these motives are combined, the public’s support for redistribution will depend on how benefits are targeted. The median voter will typically benefit from both aspects of welfare policies. If the income of the median voter decreases, the median voter approach will suggest an increase in the demand for redistribution through the substitution effect. The insurance-approach would lead to the opposite conclusion if we assume that insurance is a normal good. They conclude that greater market inequality is associated with an increase in the support for welfare spending. But when the beneficiaries are those without earnings, the outcome is predicted by the insurance model which implies reduced support for welfare expenditures. This theoretical model gets empirical support when investigating data on welfare expenditures in advanced industrial societies during 1980-95. Regression results indicate that greater inequality is associated with lower spending on programs to insure against income loss as share of both GDP and government spending.

As earlier mentioned, in the standard application of the median voter theory, the voter’s decisions on transfers and taxes are assumed to be determined solely by their position in the income distribution. Typically the theory is analyzed in the framework of simple Downsian models with only two parties competing along a single policy dimension, i.e. the level of redistributive efforts. In such a model, the party offering the redistributive policy desired by the median voter wins the election. But politics is multi-dimensional, and voters might well make decisions that are not at all beneficial for themselves in economic terms, for instance due to i.e. religion, moral issues, strong identification with a certain group or race, or some ideological conviction about what the society should look like. It seems sensible to take into consideration a broader approach to what decides the vote of the median voter. Several attempts have been made in this concern, i. ex. Dhami and el-Nowaihi (2007) who redefine the median voter so that he or she is concerned with “fairness” of the distribution and not only with individual well-being.

Following this argument, it’s interesting to once again notice Basset et al. (1999) who suggests that the median voter might react to high concentrations of wealth at the the
top of the income distribution by requesting more redistribution, even though his own income level is not affected:

“.. it is difficult to explain voting on purely rational grounds, and this may suggest that voting in part serves needs other than the pursuit of pure self-interest. One relevant possibility is that, whether because the representative (or decisive) voter works from a model of justice in which extreme disparities are viewed as inherent social bads, because that voter feels resentment against those with extraordinarily high incomes, or for some other reason, a high concentration of wealth at the top of the income distribution may lead to higher levels of transfers, all else being equal.”

The study finds such a relationship to be valid, and it’s difficult to explain this in any other way than by the voters’ perception that such an income distribution is unfair.

One could also ask if egalitarian systems have a self-reinforcing mechanism in it. In Norway, the market inequality is rather low, mainly due to the system of collective bargaining which leads to a very compressed income-structure. Is this affecting norms in such a way that the Norwegian public also prefers redistributive policy?

Barth and Moene (2012) suggest a relationship that such exists through the “equality multiplier”. The multiplier works through two mechanisms: 1) more wage equality increases welfare generosity via political competition in elections 2) a generous welfare state fuels wage equality via an empowerment of weak groups in the labor market, i.e. through access to education. The hypothesis is tested using data on 18 OECD-countries, and the authors find support to their theory.

As mentioned in the introduction to this section, there might be differences in the median voter’s ability to influence the redistributive efforts undertaken by the government. The strength of the median voter’s political influence can be the result of various factors. Level of education is already mentioned. The development of democratic institutions and political power of the economic elite are other relevant factors. Since direct democracy does not apply in most countries, there is also a danger that the voters “true” preferences might get lost on the way. This opens the door for strong interest groups to influence political decisions outside the electoral system.
Stiglitz (2012) is one of the scholars occupied with the question of how economic power also might lead to political power, undermining the mechanisms of democracy. An important assumption that needs to be fulfilled if the median voter theory is to hold is the even distribution of political influence. Usually it is assumed that political power is more evenly distributed than economic power, and that redistributive schemes will appear when the majority of voters have the power and incentives to vote for redistribution. As Stiglitz argue, this does not need not to be the case if the rich have more political influence than the poor.

There is also an observed tendency that the wealthier part of the population tends to show up at the ballots at a larger degree than the poor. In this case, the median voter and the median citizen will not be the same. Basset et al. (1999) introduces “pivotal voter”, a modified version of the median voter theory, focusing on the voter who is median among the voting population. Since the poor tend to vote less, the pivotal voter is to the right of the median. And:

“.. even if the median voter model is correct in assuming that people vote according to their pocket-books, it appears naïve in assuming that everyone carries equal weight. In actual democratic politics, the political weight carried by different groups of citizens depends, among other things, upon their success at organizing or otherwise acting in support of their interests.”
2.4 The interrelationship between redistribution, inequality and growth – are there any overall conclusions to be drawn?

So far the ambition has been to present an overview of the theories dominating research on the interrelationship between inequality, redistribution and growth. As described, the amount of literature is large, and here it has been categorized into three relationships: i) the effect of inequality and/or redistribution on growth, ii) the effect of growth on inequality and iii) the effect of inequality on redistribution.

It is hard to draw any clear conclusions. There is substantial doubt regarding the sign and strength of the relationships. Even though some hypotheses seem to gain more overall support than others, theories contradict each other, and empirical evidence does not provide definitive answers.

This might to some part be due to scarcity of data. Cross-national research on the causes and consequences of income inequality has been hindered by the limitations of existing inequality datasets. Growth data are generally available, but the scope and quality of data used on inequality and redistribution varies tremendously across studies. One may also suspect that the different use of statistical methods and inequality/redistribution measures across studies play a decisive role for the conclusions achieved. This is especially true for studies involving redistribution, as redistribution is extremely hard to measure without access to available microdata on market inequality and tax redistribution. Only during the last few years, such data has become available in longer, reliable cross-country time-series. Therefore most empirical studies have relied upon the use of a whole variety of proxies for redistribution, such as tax levels, government transfers or the overall government spending. The lack of inequality data prior to taxes and transfers is possibly also the case why several studies on inequality fail to distinguish between inequality before and after redistribution. All these factors make it hard to interpret and compare the results of different studies in a meaningful way.
The dimension focusing on the effect of growth on inequality emerges as the most unexplored one. Few theories have been presented after the Kuznets curve, even though the effect of growth on the distribution of earnings, especially among the poorest, has been the topic of quite an amount of empirical studies. There might be many reasons why this relationship gains so little attention, while the opposite causal relationship serves as the starting point for so many analyses. Previous empirical findings suggesting that growth has little effect on net inequality might be one explanation. It is worth recalling here, that in the figure 1 this causal relationship is not represented at all.

As stated in the preface, the aim of this thesis is to investigate the relation between all four variables (market inequality, net inequality, redistribution and growth). The ambition is to take advantage of the development in data-access and try to bring a little more clarity into the discussion on how inequality, redistribution and growth are interrelated.
3 Brief overview: Development in inequality, redistribution and growth in OECD-countries over time

As I approach the empirical analysis of this thesis, I choose to focus on OECD member-countries. The interrelationship between growth, inequality and redistribution might work very differently in developing countries compared to developed ones. Therefore I choose to focus on developed countries, well aware that later conclusions may not be easily transferable to developing countries.

The following section provides a brief look at how growth, inequality and redistribution have evolved in OECD over time.

Over the last five decades, the GDP growth rate for the OECD total saw the largest fluctuations during the first and the second oil shocks (1973 and 1979), the first and the second Gulf War (in the 1980s and start of the 1990s), as well as during the financial crisis in 2000 and the latest crisis that started in 2007.

Figure 3. Growths rates in selected OECD-countries, 2000-2012

Source: OECD
As seen in figure 3, there was a remarkable fall across most of the OECD member countries in relation to the financial crisis in 2008. In the aftermath of the crisis, most countries have reestablished positive growth, but not at the level of the years preceding the crisis. This has raised a fundamental discussion on the determinants of growth. Rising inequality plays a central part in this discussion, as discussed by Cingano et al. (2014). A general finding is that countries where income inequality is decreasing grow faster than those with rising inequality. The authors estimate rising inequality to have knocked more than 10 percentage points off growth in Mexico and New Zealand over the past two decades. For Italy, the United Kingdom and the United States, the cumulative growth rate would have been six to nine percentage points higher had income disparities not widened.

The study sums up the development of inequality in OECD during the last decades as follows (p. 10): “The paths and patterns of income inequality over time differ across OECD countries and regions. Income inequality first started to grow in the late 1970s and early 1980s in some of the English-speaking countries, notably in the United Kingdom and the United States, but also in Israel. From the late 1980s onwards, the increase in income inequality became more widespread. The 1990s and early 2000s witnessed a widening gap between poor and rich in some of the already high-inequality countries, such as Israel and the United States, but also, for the first time, in traditionally low-inequality countries, such as Germany and the Nordic countries.”

It seems that the financial crisis also curbed the rise in income inequality as measured by the developments in the Gini coefficient, see figure 5. However, since 2010, inequality has increased in most OECD-countries.
Ostry et al. (2014) presents the development in Gini coefficients\textsuperscript{12} for market income and post-tax income, showing that the medians of both indices have been rising since the 60s (see figure 6). It appears that the rise in inequality prior to taxes/transfers (market Gini) has been somewhat higher than the rise in inequality post taxes/transfers (net Gini). The variation in the market Gini is far less in the period of 2000-2010 compared to 1960-1980, and it is the observations in the bottom end that has disappeared. The development in the net Gini does not follow the same pattern, indicating an increase in redistributive efforts. Whether this is the result of a conscious policy-response or an automatic response as a given tax schedule now works on a more unequal market income distribution, is not obvious.

\textsuperscript{12} The Gini coefficient is a measure of inequality that varies between 0 (complete inequality) and 1 (all income goes to one individual).
Figure 6. Development in Gini coefficients for market income and post-tax/transfers income, 1960-2010

Source: Ostry et al. (2014) based on SWIID-data. Box and whisker plots represent the inter-quartile range first and third quartile values, with the middle line inside the box representing the median. The lower (higher) end if the whiskers represent the lowest data point within 1.5*IQR of the lower quartile.
4 Empirical investigation

4.1 Background

Earlier discussions of inequality, redistribution and growth suffer from a lack of available and reliable data on inequality and redistribution. Data on inequality usually differ as to coverage, reference unit, weighting and definition of income. This obviously limits the analysis and affects the results. Simultaneous analysis also requires cross-country data on both inequality market inequality\(^{13}\) and net inequality\(^{14}\). Such data have been scarce up until now, and they still suffer from imperfections. More recent studies take advantage of better data access.

While these more recent studies, to some extent, discuss the possibility of endogeneity and also take it into account by modelling the relations in a dynamic model framework to avoid biased estimates, there are still few attempts made to systematically sort out the directions of the relationships between inequality, redistribution and growth. The authors are mainly interested in the size and sign of effects. Does inequality have positive or negative effect on growth? And how large is this positive or negative effect? When revisiting figure 1, one clearly sees that all arrows are pointing from inequality and redistribution towards growth. Growth is not assumed to have any significant effect the other way around.

I find it somewhat surprising that most analyses, including the most recent ones, leave the question of “what causes what” partly or fully unanswered, also given the theoretical background (as just seen). The recent development in data access, allowing for simultaneous analysis of inequality, redistribution and growth, gives new opportunities for trying to reach closer to some conclusions - also regarding the directions of the relationships.

\(^{13}\) Inequality prior to taxes and transfers
\(^{14}\) Inequality post taxes and transfers
In this empirical investigation, I shall depart from the following dynamic relationship:

\[ \Delta Y_{i,t} = \alpha Y_{i,t-1} + \beta X_{i,t-1} + c_i + \epsilon_{i,t} \]

where \( c_i \) represent the country specific time-invariant unobservables. The time series of the variables at play (growth, inequality and redistribution) will take the places of \( Y_{i,t} \) and \( X_{i,t} \) pairwise. Granger causality tests will be conducted inside the framework of a system GMM model. A significant value for \( \beta \), then implies that the time-series \( X_{i,t} \) is Granger-causing changes in the time series \( Y_{i,t} \).

Data and method will be described in detail later in this section.

### 4.2 Data, choice of variables and descriptive statics

As mentioned in section 3, I choose to limit the analysis to OECD-countries. Firstly because of indications from earlier studies suggesting that the links between inequality, redistribution and growth differ systematically between developed and less developed economies. Typically these studies have found the link between inequality and growth to be negative among undeveloped countries and insignificant or positive among developed ones (Barro, 2000). When including both developed and developing countries in the dataset, one runs the risk of only capturing average effects and thereby getting misleading results. Secondly because this data limitation makes it possible to employ relevant and reliable long time-series for all countries in the sample. Disparity in the quality of data is always an issue in cross-country analysis, but I assume this challenge to be limited among the group of OECD-countries.

The analysis is run on a dataset that I have constructed with observations on GDP per capita, market inequality and net inequality in the period 1960 - 2011 for all OECD-members. Countries from the former East-Block are included in the dataset after 1990 post their transition to market economy.

GDP per capita-data are collected from the World Bank Database. It measures gross domestic product divided by midyear population. Data are in constant 2005 US dollars. Data on market inequality and net inequality are collected from The Standardized World Income Inequality Database (SWIID version 5.0). The SWIID
provides comparable Gini indices\textsuperscript{15} of market and net income inequality for 174 countries for as many years as possible from 1960 to the present along with estimates of uncertainty in these statistics. By maximizing comparability for the largest possible sample of countries and years, the SWIID is better suited to broadly cross-national research on income inequality than previously available sources.

To conduct my analysis, I define the following four variables:

1) $\log(GDP)$ measuring the log of real GDP per capita
2) Market inequality measuring the Gini coefficient prior to taxes and transfers
3) Net inequality measuring the Gini coefficient post taxes and transfers
4) Redistribution measured as $((\text{Market ineq.} – \text{Net ineq.})/\text{Market ineq.}) \times 100$.

I choose deliberately to let $\log(GDP)$ enter the analysis instead of actual growth rates. This is in line with Cingano (2014) and other comparable studies taking advantage of the mathematical equivalence

$$
\Delta Y_{i,t} = \alpha Y_{i,t-1} + \beta X_{i,t-1} + c_i + \epsilon_{i,t}
$$

$$
Y_{i,t} = (\alpha + 1) Y_{i,t-1} + \beta X_{i,t-1} + c_i + \epsilon_{i,t}
$$

The underlying model is the same in both specifications. The coefficient $\beta$ can be interpreted as marginal effect of $X_{i,t-1}$ on the differenced dependent variable $\Delta Y_{i,t}$ no matter whether I estimate the first or the second equation. The valid instruments on the right-hand side variables are the same, and the coefficient estimate of $\beta$ is identical.

When $\log(GDP)$ enters as the dependent variable, $\beta$ will reflect the effect of a change in the explanatory variable $X_{i,t-1}$ on growth. When $\log(GDP)$ enters as the explanatory variable, it will reflect the marginal effect of a GDP-change (i.e. growth) on the differenced dependent variable.

As previously discussed, inequality and redistribution can be measured in numerous ways. I will not go into the pros and cons of the different approaches here. Since the aim of the analysis is to sort out the directions of the interrelations between inequality, redistribution and growth, I am dependent on access to reliable, long time-series data. This limits the possibilities. I also wish to be able to compare my results to other

\textsuperscript{15} To calculate the indices, a custom missing-data algorithm was used to standardize the UNs World Income Inequality Database and data from other sources. Data collected by the Luxembourg Income Study served as the standard.
studies based on the same methodological approach. These considerations combined, makes me choose the standard Gini index as the measure of inequality.

It is worth noting here that the Gini index does not capture differences in accumulated wealth, and it does not account for access to government paid goods, such as education and health care. Attempts have been made to include such access in measures of redistributive efforts, but it is challenging to quantify it in a meaningful and comparable way. I make the choice of keeping government paid goods out of the analysis, well aware of the substantial role they play in reducing inequality in many countries.

The measure of redistribution is in line with the specification of Pechman and Okner (1974), and can be read as normalized values of achieved inequality reduction. An observation on redistribution then tells how large share of the market inequality that is eradicated through taxes and transfers.

Growth and inequality are normally sluggish variables and varies little from year to year in the absence of great external shocks. The relationships I seek to analyze will typically evolve over a longer period of time. I therefore choose to follow the approach of Cingano (2014) and exploit data with five-year intervals (s=5), starting in 1960. All observations in between are dropped. The number of observations is of course reduced dramatically through this maneuver (see table 1), but it will allow me to capture more of the within-variation in the dataset. It is important to keep in mind that a one-period lag with this specification reflects an actual lag of 5 years.
Table 1: List of country observations

<table>
<thead>
<tr>
<th>Country</th>
<th>Min</th>
<th>Max</th>
<th>Number of observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>1960</td>
<td>2010</td>
<td>11</td>
</tr>
<tr>
<td>Austria</td>
<td>1965</td>
<td>2010</td>
<td>8</td>
</tr>
<tr>
<td>Belgium</td>
<td>1965</td>
<td>2010</td>
<td>9</td>
</tr>
<tr>
<td>Canada</td>
<td>1960</td>
<td>2010</td>
<td>11</td>
</tr>
<tr>
<td>Chile</td>
<td>1965</td>
<td>2010</td>
<td>8</td>
</tr>
<tr>
<td>Czech republic</td>
<td>1990</td>
<td>2010</td>
<td>5</td>
</tr>
<tr>
<td>Denmark</td>
<td>1965</td>
<td>2010</td>
<td>10</td>
</tr>
<tr>
<td>Estonia</td>
<td>1995</td>
<td>2010</td>
<td>4</td>
</tr>
<tr>
<td>Finland</td>
<td>1965</td>
<td>2010</td>
<td>10</td>
</tr>
<tr>
<td>France</td>
<td>1965</td>
<td>2010</td>
<td>10</td>
</tr>
<tr>
<td>Germany</td>
<td>1990</td>
<td>2010</td>
<td>5</td>
</tr>
<tr>
<td>Greece</td>
<td>1965</td>
<td>2010</td>
<td>10</td>
</tr>
<tr>
<td>Hungary</td>
<td>1995</td>
<td>2010</td>
<td>4</td>
</tr>
<tr>
<td>Iceland</td>
<td>1995</td>
<td>2010</td>
<td>4</td>
</tr>
<tr>
<td>Ireland</td>
<td>1970</td>
<td>2010</td>
<td>9</td>
</tr>
<tr>
<td>Israel</td>
<td>1980</td>
<td>2010</td>
<td>7</td>
</tr>
<tr>
<td>Italy</td>
<td>1970</td>
<td>2010</td>
<td>9</td>
</tr>
<tr>
<td>Japan</td>
<td>1960</td>
<td>2010</td>
<td>11</td>
</tr>
<tr>
<td>Luxembourg</td>
<td>1970</td>
<td>2010</td>
<td>8</td>
</tr>
<tr>
<td>Mexico</td>
<td>1970</td>
<td>2010</td>
<td>9</td>
</tr>
<tr>
<td>Netherlands</td>
<td>1965</td>
<td>2010</td>
<td>9</td>
</tr>
<tr>
<td>New Zealand</td>
<td>1980</td>
<td>2010</td>
<td>7</td>
</tr>
<tr>
<td>Norway</td>
<td>1960</td>
<td>2010</td>
<td>11</td>
</tr>
<tr>
<td>Poland</td>
<td>1990</td>
<td>2010</td>
<td>5</td>
</tr>
<tr>
<td>Portugal</td>
<td>1980</td>
<td>2010</td>
<td>7</td>
</tr>
<tr>
<td>Slovak Republic</td>
<td>1995</td>
<td>2010</td>
<td>4</td>
</tr>
<tr>
<td>Slovenia</td>
<td>1995</td>
<td>2010</td>
<td>4</td>
</tr>
<tr>
<td>Spain</td>
<td>1965</td>
<td>2010</td>
<td>9</td>
</tr>
<tr>
<td>Sweden</td>
<td>1960</td>
<td>2010</td>
<td>11</td>
</tr>
<tr>
<td>Switzerland</td>
<td>1980</td>
<td>2010</td>
<td>6</td>
</tr>
<tr>
<td>Turkey</td>
<td>1965</td>
<td>2010</td>
<td>6</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>1965</td>
<td>2010</td>
<td>10</td>
</tr>
<tr>
<td>United States</td>
<td>1960</td>
<td>2010</td>
<td>11</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td><strong>265</strong></td>
</tr>
</tbody>
</table>

The list reveals that the dataset is highly unbalanced.
Even with the use of 5-year intervals, standard deviations of the variables reveal small within-variation (see table 2), indicating the need for a model tool that allows me to exploit all possible variation in the dataset in order to get significant results.

Table 2: Variance in the dataset

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>log(GDP)</strong></td>
<td>Overall</td>
<td>9,935</td>
<td>0,667</td>
<td>7,876</td>
<td>N = 265</td>
</tr>
<tr>
<td></td>
<td>Between</td>
<td>0,639</td>
<td>8,488</td>
<td>10,847</td>
<td>n = 33</td>
</tr>
<tr>
<td></td>
<td>Within</td>
<td>0,322</td>
<td>8,488</td>
<td>10,655</td>
<td>T-bar = 8,030</td>
</tr>
<tr>
<td><strong>Net Gini</strong></td>
<td>Overall</td>
<td>30,925</td>
<td>7,350</td>
<td>18,376</td>
<td>N = 265</td>
</tr>
<tr>
<td></td>
<td>Between</td>
<td>6,991</td>
<td>23,156</td>
<td>50,844</td>
<td>n = 33</td>
</tr>
<tr>
<td></td>
<td>Within</td>
<td>2,595</td>
<td>19,580</td>
<td>42,730</td>
<td>T-bar = 8,030</td>
</tr>
<tr>
<td><strong>Market Gini</strong></td>
<td>Overall</td>
<td>45,868</td>
<td>5,717</td>
<td>30,312</td>
<td>N = 265</td>
</tr>
<tr>
<td></td>
<td>Between</td>
<td>4,298</td>
<td>37,328</td>
<td>54,335</td>
<td>n = 33</td>
</tr>
<tr>
<td></td>
<td>Within</td>
<td>4,030</td>
<td>32,727</td>
<td>56,357</td>
<td>T-bar = 8,030</td>
</tr>
<tr>
<td><strong>Redistribution</strong></td>
<td>Overall</td>
<td>32,739</td>
<td>11,841</td>
<td>-2,553</td>
<td>N = 265</td>
</tr>
<tr>
<td></td>
<td>Between</td>
<td>10,742</td>
<td>4,296</td>
<td>46,000</td>
<td>n = 33</td>
</tr>
<tr>
<td></td>
<td>Within</td>
<td>5,081</td>
<td>4,835</td>
<td>48,353</td>
<td>T-bar = 8,030</td>
</tr>
</tbody>
</table>

A first glimpse of the raw-data also indicates weak relations (see figure 8). The immediate relation between net inequality and growth appears to be slightly positive, if existing at all. The relationship between market inequality and growth looks slightly negative, while redistribution seems to be negatively correlated with growth when reaching high levels. In the plotting of market inequality against net inequality, all observations (with one exception \(^{16}\)) lies below the 45 degree-line, indicating that all countries make some sort of redistributive efforts through taxes and transfers.

---

\(^{16}\) Mexico, 2000
Figure 8: Scatterplots of raw-data

Note: Scatterplots with regression lines from locally weighted regressions. GDP per capita growth measured as $\Delta \log(GDP)$. 

4.3 Econometric specification

As already stated, I am interested in exploring a dynamic regression model where the time-series of the variables $\log(GDP)$, Market inequality, Net inequality and Redistribution take the places of $Y_{i,t}$ and $X_{i,t}$ pairwise. The intention is to first test whether or not the different variables of inequality and redistribution Granger-cause growth, before I move on to test the reverse relationships – whether or not growth is Granger-causing inequality and/or redistribution.

Granger’s (1969) testable definition of causality is established as a widely used analytical tool in applied economics. Granger-testing can easily be explained as testing whether or not the history of one variable is better explained by introducing the history of another. According to Granger’s definition of causality, a stationary time series $X_{i,t}$
is said to “cause” another stationary time series $Y_{i,t}$ if—under the assumption that all
other information is irrelevant—using past values of both $Y_{i,t}$ and $X_{i,t}$ as regressors is
better than using lags of $Y_{i,t}$ alone.

In econometric practice, Granger causality tests are carried out by regressing $Y_{i,t}$ on its
own lags and lags of $X_{i,t}$. If the lags of $X_{i,t}$ are found to be jointly statistically
significant, then the null hypothesis that $X_{i,t}$ does not Granger-cause $Y_{i,t}$ can be
rejected. Therefore—in the framework of a dynamic model where the dependent and
independent variables are introduced with the same number of lags, testing for
significant regression coefficients will be equivalent to testing for Granger-causality.
Granger-tests can produce meaningful suggestions on the direction of relationships
between time series, and it can easily be done inside the framework of different
econometric modelling techniques.

In an autoregressive model like this, the lags of $Y_{i,t}$ will be correlated with the error
term, creating biased estimates for $\alpha$ and $\beta$. OLS panel data approaches are therefore
not suitable. This calls for another approach.

An option could be to do Granger testing inside the framework of a VAR-model,
allowing all variables to be endogenous, but some preliminary tests revealed this
approach to produce highly unstable results. Another alternative would be to work in a
simultaneous equation model. However, this would require having valid external
instruments for the endogenous variables, which in practice is very demanding. Hence,
GMM is a common choice when facing endogeneity problems as it uses subsequent
lags of the dependent variable as instruments.¹⁷ GMM is also considered to be
favorable (Judson and Owen, 1999) when dealing with unbalanced panels and when
the number of observations on each country is less than 20, as is the case in the present
analysis (see table 1).

Several other previous studies in this field use GMM, as the earlier mentioned works
of Ostry et al. (2014), Cingano (2014) and Halter et al. (2014). In contrast to the three
works mentioned, my aim is not first and foremost to exploit how redistribution and
inequality affect growth. My aim is to see if it is possible to come closer to obtaining

¹⁷ For further introduction to the concept of GMM-estimation, see Cameron and Trivedi, 2008, p 172-183
results on directions in general. This is possible within the GMM framework, using the concept of Granger tests for causality.

With the right specification, the GMM approach will yield consistent and asymptotically normally distributed estimators. It accounts for country level time-invariant unobservables. Further it handles the endogeneity problem through the use of instrumentation. The model leans on the assumption that

$$E[Y_{i,s}, \Delta \varepsilon_{i,t}] = 0 \text{ for } s \leq t - 2$$

meaning that the lags $Y_{i,t-2}, Y_{i,t-3} \ldots$ can be used as instruments for the first differenced $Y_i$.

Cingano points out some drawbacks of using standard first-difference GMM-estimates in the current context, the main one being that variables as inequality display notable persistence within a country. This is confirmed in the analysis of variance in my dataset. “Hence, taking first differences eliminates most of the variation in the data, and implies that the lagged levels of the explanatory variables are weak instruments for the variables in differences, giving rise to large biases and imprecision”.

It is possible to use additional moment conditions to obtain estimators with improved precision and better finite-sample properties – so called system GMM-modelling. Arellano and Bover (1995) and Blundell and Bond (1998) consider using the additional condition

$$E[\Delta Y_{i,t-1}, \Delta \varepsilon_{i,t}] = 0$$

so that the levels variables are used as instruments for the first differenced variables $\Delta Y_{i,t-1}$.

When discussing first difference GMM versus system GMM it is also worth noting that Halter et al. (2014) found the choice of GMM-method to have considerable impact on the regression results. Mechanisms generating a positive inequality-growth relationship work, according to Halter et al., mainly in the short run and are reflected in difference-based estimators. This is troublesome as many of the theoretical effects of inequality on growth may take a significant amount of time to materialise. In contrast,
mechanisms generating a negative relationship work over the longer term and are reflected in level-based estimators. When conducting system GMM, one takes advantage of both within-country and cross-country variation in the dataset, trying to avoid this problem. Cingano (2014), Ostry et al. (2014) and Halter et al. (2014) all choose to follow this approach.

Following Cingano, I assume that one lag of the dependent variable is sufficient. To conduct Granger testing, to test whether or not the introduction of the time-series $X_{i,t}$ contributes to the explanation of time-series $Y_{i,t}$, I obviously need to have the same number of lags in the second regressor.

The regressors are treated as predetermined or weakly exogenous, implying that they are correlated with past errors, but uncorrelated with future errors:

$$E[X_{i,t}, \varepsilon_{i,t}] \neq 0 \text{ for } s < t$$

and

$$E[X_{i,t}, \varepsilon_{i,t}] = 0 \text{ for } s > t$$

These regressors can therefore be instrumented using subsequent lags.

This leaves me with the following six regression specifications:

1. \[\log(GDP)_{i,t} = \alpha \log(GDP)_{i,t-1} + \beta Net Gini_{i,t-1} + c_i + \varepsilon_{i,t}\]

with the moment conditions:

$$[\log(GDP)_{i,s}, \Delta \varepsilon_{i,t}] = 0 \text{ for } s \leq t - 2$$

$$E[\Delta \log GDP_{i,t-1}, \Delta \varepsilon_{i,t}] = 0$$
2. \( \log(GDP)_{i,t} = \alpha \log(GDP)_{i,t-1} + \beta \text{Market Gini}_{i,t-1} + c_i + \varepsilon_{i,t} \)

with the moment conditions:

\[
E[\log(GDP)_{i,s}, \Delta \varepsilon_{i,t}] = 0 \text{ for } s \leq t - 2
\]
\[
E[\Delta \log GDP_{i,t-1}, \Delta \varepsilon_{i,t}] = 0
\]

3. \( \log(GDP)_{i,t} = \alpha \log(GDP)_{i,t-1} + \beta \text{Redistribution}_{i,t-1} + c_i + \varepsilon_{i,t} \)

with the moment conditions:

\[
E[\log(GDP)_{i,s}, \Delta \varepsilon_{i,t}] = 0 \text{ for } s \leq t - 2
\]
\[
E[\Delta \log GDP_{i,t-1}, \Delta \varepsilon_{i,t}] = 0
\]

4. \( \text{Net Gini}_{i,t} = \alpha \text{Net Gini}_{i,t-1} + \beta \log(GDP)_{i,t-1} + c_i + \varepsilon_{i,t} \)

With the moment conditions:

\[
E[\text{Net Gini}_{i,s}, \Delta \varepsilon_{i,t}] = 0 \text{ for } s \leq t - 2
\]
\[
E[\Delta \text{Net Gini}_{i,t-1}, \Delta \varepsilon_{i,t}] = 0
\]

5. \( \text{Market Gini}_{i,t} = \alpha \text{Market Gini}_{i,t-1} + \beta \log(GDP)_{i,t-1} + c_i + \varepsilon_{i,t} \)

with the moment conditions:

\[
E[\text{Market Gini}_{i,s}, \Delta \varepsilon_{i,t}] = 0 \text{ for } s \leq t - 2
\]
\[
E[\Delta \text{Market Gini}_{i,t-1}, \Delta \varepsilon_{i,t}] = 0
\]
6. Redistribution_{i,t} = \alpha \text{Redistribution}_{i,t-1} + \beta \log(GDP)_{i,t-1} + c_i + \epsilon_{i,t} \\

with the moment conditions:

\[
E[\text{Redistribution}_{i,s}, \Delta \epsilon_{i,t}] = 0 \text{ for } s \leq t - 2 \\
E[\Delta\text{Redistribution}_{i,t-1}, \Delta \epsilon_{i,t}] = 0
\]

The potential number of instruments in these models is large. If too many instruments are used, asymptotic theory provides a poor finite-sample approximation to the distribution of the estimator (Cameron and Trivedi, 2009, p 289). Roodman (2009) also points at the problem of too many instruments. In my specification, the number of instruments is restricted to using only the second lag of the differentiated data and the first differences of the level data.

Because the model is overidentified, it allows the use of optimal or two-step GMM. According to Arrellano and Bond (1991), standard errors reported using standard textbook formulas for the two-step GMM estimator are downward biased in finite samples. I therefore use the more robust estimate of the standard error proposed by Windmeijer (2005). These standard errors allows for heteroscedasticity in the error terms.

For consistent estimation, the error terms must be serially uncorrelated. Since I am using the second lag of the regressors as instruments, I need to test for autocorrelation in the second lag of the first-differenced errors. This is done using the Arellano-Bond test for zero autocorrelation in first differenced errors. The results for the second lag are reported in table 3.18.

Since system GMM uses lagged first-differences as instruments for the levels of the right hand side variables, it rests on the assumption that first-differences are not correlated with the time invariant country-specific effect. To detect possible violation

\[ H_0: \text{no autocorrelation. The null is not rejected for } p>0.05. \]
of this requirement, I apply difference-in-Hansen tests to the instruments for the level equation, as suggested by Roodman (2009). The p-values of the Hansen-tests are also reported in table 3.

4.4 Discrimination between specifications

Most Granger-causality tests that can be found in the literature involve only two variables. One might righteously ask whether the assumption that “all other information is irrelevant” is fulfilled in such cases. But when working within the system GMM framework, it is possible to test variables pairwise getting consistent results. The time-invariant country-specific effects are accounted for. The model is dynamic with the lagged version of the dependent variable included. That means I also control for the history of the dependent variable. A significant coefficient, β, on the independent variable, therefore suggests that this variable Granger-causes the dependent variable

---

19 H0: all instruments are valid. The null is not rejected for p>0.05
20 This test requires the errors to be i.i.d., and the Windmeijer-errors cannot be used. Therefore the regression is also run without this option for the purpose of conducting the Hansen-test
4.5 Results

Table 3 shows the main results of this study, given the 6 different specifications. The $\beta$-coefficients are reported in bold.

Table 3: Baseline results

<table>
<thead>
<tr>
<th></th>
<th>1. $\Delta \log(GDP)$</th>
<th>2. $\Delta \log(GDP)$</th>
<th>3. $\Delta \log(GDP)$</th>
<th>4. $\Delta$ Net ineq.</th>
<th>5. $\Delta$ Market ineq.</th>
<th>6. $\Delta$ Redistribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>log($GDP$)$_{t-1}$</td>
<td>0.0065***</td>
<td>0.0132***</td>
<td>0.0176***</td>
<td>0.7640**</td>
<td>1.5517***</td>
<td>1.4548**</td>
</tr>
<tr>
<td></td>
<td>(0.0043)</td>
<td>(0.0181)</td>
<td>(0.0045)</td>
<td>(0.2634)</td>
<td>(0.2726)</td>
<td>(0.5428)</td>
</tr>
<tr>
<td>Net inequality$_{t-1}$</td>
<td>0.0017</td>
<td></td>
<td>-0.2532***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0014)</td>
<td></td>
<td>(0.091)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market inequality$_{t-1}$</td>
<td>0.0004</td>
<td></td>
<td>-0.3279***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0025)</td>
<td></td>
<td>(0.0608)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Redistribution$_{t-1}$</td>
<td>-0.0019</td>
<td></td>
<td></td>
<td>-0.4079***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0014)</td>
<td></td>
<td></td>
<td>(0.1632)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Arellano-Bond (p-value)</td>
<td>0.3764</td>
<td>0.3986</td>
<td>0.4336</td>
<td>0.4422</td>
<td>0.3291</td>
<td>0.5111</td>
</tr>
<tr>
<td>Hansen (p-value)</td>
<td>0.5424</td>
<td>0.5180</td>
<td>0.5908</td>
<td>0.6249</td>
<td>0.5293</td>
<td>0.5291</td>
</tr>
<tr>
<td>Observations</td>
<td>225</td>
<td>225</td>
<td>225</td>
<td>225</td>
<td>225</td>
<td>225</td>
</tr>
<tr>
<td>Number of countries</td>
<td>33</td>
<td>33</td>
<td>33</td>
<td>33</td>
<td>33</td>
<td>33</td>
</tr>
<tr>
<td>Number of instruments</td>
<td>36</td>
<td>36</td>
<td>36</td>
<td>36</td>
<td>36</td>
<td>36</td>
</tr>
</tbody>
</table>

Note: * p<.05, ** p<.01, *** p<.001. Coefficients from system GMM (Arellano-Bond) regressions (standard errors in parentheses). A variable X is said to Granger-cause Y if X has an effect on Y after control for the entire history of Y. Thus, coefficients on variables other than the lagged dependent variable are tests of Granger causality in each model (marked in bold). Redistribution is measured as 100*[Market ineq. – Net ineq.]/Market ineq.].

The results show no significant effects of neither net inequality, market inequality nor redistribution on growth (models 1, 2 and 3). When I flip the coin, however, and test whether or not the development of growth over time contributes to the explanation of inequality and redistribution, I find a substantial and highly significant effect of growth on all three variables (models 4, 5 and 6).
4.6 Discussion

4.6.1 The effect of inequality and redistribution on growth

As already discussed, the previous literature appears to be undecisive on this point, and the present analysis does not suggest any significant effect of neither inequality nor redistribution on growth. It is important to recall here that the dataset is limited to OECD-member countries, i.e. quite well-developed economies. As already mentioned, Barro (2000) finds - based on the analysis of a broad sample of countries – that the link between inequality and growth tend to be negative among less developed countries and positive or insignificant among developed ones. Halter et al. (2014) make a similar finding. When conducting system GMM analysis on a set of 90 countries, they find a slightly positive effect\textsuperscript{21} of net inequality on growth in rich countries. The effect is negative in the poor countries. Ostry et al. (2014) using the same methodic approach, also on 90 countries but with a different data-source, find the effect of net inequality to be negative\textsuperscript{22}, but his analysis is not divided into subsamples. There are in other words a possibility that differing effects in rich and poor countries are offsetting each other. Cingano (2014) on the other hand, finds a substantial and negative coefficient\textsuperscript{23} of net inequality on growth when conducting system GMM analysis control variables and for a sample of OECD-countries.

Length of the time series might play a partial role in explaining the difference in Cingano’s results compared to mine. When examining the empirical literature on inequality and growth, Halter et al. (2014) find that estimators based on time series-variation often indicate a positive linke, while estimators exploiting the cross-sectional variation suggest a negative relationship. The idea of system GMM compared to first-difference GMM is to take advantage of both the time-variation and the cross-sectional variation in the dataset. Therefore, when I conduct system GMM regression on a dataset consisting of the same countries (OECD), but with longer time series, there might be more time-specific variation influencing my results compared to Cingano’s.

\textsuperscript{21}0.0021** (0.011). The results are reported in Appendix B.3.
\textsuperscript{22}-0.1435*** (0.0444). The results are reported in Appendix B.1.
\textsuperscript{23}-0.774**(0.319). The results are reporten in Appendix B.2.
According to the redistribution hypothesis, it is inequality prior to taxes and transfers that will trigger the demand for redistributive action. In my analysis, neither market inequality nor redistribution turn out to have a significant effect on growth. This is in line with the findings of both Ostry et al. (2014) and Cingano (2014).

**4.6.2 The effect of growth on inequality and redistribution**

The effect of growth on the market income distribution is not very well explored. The view of Ostry et al. (2014) that this is something that for a large part can be ignored due to empirical studies suggesting no net effect is common. My results suggest a story containing an initial increase in inequality countered by increased redistribution which partly offsets this initial effect. This is challenging the common view that growth is to be treated as the endogenous variable when exploring the relationship between inequality, redistribution and growth.

As earlier stated, there has been a paucity of studies where the aim is to go systematically through the directions of these relationships for a broad set of countries, but some contributions have been made for narrower panels.

Jihène and Gazi (2013) examine empirically causality between growth and income inequality in a bivariate VAR structure for a sample of 9 countries in the Middle East and North Africa in the period 1960-2011. Their analysis provides that “income inequality does not seem to affect positively the long-run economic growth. Indeed, the results of this paper clearly indicate that a strong evidence exist in favor of a reverse causations running from growth to inequality for 4 countries”. Assane et al. (2003) apply multivariate cointegration analysis to US data and find that growth unidirectionally and significantly Granger causes inequality. Hassan (2008) conduct Granger tests in a VAR-framework to analyze the relationships between growth, inequality and poverty in Sudan in the period 1956-2003, and finds that growth, poverty and inequality are cointegrated when poverty and inequality are the dependent variable, but are not cointegrated when growth is the dependent variable.

In my study, the effect of growth on market inequality turns out to be the most dominating relationship of all, indicating that growth might be the key mover in the interrelationship between inequality, redistribution and growth. Again revisiting
Figure 1, it is my suggestion that a representative figure of interrelations should include arrows pointing \textit{from} growth – not only towards growth, as illustrated in Figure 9.

\textbf{Figure 9: The relationships of Ostry et al. (2014) revisited}

The analysis also reveals a strong, significant and positive effect of growth on redistribution. The effect might be direct and/or work indirectly through market inequality. Recalling section 2, there exist several theories suggesting a relationship between market inequality and redistribution. Figure 11 provides a possible rationalization of the combined effects with increased market inequality and a redistributive response following from growth.
Ostry et al. refers to several studies which find no overall correlation between net and market inequality. Greater sharegain of the poor through redistribution tend to compensate for higher market income inequality when making across-country comparisons. The results found in the present study lead me to present an alternative direction as the effect on net inequality turns out to be both positive and significant. Redistributive efforts only partly offset the increased market inequality following growth. If equality is a political goal, this study suggests that growth comes with a price.

Recalling section 2.2 it is not straightforward to find established theories to lean on when trying to explain the mechanisms that might lead to growth increasing inequality. It should be clear the “inverted U”-relation of Kuznets has little to offer, as one can hardly claim the OECD-countries to represent the developing economies of the world.

But the findings clearly indicate that those already in a favorable position gain most from economic growth in line with the theory of cumulative advantage. As discussed in section 2.2, this might be linked to the characteristics of the forces driving economic growth in the developed world.

According to traditional trade-theory, when a country opens up for free-trade, the economic gain lies in the possibility to exhaust the comparative advantages of that country, as discussed in section 2.2. That will necessarily be a game of winners and losers. The typical story of a developed country opening up for more free trade, will be
one where the industries with the lowest productivity and highest labor-intensity is outcompeted, releasing both labor and capital that can contribute to more high-productive economic activities. One might think that those with the highest ability to adapt – the most privileged - will gain most from it, and not only through changed factor propositions at home. Typically, a free-trade agreement will also broaden the investment possibilities abroad for capital holders, and could contribute to a development where the rich get richer, both in absolute and relative terms.

Recalling the study of Aghion et al. (1999), the widening earnings distribution in developed countries was claimed to be directly linked to the nature of the forces driving growth during the last decades: trade liberalization, technological development and organizational change, with technological change playing the most prominent role:

“Overall, technological change appears both as the major source of economic growth and as the main vector through which the growth process is likely to affect the distribution of earnings. It is therefore at the core of the relationship from growth to inequality.” And further: “This suggests that, if greater equality is to be a target of economic policy, it has to be tackled directly since market forces by themselves will, most likely, not do it at all.”

This appears as an argument for strong, automatic redistributive arrangements to counteract the rising wage inequality stemming from growth. The economic advantages might be so high that it is possible to make everybody better off, but this will require a model where the gain is redistributed among the population, offsetting the losers. My analysis, showing a positive effect of growth on market inequality followed by a redistributive response partly offsetting this initial increase, could be an indication of something like that going on. The results can be read as a confirmation of the redistribution hypothesis predicting that more unequal societies will redistribute more.

Whether or not technological change will lead to increasing wage inequality in the first place, will also crucially depend on institutional characteristics of the countries. Deunionization and a sharp decrease in minimum wages are according to Aghinon et
al. (1999) found to have noticeably contributed to the rise in wage inequality in the US and the UK over the last decade.

4.7 Modifications

4.7.1 The consistency of the results (use of controls)

There is obviously a huge amount of variables outside of my model that might have an influence on inequality, redistribution and growth. When conducting growth regressions, it is common to use a traditional Solow-model as the starting point and include the standard growth determinants physical and human capital, often proxied by some measures for investments and education level. Several studies also include different variables trying to capture political and institutional differences, such as openness, democracy and trust in institutions. Growth and/or redistribution measures are also introduced in different ways, depending on the aim of the study.

As earlier mentioned, the concept of Granger testing is to sort out whether or not the introduction of the history of one variable contributes significantly to explain the history of another variable, and it is therefore expedient to test the time-series pairwise against each other. I am not mainly interested in interpreting the size of the effects and how they might change with various controls, but to get a consistent estimator indicating the direction of a relationship.

By using system GMM all time-invariant country-specific effects and the history of the dependent variable are controlled for. Instrumental variable techniques are used to handle the endogeneity issue arising from the introduction of the lagged dependent variable as a regressor. There might still be endogeneity problems due to omitted variables, but it is reassuring to see Cingano using the same baseline regression as I do with growth as the dependent and net inequality as the independent variable. When Cingano introduces different controls, it does not really affect the magnitude of inequality’s effect on growth (see Appendix B2).
4.7.2 Non-stationarity

Non-stationarity is a common problem when dealing with time-series data. Looking at the results of my analysis, one obvious objection is the possibility of non-stationarity in GDP-data accounting for most of the effect of $\log(GDP)$ on the dependent variables in models 4, 5 and 6. And indeed, unit-root testing prior to estimation reveals this to be a challenge. Some of the time-series of $\log(GDP)$ most likely contain unit roots. This is not relevant for models 1, 2 and 3 where $\log(GDP)$ enters in differences on the left hand side of the equation. Unit root-testing detected no signs of non-stationarity in the first-differenced time series. But in models 4, 5 and 6 the GDP-data enter in levels, which might explain why I find so much stronger effects when $\log(GDP)$ is used as an independent variable.

One way to meet this challenge would obviously be to introduce growth rates instead of GDP-levels in my models. As explained in section 4.1 I choose to follow other recent studies, as Cingano (2014) and Ostry et al. (2014) on this for the sake of getting comparable results on the effects of inequality and redistribution on growth. For the Granger-tests to make sense, it is also impossible to change the specification when turning the equations around. I must therefore find another strategy to try to detect whether or not the strong and significant effects found in models 4, 5 and 6 are solely a result of time-trends in GDP-data.

The first test I run implies introducing a control for a linear time-trend in combination with a time-dummy for the period 2005-2010 to account for the financial crisis to check whether or not this modification substantially change my results.

The second approach is to conduct the analysis using first-difference GMM. This solves the problem of non-stationarity as the variables enter as first-differences. First-difference GMM exploits less of the variation in the dataset compared to system GMM, and thereby it produces less significant results when analyzing data with so little variation as in the present case. But the results will anyhow give an indication on whether or not the effects suggested by the system GMM analysis still appears when non-stationarity is not an issue.
All six models are run with these modifications, and all results are reported in Appendix A1. A comparison of the \( \beta \)-coefficient in all six models with the three different specifications, gives an indication of the solidity of the results, see table 4.

**Table 4: Comparison of \( \beta \)-coefficients under different specifications**

<table>
<thead>
<tr>
<th>Model</th>
<th>System GMM</th>
<th>System GMM with time controls</th>
<th>First-diff. GMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0017</td>
<td>0.0022</td>
<td>0.0003</td>
</tr>
<tr>
<td>2</td>
<td>-0.0004</td>
<td>0.0059*</td>
<td>0.0013</td>
</tr>
<tr>
<td>3</td>
<td>-0.0019</td>
<td>-0.0001</td>
<td>0.0007</td>
</tr>
<tr>
<td>4</td>
<td>0.7640**</td>
<td>0.7324*</td>
<td>0.7573</td>
</tr>
<tr>
<td>5</td>
<td>1.5517**</td>
<td>1.8493**</td>
<td>3.7560</td>
</tr>
<tr>
<td>6</td>
<td>1.4158**</td>
<td>1.2908**</td>
<td>3.7807*</td>
</tr>
</tbody>
</table>

Note: * \( p<.05 \), ** \( p<.01 \), *** \( p<.001 \)

As expected, the modifications do not influence the coefficient in models 1, 2 and 3 much. They continue to be small and insignificant with the exception of model 2, where the effect of Market Gini on \( \Delta \log(GDP) \) becomes significant when introducing time controls. The coefficient is still estimated to be close to zero.

Looking at model 4, 5 and 6 it is interesting to note that the size of the effect of a change in \( \log(GDP) \) on Net Gini is almost unaffected by the modifications, but the result is no longer significant when conducting first-difference GMM. The story of growth increasing both Market Gini and Redistribution also survives the introduction of time-controls. Interestingly, when conducting first-difference GMM these effects are suggested to be more than twice as big as in the baseline model, but again significance is lost.

A clear conclusion on the significance of the problem of non-stationarity cannot be reached on the background of these tests, but I interpret the results as an indication that the main conclusion of the baseline regression might have something to it.
4.7.3 The possibility of mechanical correlation between inequality and redistribution

As earlier stated, my results might be interpreted as a confirmation of the redistribution hypothesis, with a strong and highly significant effect of growth on market inequality, triggering a redistributive response such that the effect on net inequality is substantially lower. Still there are some serious considerations that need to be made about automatic stabilization and the possibility of high mechanic correlation between market inequality and redistribution as the most prominent one.

The median voter approach suggests that higher market inequality would increase the median voter’s demand for redistribution, and thereby a policy response towards stronger redistributive efforts, and that is why the redistribution hypothesis holds. But it could clearly be the case that the observed increase in redistribution is only due to automatic response in the tax system, and not a result of direct political intervention. If, for instance, a country has implemented a progressive tax-system, an increase in market inequality could automatically lead to increased redistribution without the implementation of any new redistribution schemes. Kentworthy and McCall (2008) in their critique of the redistribution hypothesis, argues that one needs to focus on legal rules and not the observed amount of redistribution to find out whether the public prefers a more generous system. To pursue this view, they use scores of “intended generosity” of the pension system, unemployment benefits, child benefits and social assistance in their analysis of eight advanced economies. Milanovic (2010) on the other hand, comments upon this critique by stating that this automatic response might very well be intended by both the public and the policy makers: “It is important to realize that the political coalition that brought about such a system of redistribution must have taken into account, in cases of business cycles, it might lead to large redistributions”.

The case of mechanic correlation is somewhat different. If market income is nearly evenly distributed, it does not matter whether the chosen redistribution scheme is high or low since everyone will pay more or less the same in taxes (Lind, 2005). Even if tax-rates are high, the measured redistributive efforts would be low. On the other hand - very market-unequal countries would achieve a great deal of redistribution, even with a rather moderate tax-scheme. Still Milanovic (2010) argues, if we take both
taxes and transfers into account and the sharegain of the poor is low – the conclusion that the poor gain little from the tax- and transfer system is a very real one. In an analysis like mine, where market inequality is changing over time, the degree of redistributive response to increased market inequality is interesting, even though the country might initially have had an economy with little redistribution due to low market inequality.

4.7.4 Data reliability and measurement issues

Even though data-access has improved significantly during the last years, there are still issues concerning reliability, especially when it comes to the measuring of market inequality and redistribution. Lambert, Nesbakken and Thoresen (2015) address the challenge of different concepts of redistribution and how the standard methods of measurement fail to take into account how distribution prior to taxes and transfers in comparative countries might differ markedly.

In the SWIID-dataset, comparable Gini indices are presented for both market inequality and net inequality, and the redistribution-measure used in this analysis relies on both of them. Still, these are for a large part estimates – not accurate data - presented along with estimates of uncertainty. This uncertainty should be taken into account when interpreting the results.

Another relevant question to ask is what we actually capture by measuring inequality in terms of the Gini-statistics. There are many theoretical mechanisms through which inequality can affect growth. Various theories are associated with inequality in different parts of the income distribution. If we believe the theory on human capital accumulation and reduced opportunities for the poor to be of importance, increasing inequality at the bottom end of the distribution will be most relevant. On the other hand, the theory on excessive risk taking and financial stability will first and foremost be associated with inequality at the top end. When using a single inequality statistic, like the Gini coefficient, one might end up capturing rather unimportant average effects of inequality. More complex measures could have been used. Also the Gini-coefficient focuses on relative income distribution rather than real income –levels. The same Gini may therefore result from very different income distributions. Underlying demographic structure will also influence the result. This might be part of the
explanation of why the model fails to identify any mentionable effect of inequality on growth.

An obvious shortfall of this analysis is how redistribution is measured purely in terms of income. The substantial amount of redistribution taking place through public services etc. is not taken into account, meaning that the actual amount of redistributive efforts undertaken by the countries in my sample, are underestimated. The results must therefore be interpreted as effects on/of income redistribution and income inequality - not the effects on/of overall inequality and redistribution.
5 Conclusion

The aim of this thesis was to take advantage of the recent development of reliable time-series data on inequality in an attempt to bring some more clarity into the directions of the relationship between growth, inequality and redistribution. Granger tests for causality have been conducted on the variables within the framework of a system GMM-model.

Traditionally, the literature has treated growth as the endogenous variable, while inequality and/or redistribution has entered the analysis as explanatory variables. The results of my analysis challenge this approach. While the effects of inequality and redistribution on growth are non-significant, growth appears to have a strong and significant effect on both inequality and redistribution. This is in line with the findings of other studies examining the causal directions of inequality and growth using narrower panels. In brief the results of the present analysis suggest the following: growth increase market inequality, which in turn triggers a redistributive response. This can be read as a confirmation of the redistribution hypothesis, claiming that more unequal societies will to redistribute more. Still it is important to note that redistribution only partly offsets the increased market inequality. If preventing rising inequality is a political goal, my results indicate that growth comes with a price. Permanent redistribution schemes are necessary to control the level of inequality in growing economies.

A key question is then why growth tends to increase inequality. Studies looking at the widening income dispersion during the last decades, claims this to be directly linked to the nature of the forces driving growth: trade liberalization, technological development and organizational change, with technological change playing the most prominent role. This is interesting in the light of ongoing public debates on digitalization and automatization and how this development will change the structure of future labor markets. A large part of this debate is centered round the worry that jobs will disappear in an amount that is not replaced. But there are also voices claiming that the most prominent threat is linked to increased wage differences as a
result of skill-biased growth. My study suggests that these worries should be taken seriously. On the other hand, if we are facing a permanent economic slowdown in the future, perhaps the need for public policy redistribution will be reduced.

Needless to say, my results are preliminary, and more research is required. It would for instance be of great interest to look more closely at the distributional effects of the sharp decline in GDP growth rates following the financial crisis of 2008. It seems as if the crisis has had a halting effect on inequality, suggesting that declining growth rates hit hardest on the wealthiest.

---

References


Lambert, Peter J.; Nesbakken, Runa; Thoresen, Thor Olav. 2015. “A common base answer to “Which country is most redistributive?””, Statistics Norway, Research Department, Discussion Papers No. 811.


Ostry, Jonathan D.; Berg, Andrew; Tsangarides, Charalambos G. 2014. “Redistribution, Inequality and Growth”, IMF Staff Discussion Note, SDN/14/02.


Appendix

A: Sensitivity tests

A.1

Comparison of Granger causality tests results conducted within the framework of:

1) system GMM as reported in the main text
2) system GMM with control for a linear time trend and a time-dummy for period 11 (2005-2010) to account for the financial crisis
3) first-difference GMM

All models pass the Arrelano-Bond test for zero autocorrelation in the first differenced errors and the Hansen-test for the validity of instruments.

System GMM is chosen as method in this thesis due to its efficiency and for the sake of comparability of results with other recent studies. However, this leaves me with a possible problem of non-stationarity in GDP-data when lagged GDP enters as an explanatory variable in models 4, 5 and 6. To try to detect whether the positive, significant effect of lagged GDP on all dependent variables is mainly a result of non-stationarity, I introduce a control for a linear time trend in combination with a dummy for the time period 2005-2010 to account for the financial crisis. This modification does not change the main results much. I also choose to conduct all the analyses using first-difference GMM. This solves the problem of non-stationarity as the variables enter as first-differences. Unit root-testing prior to the analysis revealed that all my time-series are stable in first-differences. First-difference GMM exploits less of the variation in the dataset than system GMM due to less moment conditions, and thereby it produces less significant results. But the results are anyhow in line with the directions of the relationships suggested by the system GMM analysis.

Although non-stationarity probably accounts for a significant share of the effects of log(GDP) on inequality and redistribution, the results of these sensitivity tests suggest that the main results might reflect more than just a time-trend in GDP-data.
### Model 1: $\Delta \log(\text{GDP})$ dependent, $\text{Net inequality}_{t-1}$ independent

<table>
<thead>
<tr>
<th></th>
<th>System GMM</th>
<th>System GMM</th>
<th>First-diff. GMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\log(\text{GDP})_{t-1}$</td>
<td>0.0065***</td>
<td>0.0110***</td>
<td>-0.1229***</td>
</tr>
<tr>
<td></td>
<td>(0.0043)</td>
<td>(0.0059)</td>
<td>(0.0261)</td>
</tr>
<tr>
<td>$\text{Net inequality}_{t-1}$</td>
<td>0.0017</td>
<td>0.0022</td>
<td>0.0003</td>
</tr>
<tr>
<td></td>
<td>(0.0014)</td>
<td>(0.0016)</td>
<td>(0.0042)</td>
</tr>
<tr>
<td>$T$</td>
<td>-0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0032)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{yrd 11}$</td>
<td>-0.0680***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0194)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Observations: 225  
Number of countries: 33  
Number of instruments: 36

Note: * $p<.05$, ** $p<.01$, *** $p<.001$

### Model 2: $\Delta \log(\text{GDP})$ dependent, $\text{Market inequality}_{t-1}$ independent

<table>
<thead>
<tr>
<th></th>
<th>System GMM</th>
<th>System GMM</th>
<th>First-diff. GMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\log(\text{GDP})_{t-1}$</td>
<td>0.0132***</td>
<td>0.0076***</td>
<td>-0.1292***</td>
</tr>
<tr>
<td></td>
<td>(0.0108)</td>
<td>(0.0113)</td>
<td>(0.0263)</td>
</tr>
<tr>
<td>$\text{Market inequality}_{t-1}$</td>
<td>-0.0004</td>
<td>0.0059*</td>
<td>0.0013</td>
</tr>
<tr>
<td></td>
<td>(0.0025)</td>
<td>(0.0025)</td>
<td>(0.0034)</td>
</tr>
<tr>
<td>$T$</td>
<td>-0.0076*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0030)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{yrd 11}$</td>
<td>-0.0762***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0185)</td>
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<td></td>
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</table>

Observations: 225  
Number of countries: 33  
Number of instruments: 36

Note: * $p<.05$, ** $p<.01$, *** $p<.001$
### Model 3: \( \Delta \log(GDP) \) dependent, \( \textit{Redistribution}_{t-1} \) independent

<table>
<thead>
<tr>
<th></th>
<th>System GMM</th>
<th>System GMM</th>
<th>First-diff. GMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \log(GDP)_{t-1} )</td>
<td>0.0176***</td>
<td>0.0174***</td>
<td>-0.1187***</td>
</tr>
<tr>
<td></td>
<td>(0.0045)</td>
<td>(0.0052)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>( \textit{Redistribution}_{t-1} )</td>
<td>-0.0019</td>
<td>-0.0001</td>
<td>0.0007</td>
</tr>
<tr>
<td></td>
<td>(0.0014)</td>
<td>(0.0012)</td>
<td>(0.0021)</td>
</tr>
<tr>
<td>( T )</td>
<td>-0.0053</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0041)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( yrd 11 )</td>
<td>-0.0776***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Observations         | 225        | 225        | 225            |
| Number of countries  | 33         | 33         | 33             |
| Number of instruments | 36         | 38         | 26             |

Note: * p<.05, ** p<.01, *** p<.001

### Model 4: \( \Delta \textit{Net inequality} \) dependent, \( \log(GDP)_{t-1} \) independent

<table>
<thead>
<tr>
<th></th>
<th>System GMM</th>
<th>System GMM</th>
<th>First-diff. GMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \textit{Net inequality}_{t-1} )</td>
<td>-0.2532 ***</td>
<td>0.0174***</td>
<td>-0.1187***</td>
</tr>
<tr>
<td></td>
<td>(0.0091)</td>
<td>(0.0052)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>( \log(GDP)_{t-1} )</td>
<td>0.7640**</td>
<td>0.7324*</td>
<td>0.7573</td>
</tr>
<tr>
<td></td>
<td>(0.2634)</td>
<td>(0.3412)</td>
<td>(1.0207)</td>
</tr>
<tr>
<td>( T )</td>
<td>0.1515</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0813)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( yrd 11 )</td>
<td>-1.0124*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.477)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Observations         | 225        | 225        | 225            |
| Number of countries  | 33         | 33         | 33             |
| Number of instruments | 36         | 38         | 26             |
### Model 5: $\Delta$Market inequality dependent, $\log(\text{GDP})_{t-1}$ independent

<table>
<thead>
<tr>
<th></th>
<th>System GMM</th>
<th>System GMM</th>
<th>First-diff. GMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Market\ inequality_{t-1}$</td>
<td>-0.3279***</td>
<td>-0.475***</td>
<td>-0.3352***</td>
</tr>
<tr>
<td></td>
<td>(0.0608)</td>
<td>(0.0829)</td>
<td>(0.1178)</td>
</tr>
<tr>
<td>$\log(\text{GDP})_{t-1}$</td>
<td>1.5517***</td>
<td>1.8493***</td>
<td>3.3756</td>
</tr>
<tr>
<td></td>
<td>(0.2726)</td>
<td>(0.3208)</td>
<td>(1.8492)</td>
</tr>
<tr>
<td>$T$</td>
<td>-0.1782</td>
<td></td>
<td>(0.08493)</td>
</tr>
<tr>
<td>$yrd\ 11$</td>
<td>-0.8493</td>
<td></td>
<td>(0.6703)</td>
</tr>
</tbody>
</table>

Observations: 225 225 225  
Number of countries: 33 33 33  
Number of instruments: 36 38 26

Note: * p<.05, ** p<.01, *** p<.001

### Model 6: $\Delta$Redistribution dependent, $\log(\text{GDP})_{t-1}$ independent

<table>
<thead>
<tr>
<th></th>
<th>System GMM</th>
<th>System GMM</th>
<th>First-diff. GMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Redistribution_{t-1}$</td>
<td>-0.4079***</td>
<td>-0.4482**</td>
<td>-0.5989*</td>
</tr>
<tr>
<td></td>
<td>(0.1632)</td>
<td>(0.1859)</td>
<td>(0.1618)</td>
</tr>
<tr>
<td>$\log(\text{GDP})_{t-1}$</td>
<td>1.4158**</td>
<td>1.2908**</td>
<td>3.7807*</td>
</tr>
<tr>
<td></td>
<td>(0.5428)</td>
<td>(0.4839)</td>
<td>(1.8561)</td>
</tr>
<tr>
<td>$T$</td>
<td>-0.3307</td>
<td></td>
<td>(0.2155)</td>
</tr>
<tr>
<td>$yrd\ 11$</td>
<td>-0.2553</td>
<td></td>
<td>(0.9189)</td>
</tr>
</tbody>
</table>

Observations: 225 225 225  
Number of countries: 33 33 33  
Number of instruments: 36 38 26

Note: * p<.05, ** p<.01, *** p<.001
A.2

All six regression-models are run with countries eliminated from the dataset one by one. The β-coefficients on the independent variable are reported with asterixes indicating if the Granger-test for causality is significant. The results appear altogether stable.

<table>
<thead>
<tr>
<th>Country eliminated</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>0.0017</td>
<td>-0.0006</td>
<td>-0.0024</td>
<td>0.7479**</td>
<td>1.6336***</td>
<td>1.4837**</td>
</tr>
<tr>
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<td>-0.0004</td>
<td>-0.0018</td>
<td>0.7193**</td>
<td>1.5174***</td>
<td>1.4087*</td>
</tr>
<tr>
<td>Belgium</td>
<td>0.0016</td>
<td>-0.0003</td>
<td>-0.0015</td>
<td>0.7053*</td>
<td>1.5399***</td>
<td>1.3659*</td>
</tr>
<tr>
<td>Canada</td>
<td>0.0016</td>
<td>-0.0002</td>
<td>-0.0019</td>
<td>0.6368**</td>
<td>1.5430***</td>
<td>1.3686*</td>
</tr>
<tr>
<td>Chile</td>
<td>0.0023*</td>
<td>-0.0008</td>
<td>-0.0023</td>
<td>1.0430**</td>
<td>1.7577***</td>
<td>1.4416**</td>
</tr>
<tr>
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<td>-0.0007</td>
<td>-0.0016</td>
<td>0.7664**</td>
<td>1.5628***</td>
<td>1.4436*</td>
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<td>0.0015</td>
<td>-0.0003</td>
<td>-0.0019</td>
<td>0.6760**</td>
<td>1.3577***</td>
<td>1.4965**</td>
</tr>
<tr>
<td>Estonia</td>
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<td>-0.0009</td>
<td>-0.0019</td>
<td>0.7693**</td>
<td>1.5514***</td>
<td>1.4344**</td>
</tr>
<tr>
<td>Finland</td>
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<td>-0.0006</td>
<td>-0.002</td>
<td>0.8305**</td>
<td>1.5887***</td>
<td>1.4839**</td>
</tr>
<tr>
<td>France</td>
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<td>-0.0007</td>
<td>-0.0018</td>
<td>0.6573**</td>
<td>1.5359***</td>
<td>0.8593*</td>
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<tr>
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<td>0.0018</td>
<td>-0.0002</td>
<td>-0.0018</td>
<td>0.7440**</td>
<td>1.5571***</td>
<td>1.3975*</td>
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<tr>
<td>Greece</td>
<td>0.0013</td>
<td>-0.0008</td>
<td>-0.0017</td>
<td>0.7164**</td>
<td>1.4254***</td>
<td>1.4167**</td>
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<tr>
<td>Hungary</td>
<td>0.0016</td>
<td>-0.0001</td>
<td>-0.0017</td>
<td>0.7629**</td>
<td>1.5720***</td>
<td>1.4257*</td>
</tr>
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<td>-0.0004</td>
<td>-0.002</td>
<td>0.7827*</td>
<td>1.5027***</td>
<td>1.4465**</td>
</tr>
<tr>
<td>Ireland</td>
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<td>-0.0009</td>
<td>-0.0019</td>
<td>0.7356**</td>
<td>1.4749***</td>
<td>1.4196*</td>
</tr>
<tr>
<td>Israel</td>
<td>0.0019</td>
<td>-0.0004</td>
<td>-0.002</td>
<td>0.7300**</td>
<td>1.5907***</td>
<td>1.4410**</td>
</tr>
<tr>
<td>Italy</td>
<td>0.0015</td>
<td>-0.0002</td>
<td>-0.0016</td>
<td>0.7319**</td>
<td>1.5522***</td>
<td>1.4458**</td>
</tr>
<tr>
<td>Japan</td>
<td>0.0026</td>
<td>-0.0019</td>
<td>-0.0009</td>
<td>0.7006**</td>
<td>1.7335***</td>
<td>1.3294*</td>
</tr>
<tr>
<td>Luxembourg</td>
<td>0.002</td>
<td>-0.0005</td>
<td>-0.002</td>
<td>0.7149**</td>
<td>1.4706***</td>
<td>1.4106**</td>
</tr>
<tr>
<td>Mexico</td>
<td>0.0022</td>
<td>-0.0007</td>
<td>-0.0021</td>
<td>0.8353**</td>
<td>1.4987***</td>
<td>1.4056*</td>
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<tr>
<td>Netherlands</td>
<td>0.0013</td>
<td>-0.0008</td>
<td>-0.0022</td>
<td>0.7781*</td>
<td>1.4843***</td>
<td>1.3939*</td>
</tr>
<tr>
<td>New Zealand</td>
<td>0.0015</td>
<td>-0.0002</td>
<td>-0.0015</td>
<td>0.7541**</td>
<td>1.5308***</td>
<td>1.4037*</td>
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<td>0.0017</td>
<td>-0.0004</td>
<td>-0.0019</td>
<td>0.7855*</td>
<td>1.5634***</td>
<td>1.3746**</td>
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<td>-0.0021</td>
<td>0.7304**</td>
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<td>1.4404**</td>
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<td>-0.0012</td>
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<td>Slovak Republic</td>
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<td>-0.0017</td>
<td>0.7430**</td>
<td>1.5371***</td>
<td>1.4303**</td>
</tr>
<tr>
<td>Slovenia</td>
<td>0.0014</td>
<td>-0.0005</td>
<td>-0.0017</td>
<td>0.7712**</td>
<td>1.5284***</td>
<td>1.4290**</td>
</tr>
<tr>
<td>Spain</td>
<td>0.0021</td>
<td>0.0001</td>
<td>-0.0016</td>
<td>0.7932**</td>
<td>1.5554***</td>
<td>1.3570*</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.0011</td>
<td>-0.0013</td>
<td>-0.0017</td>
<td>0.8238**</td>
<td>1.5246***</td>
<td>1.4760**</td>
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<tr>
<td>Switzerland</td>
<td>0.0015</td>
<td>-0.0006</td>
<td>-0.0019</td>
<td>0.7625**</td>
<td>1.5766***</td>
<td>1.4426**</td>
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<tr>
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<td>-0.0017</td>
<td>0.8393**</td>
<td>1.5411***</td>
<td>1.4427**</td>
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<tr>
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<td>0</td>
<td>-0.0017</td>
<td>0.7066**</td>
<td>1.5356***</td>
<td>1.3934*</td>
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<tr>
<td>United States</td>
<td>0.0009</td>
<td>-0.0005</td>
<td>-0.0014</td>
<td>0.7745**</td>
<td>1.6043***</td>
<td>1.4541**</td>
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</tbody>
</table>

Note: * p<.05, ** p<.01, *** p<.001
A.3

The main analysis is run using observations on GDP, Net inequality, Market inequality and Redistribution from every 5 years, starting in 1960 until 2010. All other observations are dropped. By changing the specification of 5-year intervals I run the same analysis, but with a different set of data. The main conclusions are not affected by using the two alternative datasets starting in 1961 and 1964.

a) 1961-2011

<table>
<thead>
<tr>
<th></th>
<th>1. $\Delta \log(\text{GDP})$</th>
<th>2. $\Delta \log(\text{GDP})$</th>
<th>3. $\Delta \log(\text{GDP})$</th>
<th>4. $\Delta \text{Net ineq.}$</th>
<th>5. $\Delta \text{Market ineq.}$</th>
<th>6. $\Delta \text{Redistribution}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\log(\text{GDP})_{t-2}$</td>
<td>0.0024***</td>
<td>0.0151***</td>
<td>0.0141***</td>
<td>0.3671*</td>
<td>1.6386***</td>
<td>1.6215***</td>
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<tr>
<td></td>
<td>(0.0066)</td>
<td>(0.0109)</td>
<td>(0.0042)</td>
<td>(0.1834)</td>
<td>(0.345)</td>
<td>(0.4432)</td>
</tr>
<tr>
<td>Net ineq$_{t-2}$</td>
<td>0.0029</td>
<td></td>
<td></td>
<td>-0.1214***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td></td>
<td></td>
<td>(0.0617)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market ineq$_{t-2}$</td>
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<td></td>
<td></td>
<td>-0.3508***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0024)</td>
<td></td>
<td></td>
<td>(0.0757)</td>
<td></td>
<td></td>
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<tr>
<td>Redistribution$_{t-2}$</td>
<td>0.0009</td>
<td></td>
<td></td>
<td></td>
<td>-0.4882***</td>
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</tr>
<tr>
<td></td>
<td>(0.0013)</td>
<td></td>
<td></td>
<td></td>
<td>(0.1324)</td>
<td></td>
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<tr>
<td>Observations</td>
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<td>225</td>
<td>225</td>
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<td>Number of countries</td>
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<tr>
<td>Number of instruments</td>
<td>36</td>
<td>36</td>
<td>36</td>
<td>36</td>
<td>36</td>
<td>36</td>
</tr>
</tbody>
</table>
b) 1964-2009 (one t is lost at 1960 is the first year of data)

<table>
<thead>
<tr>
<th>Variable</th>
<th>1. $\Delta \log(GDP)$</th>
<th>2. $\Delta \log(GDP)$</th>
<th>3. $\Delta \log(GDP)$</th>
<th>4. $\Delta$ Net ineq.</th>
<th>5. $\Delta$ Market ineq.</th>
<th>6. $\Delta$ Redistribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\log(GDP)_{t-1}$</td>
<td>0.0105***</td>
<td>0.0092***</td>
<td>0.0175***</td>
<td>0.3610*</td>
<td>1.5605***</td>
<td>1.3895**</td>
</tr>
<tr>
<td></td>
<td>(0.0052)</td>
<td>(0.0108)</td>
<td>(0.0053)</td>
<td>(0.1756)</td>
<td>(0.2739)</td>
<td>(0.4348)</td>
</tr>
<tr>
<td>$Net\ inequality_{t-1}$</td>
<td>0.0001</td>
<td></td>
<td></td>
<td>-0.1192***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0017)</td>
<td></td>
<td></td>
<td>(0.0567)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$Market\ inequality_{t-1}$</td>
<td></td>
<td></td>
<td></td>
<td>0.0003</td>
<td>-0.3333***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.0023)</td>
<td>(0.0608)</td>
<td></td>
</tr>
<tr>
<td>Redistribution$_{t-1}$</td>
<td></td>
<td></td>
<td></td>
<td>-0.0021</td>
<td>-0.4021***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.0016)</td>
<td>(0.1279)</td>
<td></td>
</tr>
</tbody>
</table>

Observations: 209 209 209 209 209 209 209
Number of countries: 33 33 33 33 33 33 33
Number of instruments: 32 32 32 32 32 32 32

Note: * $p<.05$, ** $p<.01$, *** $p<.001$. Coefficients from system GMM (Arellano-Bond) regressions (standard errors in parentheses). A variable X is said to Granger-cause Y if X has an effect on Y after control for the entire history of Y. Thus, coefficients on variables other than the lagged dependent variable are tests of Granger causality in each model (marked in bold). Redistribution is measured as $100\times\frac{(Market\ Gini – Net\ Gini)}{Market\ Gini}$. 
### B: Regression results of comparable studies

#### B1 The system GMM regression results of Ostry et al. (2014)

#### Table 3. The effect of inequality and redistribution on growth 1/

<table>
<thead>
<tr>
<th></th>
<th>Dependent Variable: growth rate of per capita GDP</th>
<th>Baseline</th>
<th>Baseline + controls</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(initial income)</td>
<td>-0.0069***</td>
<td>-0.0081**</td>
<td>-0.0140***</td>
</tr>
<tr>
<td></td>
<td>(0.0034)</td>
<td>(0.0035)</td>
<td>(0.0037)</td>
</tr>
<tr>
<td>Net inequality</td>
<td>-0.1435***</td>
<td>-0.0914***</td>
<td>-0.0739***</td>
</tr>
<tr>
<td></td>
<td>(0.0444)</td>
<td>(0.0336)</td>
<td>(0.0266)</td>
</tr>
<tr>
<td>Redistribution</td>
<td>0.0046</td>
<td>0.0258</td>
<td>0.0109</td>
</tr>
<tr>
<td></td>
<td>(0.0492)</td>
<td>(0.0516)</td>
<td>(0.0428)</td>
</tr>
<tr>
<td>Log(investment)</td>
<td>0.0241***</td>
<td>0.0250***</td>
<td>0.0075</td>
</tr>
<tr>
<td></td>
<td>(0.0077)</td>
<td>(0.0094)</td>
<td>(0.0125)</td>
</tr>
<tr>
<td>Log(population growth)</td>
<td>-0.0159</td>
<td>-0.0215</td>
<td>-0.0084</td>
</tr>
<tr>
<td></td>
<td>(0.0182)</td>
<td>(0.0174)</td>
<td>(0.0150)</td>
</tr>
<tr>
<td>Log(total education)</td>
<td>0.0208***</td>
<td>0.0164*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0073)</td>
<td>(0.0069)</td>
<td></td>
</tr>
<tr>
<td>Large negative terms of trade shock</td>
<td></td>
<td>-0.0424***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0159)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Political institutions</td>
<td>-0.0011</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Openness</td>
<td>0.0091</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0082)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Debt liabilities</td>
<td>-0.0196***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0059)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.1262***</td>
<td>0.0718</td>
<td>0.0965**</td>
</tr>
<tr>
<td></td>
<td>(0.0389)</td>
<td>(0.0456)</td>
<td>(0.0389)</td>
</tr>
</tbody>
</table>

Source: Income, investment/GDP, population growth and openness (Penn World Tables 7.1); redistribution and gini (SWIID 3.1); average years of primary and secondary schooling (Barro and Lee, 2012); political institutions from -10 (most autocratic) to 10 (most democratic) (Polity IV); external debt/GDP (Lane and Millesi-Ferretti, 2007, updated); goods terms-of-trade = 1 when the annual change is in the bottom 3 deciles (WEO). For details see Berg et al. (2012).

1/ System GMM estimation. Robust standard errors in brackets where *, **, and *** indicate statistical significance at the 10, 5 and 1 percent levels, respectively.
The system GMM regression results of Cingano (2014)

### Table 1. The inequality-growth nexus in OECD countries: baseline results

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
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</thead>
<tbody>
<tr>
<td>Net Inequality (t-1)</td>
<td>-0.774**</td>
<td>-0.800**</td>
<td>-0.809***</td>
<td>-1.003**</td>
<td>-1.257**</td>
<td>-1.297**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.319)</td>
<td>(0.306)</td>
<td>(0.282)</td>
<td>(0.376)</td>
<td>(0.517)</td>
<td>(0.473)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gross Inequality (t-1)</td>
<td>-0.640</td>
<td>0.138</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.092)</td>
<td>(0.595)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Gross–Net) ineq. (t-1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.064</td>
<td>-0.365</td>
<td></td>
<td></td>
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<tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.706)</td>
<td>(1.476)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>y (t-1)</td>
<td>-0.136**</td>
<td>-0.080</td>
<td>-0.054</td>
<td>-0.079</td>
<td>0.038</td>
<td>-0.070</td>
<td>-0.079</td>
<td>0.133</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(0.051)</td>
<td>(0.057)</td>
<td>(0.106)</td>
<td>(0.178)</td>
<td>(0.121)</td>
<td>(0.131)</td>
<td>(0.251)</td>
</tr>
<tr>
<td>Human Capital (t-1)</td>
<td>-0.005</td>
<td>-0.007</td>
<td>-0.000</td>
<td>0.006</td>
<td>-0.009</td>
<td>-0.010</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.007)</td>
<td>(0.015)</td>
<td>(0.021)</td>
<td>(0.011)</td>
<td>(0.012)</td>
<td></td>
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</tr>
<tr>
<td>Investment (t-1)</td>
<td>0.197</td>
<td>0.428</td>
<td>0.045</td>
<td>1.545</td>
<td>-0.245</td>
<td>-0.243</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.318)</td>
<td>(0.544)</td>
<td>(1.311)</td>
<td>(1.304)</td>
<td>(1.310)</td>
<td>(1.477)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M2 (p-val)</td>
<td>0.722</td>
<td>0.558</td>
<td>0.623</td>
<td>0.723</td>
<td>0.860</td>
<td>0.606</td>
<td>0.665</td>
<td>0.916</td>
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<tr>
<td>Hansen Statistics (p-val)</td>
<td>0.847</td>
<td>0.614</td>
<td>0.377</td>
<td>0.129</td>
<td>0.471</td>
<td>0.129</td>
<td>0.174</td>
<td>0.535</td>
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<td>127</td>
<td>127</td>
<td>124</td>
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<td>Number of countries</td>
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<td>Number of instruments</td>
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<td>16</td>
<td>16</td>
<td>18</td>
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</tbody>
</table>

**Note:** The dependent variable is $\Delta y_{it}$, where $y_{it}$ is per capita GDP, and $t=(t-1)$ is a 5-year period. Inequality is measured by Gini indexes. Robust, 2-step System GMM estimator with Windmeijer-corrected standard errors. All regressions include country and period dummies. M2 are the p-values of the tests for second order serial correlation in the differenced error terms; Hansen denotes the p-value on the Hansen test of over identifying restrictions. ***, **, * denote significance at the 1, 5, 10% levels, respectively.
B3  The system GMM regression results of Halter et al. (2014)

<table>
<thead>
<tr>
<th>Table 3</th>
<th>System GMM estimation results</th>
<th>5-year growth rate of the real GDP p.c. (5-year periods)</th>
<th>10-year growth rate of the real GDP p.c. (10-year periods)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Full sample</td>
<td>(2) Full sample / high</td>
<td>(3) Full sample / up-mid</td>
</tr>
<tr>
<td>log(GDP)</td>
<td>0.0047</td>
<td>-0.046</td>
<td>-0.1874</td>
</tr>
<tr>
<td>(0.011)</td>
<td>(0.231)</td>
<td>(0.300)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Gini coefficient</td>
<td>-0.0013</td>
<td>0.0021</td>
<td>0.0006</td>
</tr>
<tr>
<td>(0.191)</td>
<td><strong>(0.011)</strong></td>
<td>(0.55)</td>
<td><strong>(0.02)</strong></td>
</tr>
<tr>
<td>Male schooling (yrs.)</td>
<td>0.0007</td>
<td>0.0209</td>
<td>0.0218</td>
</tr>
<tr>
<td>*<strong>(0.007)</strong></td>
<td>(0.121)</td>
<td>(0.553)</td>
<td>(0.946)</td>
</tr>
<tr>
<td>Female schooling (yrs.)</td>
<td>-0.0782</td>
<td>-0.0158</td>
<td>-0.0228</td>
</tr>
<tr>
<td>*<strong>(0.034)</strong></td>
<td>(0.437)</td>
<td>(0.407)</td>
<td>(0.345)</td>
</tr>
<tr>
<td>Price level of investment</td>
<td>-0.0014</td>
<td>-0.0013</td>
<td>-0.0016</td>
</tr>
<tr>
<td>*<strong>(0.02)</strong></td>
<td><strong>(0.004)</strong></td>
<td>*<strong>(0.001)</strong></td>
<td><strong>(0.372)</strong></td>
</tr>
<tr>
<td>Number of countries</td>
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<td>26</td>
<td>14</td>
</tr>
<tr>
<td>Number of observations</td>
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<td>154</td>
<td>79</td>
</tr>
<tr>
<td>Number of instruments</td>
<td>176</td>
<td>150</td>
<td>77</td>
</tr>
<tr>
<td>M1</td>
<td>-1.08</td>
<td>-2.53</td>
<td>-2.16</td>
</tr>
<tr>
<td>M2</td>
<td>-1.27</td>
<td>-0.08</td>
<td>-1.55</td>
</tr>
<tr>
<td>Hansen</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

All coefficients are estimated by system GMM. *, **, *** denote significance at the 1, 5, 10% levels, respectively. p-values in parentheses. M1 and M2 are the results of the tests for, respectively, first-order and second-order serial correlation in the differenced error terms. Hansen denotes the p-value of the Hansen test of over-identifying restrictions.
C: STATA do-file

capture log c
log using mma_final.log, replace
est drop _all

cd c:\data\swiid
use mma_final.dta, clear

tabstat year, by(country) s(mi ma n)

gen yr5=.
forv q=1960(5)2010 {'
replace yr5=`q' if year==`q'
}
drop if yr5=-.
egen t=group(yr5)

to country yr5
tabstat yr5, by(country) s(mi ma n)
egen cid=group(country)
xtset cid t

xtsum lngdp gini_net gini_market po_redist

lowess D.lngdp gini_net, lineopts(lc(black) lp(solid)) ///
ms(o) mc(black) graphregion(fc(white) lc(white)) ///
xlabel(20(10)65, nogrid) ylabel(0 "0" .2 ".2" .4 ".4", nogrid) ///
legend(off) note("") ti("GDP per capita growth") saving(gr1.gph, replace)

lowess D.lngdp gini_market, lineopts(lc(black) lp(solid)) ///
ms(o) mc(black) graphregion(fc(white) lc(white)) ///
xlabel(20(10)65, nogrid) ylabel(0 "0" .2 ".2" .4 ".4", nogrid) ///
legend(off) note("") ti("GDP per capita growth") saving(gr2.gph, replace)

lowess D.lngdp po_redist, lineopts(lc(black) lp(solid)) ///
ms(o) mc(black) graphregion(fc(white) lc(white)) ///
xlabel(0(20)60, nogrid) ylabel(0 "0" .2 ".2" .4 ".4", nogrid) ///
legend(off) note("") ti("GDP per capita growth") ///
xti("Redistribution") saving(gr3.gph, replace)
gen y=_n if _nc=100
replace y=. if y<20 | y>65

lowess gini_net gini_market , lineopts(lc(black) lp(solid)) ///
ms(o) mc(black) graphregion(fc(white) lc(white)) ///
addplot(if y y, lc(black) lp(dash)) ///
xlabel(20(10)65, nogrid) ylabel(20(10)65, nogrid) ///
legend(off) note("") ti("") saving(gr4.gph, replace)

graph combine gr1.gph gr2.gph gr3.gph gr4.gph, graphregion(fc(white) lc(white))
foreach q in gdp lngdp growth gini_net gini_market po_redist {
    xtunitroot fisher `q', dfuller lag(1)
}

foreach q in lngdp growth gini_net gini_market po_redist {
    gen double 1_`q'=-L.`q'
}

ta yr5, gen(yrd)
gen lnt=ln(t)

gen double D1_lngdp=D.1_lngdp
xtunitroot fisher D1_lngdp, dfuller lag(1)

// mod 1:
xtdpdsys lngdp, nocons ///
  lags(1) maxldepl(1) pre(l_gini_net, lag(0,1)) twostep vce(robust) artest(2)
est store mod1
estat abond
qui xtdpdsys lngdp, nocons ///
  lags(1) maxldepl(1) pre(l_gini_net, lag(0,1)) twostep artest(2)
est sargan

xtdpdsys lngdp t yrd11, nocons ///
  lags(1) maxldepl(1) pre(l_gini_net, lag(0,1)) twostep vce(robust) artest(2)
est store ala
estat abond
qui xtabond lngdp, nocons ///
  lags(1) maxldepl(2) pre(l_gini_net, lag(0,1)) twostep vce(robust) artest(2)
est store alb
estat abond
qui xtabond lngdp, nocons ///
  lags(1) maxldepl(2) pre(l_gini_net, lag(0,1)) twostep artest(2)
est sargan

// mod 2:
xtdpdsys lngdp, nocons ///
  lags(1) maxldepl(1) pre(l_gini_market, lag(0,1)) twostep vce(robust) artest(2)
est store mod2
estat abond
qui xtdpdsys lngdp, nocons ///
  lags(1) maxldepl(1) pre(l_gini_market, lag(0,1)) twostep artest(2)
est sargan

xtdpdsys lngdp t yrd11, nocons ///
  lags(1) maxldepl(1) pre(l_gini_market, lag(0,1)) twostep vce(robust) artest(2)
est store a2a
estat abond
xtabond lngdp, nocons ///
  lags(1) maxlde(2) pre(l_gini_market, lag(0,1)) twostep vce(robust) artest(2)
est store a2b
estat abond
qui xtabond lngdp, nocons ///
lags(1) maxlde(2) pre(l_gini_market, lag(0,1)) twostep artest(2)
estat sargan

// mod 3:
xtdpdys lngdp, nocons ///
lags(1) maxlde(1) pre(l_po_redist, lag(0,1)) twostep vce(robust) artest(2)
est store mod3
estat abond
qui xtdpdys lngdp, nocons ///
lags(1) maxlde(1) pre(l_po_redist, lag(0,1)) twostep artest(2)
estat sargan

xtdpdys lngdp t yrd11, nocons ///
lags(1) maxlde(1) pre(l_po_redist, lag(0,1)) twostep vce(robust) artest(2)
est store a3a
estat abond
qui xtabond lngdp, nocons ///
lags(1) maxlde(2) pre(l_po_redist, lag(0,1)) twostep vce(robust) artest(2)
est store a3b
estat abond
qui xtabond lngdp, nocons ///
lags(1) maxlde(2) pre(l_po_redist, lag(0,1)) twostep artest(2)
estat sargan

// mod 4:
xtdpdys gini_net, nocons ///
lags(1) maxlde(1) pre(l_lngdp, lag(0,1)) twostep vce(robust) artest(2)
est store mod4
estat abond
qui xtdpdys gini_net, nocons ///
lags(1) maxlde(1) pre(l_lngdp, lag(0,1)) twostep artest(2)
estat sargan

xtdpdys gini_net t yrd11, nocons ///
lags(1) maxlde(1) pre(l_lngdp, lag(0,1)) twostep vce(robust) artest(2)
est store a4a
estat abond
qui xtabond gini_net, nocons ///
lags(1) maxlde(2) pre(l_lngdp, lag(0,1)) twostep vce(robust) artest(2)
est store a4b
estat abond
qui xtabond gini_net, nocons ///
lags(1) maxlde(2) pre(l_lngdp, lag(0,1)) twostep artest(2)
estat sargan
// mod 5:
xtglim gini_market, nocons ///
lags(1) maxl1dep(1) pre(l_lngdp, lag(0,1)) twostep vce(robust) artest(2)
est store mod5
estat abond
qui xtdpdsys gini_market, nocons ///
lags(1) maxl1dep(1) pre(l_lngdp, lag(0,1)) twostep artest(2)
est sargan

xtglim gini_market t yrd11, nocons ///
lags(1) maxl1dep(1) pre(l_lngdp, lag(0,1)) twostep vce(robust) artest(2)
est store a5a
estat abond
qui xtabond gini_market, nocons ///
lags(1) maxl1dep(2) pre(l_lngdp, lag(0,1)) twostep vce(robust) artest(2)
est store a5b
estat abond
qui xtabond gini_market, nocons ///
lags(1) maxl1dep(2) pre(l_lngdp, lag(0,1)) twostep artest(2)
est sargan

// mod 6:
xtglim po_redist, nocons ///
lags(1) maxl1dep(1) pre(l_lngdp, lag(0,1)) twostep vce(robust) artest(2)
est store mod6
estat abond
qui xtdpdsys po_redist, nocons ///
lags(1) maxl1dep(1) pre(l_lngdp, lag(0,1)) twostep artest(2)
est sargan
xtglim po_redist t yrd11, nocons ///
lags(1) maxl1dep(1) pre(l_lngdp, lag(0,1)) twostep vce(robust) artest(2)
est store a6a
estat abond
qui xtabond po_redist, nocons ///
lags(1) maxl1dep(2) pre(l_lngdp, lag(0,1)) twostep vce(robust) artest(2)
est store a6b
estat abond
qui xtabond po_redist, nocons ///
lags(1) maxl1dep(2) pre(l_lngdp, lag(0,1)) twostep artest(2)
est sargan