Aalto University
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Income inequality in the OECD area
On measuring its possible effects on economic growth

Economics

Master's thesis

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Abstract of master's thesis

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Abstract

This thesis studies possible effects income inequality might have on economic growth and examines whether it is reasonable to measure these effects in detail with the tools provided by growth econometrics. Recently published research indicates a strong negative effect of net income inequality on growth and this thesis assesses whether these findings can be considered reliable and significant.

This objective is accomplished by inspecting recent literature concerning the subject with a detailed emphasis on a particular OECD working paper stating a robust negative effect of net income inequality on growth. Said working paper, Cingano (2014), is constructed on the MRW augmented Solow model, which is introduced and assessed. Moreover, the estimation model and method as well as the data sets used in Cingano (2014) are examined in detail. Furthermore, development of income inequality in the OECD area in recent decades and theoretical channels through which income inequality might affect growth are introduced and discussed.

This thesis finds that overly specific conclusions about the strength of the estimated effects should not be made based on growth regressions on the subject. This conclusion is reached because the estimates often lack sufficient data and there are problems concerning the estimation models and methods. This thesis finds considerable difficulties concerning Cingano (2014) that are also linked to other literature addressing the effects of income inequality on growth in general. Based on the findings in this thesis, it seems unreasonable to interpret the findings of the literature in such a detailed manner as they are expressed. However, this thesis does not suggest that the subject and research about it lacks importance, but suggests that the focus ought to be directed to micro-level data and channels where genuine progress could be accomplished.

Keywords income inequality, net income inequality, disposable income inequality, income distribution, economic growth, effects of inequality on growth, OECD, Gini coefficient, augmented Solow Model, human capital, physical capital, System GMM, growth econometrics, Cingano (2014), MRW, redistribution

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1. Introduction

Income inequality is a topic often visited in the societal discussion, both in Finland and abroad. Historically the questions have been largely concentrating in the differences between rich and poor countries, however, there has also been an increasing interest to analyze the income distributions within societies in the developed countries. For some, it seems reducing the differences in income between the poorest and the richest within a country using policy measures, such as taxation and redistribution, is a desired goal, while others ask whether such policies have a negative effect in the society and its economy.

There has also been a lot of discussion about whether income inequality plays a significant part in the growth patterns of national economies. Income and wealth inequality within a country, and across countries, is a subject that has been studied rather extensively in the field of economics, however, little is known about the effect, strength and size that it might have in determining future economic growth.

In December 2014, the Organization for Economic Co-operation and Development (OECD) published a report called "Focus on inequality and growth" with findings stating that increased income inequality measured from 1985 onwards has had a decreasing effect on the economic growth in the OECD countries between 1990 and 2010. Furthermore, the report concludes that tackling inequality can make our societies fairer and our economies stronger. (OECD 2014.) The publication was reported widely in the media globally, and it has also been used as a reference study in the Finnish political debate ever since. The OECD consists of 34 member countries listed in Appendix 1.

The report of the OECD is based on an OECD working paper by Federico Cingano titled "Trends in income inequality and its impact on economic growth". Although the working paper is informed to represent the views of its author instead of the whole organization, the widely reported public statement of the OECD used the findings of this research as its main source of information. Cingano (2014) notes that according to several OECD studies, the disparities in household incomes have been on the rise over the past three decades in most OECD countries. Most commonly measured with the Gini coefficient explained in chapter 2, this argument is considerably backed up by the OECD statistics obtained from the member countries. In the first empirical section of the research, Cingano (2014) finds that disposable (net) income inequality has had a strong and significant negative effect on subsequent economic growth in the OECD area between 1970 and 2010. The second part of the analysis argues that the channel through which income inequality affects growth is reduced investments in education in the bottom end of the income distribution.

In many developed countries, rising income inequality has been a hot topic in recent years with large demonstrations and political contentions surrounding the debate. This is partly due to worries that a persistently unbalanced sharing of the growth dividend will result in social resentment, fuelling populist and protectionist sentiments, and leading to political instability (Cingano 2014).

Many notable economists, such as Joseph Stiglitz and Raghuram Rajan, have emphasized the role increased income inequality has played in the financial crisis that hit the world economy in 2007-2008, as well as warned that, should income inequality continue the observed increasing development, it might impose severe consequences on the societies in the future. While this discussion has largely been associated with the developments in the US and the UK, the warning voices have echoed throughout the rest of the developed countries as well, especially after the Eurozone crisis and the prolonged negative effects it has caused in the economies in Europe, most notably in Greece. Simultaneously, noteworthy arguments to explain the necessity of, at least to some extent, unequal income distributions have been provided, such as the role in offering incentives to work hard.

This thesis discusses the possible effects income inequality might have on future economic growth and the ways in which these effects might be measured through a careful analysis of Cingano (2014) and other literature of the subject. More specifically, the thesis attempts to find out whether the findings behind the statement of the OECD can economically be considered as significant as reported. In part, the research attempts to answer the following questions:

- What kind of effects income inequality might have on economic growth?
- Can it truly be concluded that in almost all of the OECD countries, increased net income inequality has resulted in slower economic growth than would have been possible to achieve with a more equal income distribution?
- How are the results in Cingano (2014) obtained and can they be considered reliable and significant?
- How are these findings compared to other literature on the subject?

Another objective of the thesis is to link this discussion in the context of the Finnish economy and the development of income inequality in Finland. Is there something to learn from this recent discussion from the perspective of the Finnish economy? Overall the thesis, the discussion will have an emphasis on the Finnish economy alongside with the rest of the OECD countries.

In chapter 2, income inequality in the economic perspective is discussed. This chapter presents theories about the direction and the ways in which income inequality might affect economic growth as well as some key terminology used in discussing the subject. Furthermore, an overview of the recent trends in income inequality in the OECD area is presented.

Chapter 3 presents the Solow growth model and its augmentation to include human capital, a theory on which the research of Cingano (2014) is based on. Furthermore, the empirical specifications of the augmented Solow model are introduced as well as discussion on the model's suitability in growth regression analyses.

In chapters 4 and 5, a detailed analysis of the research of Cingano (2014) is constructed. Chapter 4 discusses the model and its empirical specification used in Cingano (2014), as well as the differences there are compared to the original model. The empirical methodology, namely the system Generalized Method of Moments (GMM) estimation method is explained and assessed. Moreover, descriptions of the data sources in use are constructed and their compatibility discussed. In chapter 5, the results in Cingano (2014) are addressed thoroughly. Overall, the model, methods, data and results of the research are carefully reported and examined in these two chapters. Based on this examination, it seems that the findings in Cingano (2014) are rather debatable and that overly specific conclusions regarding the strength and extent about the effects of income inequality on subsequent growth should not be made based on the research.

The sixth chapter further discusses the findings and their relevance in light of related research and the final chapter concludes.

2. Economic perspective on income inequality

This chapter presents different theories about how income inequality might affect economic growth. The Gini coefficient is introduced as a way to measure income inequality within a country. Furthermore, recent trends in the development of income inequality in the OECD area and Finland are discussed.

2.1. Possible ways how income inequality might affect economic growth

The mechanisms through which income inequality might have an effect on subsequent economic growth have been widely discussed in theoretical literature and empirical studies. Channels for both positive and negative effects have been proposed, while the empirical studies have struggled to determine a conclusive view on whether income inequality is good or bad for subsequent economic growth. This section will present arguments and theoretical views from both perspectives introducing some of the mechanisms in play.

2.1.1. Good for growth

Weil (2009) describes accumulation of physical capital as a channel through which income inequality might affect economic growth beneficially. Based on the basic Solow growth model introduced in chapter 3, a country with a higher saving rate, leading to the accumulation of physical capital, will have a higher steady state level of income per capita. Saving rates tend to rise with income. For example, Dynan et al. (2004) concluded that households aged 30-59 with higher incomes over their lifetime save a larger fraction of their income. Based on these conditions, more unequal income distribution would lead to higher capital accumulation, which in turn leads to a higher level of income per capita.

Lazear and Rosen (1979) explain that unequal compensation systems provide incentives to work harder, invest and take risks to benefit from higher rates of return. For example, if highly educated people are much more productive, then high differences in rates of return may encourage more people to seek education (Cingano 2014).

Although originally associated with wealth inequality, a theoretical model in Matsuyama (2000) is also applicable to explain how income inequality might have a positive effect on growth. When the financial system is imperfect, an individual's access to external finance is dependent on initial wealth or expected future wealth. Therefore, if income and wealth are evenly distributed within the society, a situation may arise, where nobody will be able to raise sufficient funds to execute projects that require large investments but possibly yield high returns. Under these assumptions, more unequal income and wealth distributions could enable at least some amount of entrepreneurs to realize such "high risk, high return" - projects, and thus boost growth.

2.1.2. Bad for growth

Unlike with physical capital, Weil (2009) argues that income inequality hurts the accumulation of human capital and thus hurts economic growth. In a theoretical simplification adapted from Galor and Zeira (1993), Weil (2009) explains how under imperfect financial markets, sufficiently unequal income distribution leads to underinvestment in human capital by the poorer people. Meanwhile, the better off invest equal to their marginal product to human capital, while the rest of their investment is directed to physical capital. This is because the marginal product for human capital is decreasing but for physical capital it is expected to be constant. In this framework, redistribution from the rich to the poor would lead to both higher investment in human capital and higher level of total output. Galor and Moav (2004) further contribute to the argument, describing how human capital accumulation has replaced physical capital accumulation as a prime engine of growth in the developed countries. According to their model, this development has reversed the positive impact income inequality has had on the growth process.

Contrary to the model discussed above, redistribution is also suggested to affect the efficiency of production in a harmful manner through taxation. Alesina and Rodrik (1994) present a theory, where redistribution through taxation and providing government services are the only actions for the government. Individuals differ in their relative factor endowments. Capital, consisting of all growth-producing assets, is an accumulated factor while unskilled labor is considered a non-accumulated factor. Thus, growth is determined by accumulation of the capital stock determined by individual saving. The aggregate production function is considered linearly homogenous in capital and productive government services while the provision of government services is financed by a tax on capital. Since government services are productive, a tax on capital benefits all participants. This tax is interpreted as any redistributive policy transferring income to unskilled labor while reducing incentive to accumulate capital. Due to the differences in the factor endowments, individuals prefer different tax rates, and capital accumulation being the driver for growth, the decision on the tax rate affects the growth rate as well. The lower a person's share of capital income relative to labor income, the higher is the preferred tax rate and thus lower the growth rate. Under the median voter theorem, that is when the government chooses a tax rate preferred by the median voter, the outcome of the model is that more growth-decreasing redistribution is likely to occur when the income is distributed more unevenly.

Adapted from the framework above, Weil (2009) analyzes the effect of income distribution on the level of taxes and therefore efficiency. Figure 1 illustrates how pre-tax income distribution affects the desired tax rate.

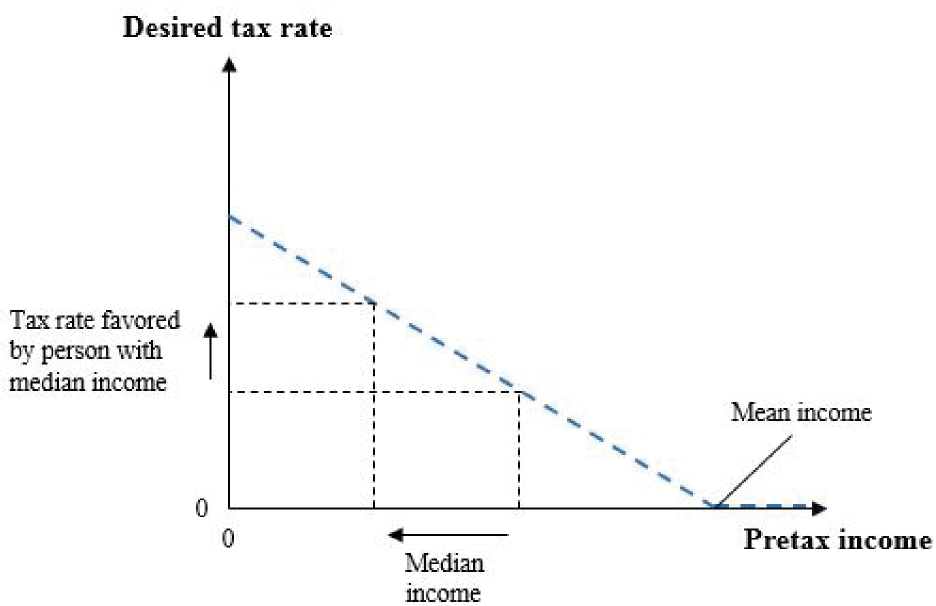

Figure 1: How an increase in income inequality affects the desired tax rate
(Source: Weil 2009, 396.)

When the distribution of pre-tax income becomes more unequal while mean income stays at the previous level, the median level of pre-tax income falls farther behind the mean income.

This leads to a higher desired rate of taxation by the median voter. Thus, higher inequality has led to higher level of redistribution and more inefficiency.

Assuming a more realistic view and acknowledging that decision-making might not be done by simple majority voting, Weil (2009) suggests sociopolitical unrest as one channel through which income inequality might affect growth. Income inequality leads to more pressure for redistribution, but not necessarily to more actual redistribution. This might in turn lead to political instability and thus result in decreasing investments due to, for example, increases in uncertainty regarding property rights and the level of crime.

Cingano (2014) explains that income inequality can be harmful to growth if minimum critical amount of domestic demand is necessary for adopting new technologies. Originated by Murphy et al. (1988), initially this argument was considered critical for countries on their way to industrialization. However, recently it has been reintroduced in public debate especially in the United Kingdom and the United States due to reports stating that real wages have been stagnated for a long period and it has resulted in relatively decreased consumption possibilities of the low and middle class workers. Furthermore, this stagnation has been linked to substantial development of increased private lending, a phenomenon considered to have been accelerated since deregulation of the financial sector in the beginning of the 1980's in the US and the UK, and expected to have played its part in the making of the financial crisis in 2007-2008. [e.g. (Lansley 2012; Stiglitz 2013).]

2.2. The Gini coefficient

Weil (2009) explains, that the most common way to measure income inequality on a country-level is done with the adaption of the Gini coefficient. Using this measure, it is possible to compare income inequality among countries or study the trends in inequality within a single country over time. To construct the Gini coefficient for income inequality in a given country, data on the incomes of all the households, or the representative sample of households, is required. This data is then arranged in an ascending order and the fractions of the income earned by different percentiles of the households are calculated. Figure 2 illustrates such data concerning Finnish households in year 2013 in a graph together with a linear line ascending in a 45 degree angle. The latter represents the line of perfect inequality, while the Finnish data forms a curved line expressing the Lorenz curve for Finland in 2013. The data, provided in

Appendix 2, are obtained from the Official Statistics of Finland and its total statistics on income distribution. The data are based on equivalised disposable (net) household income. This way of measuring is used in general throughout this thesis when discussing the Gini coefficients.

As shown in figure 2, in the year 2013, the poorer half of the Finnish households earned approximately 31,5% of the cumulative household income in the country, whereas the richer half received a fraction over two thirds of the total income. Moreover, 70% of the households accounted for circa 51,4% of the earnings and the richest 10% earned almost 23% of the total income.

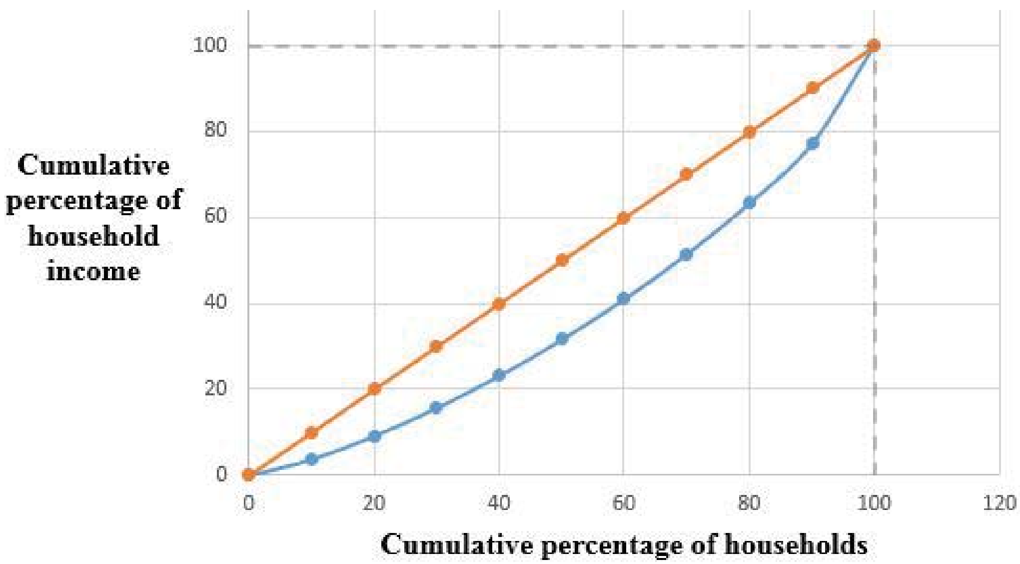

Figure 2: The Lorentz Curve for Finland in 2013
(Source: Official Statistics of Finland.)

In general, the more the Lorenz curve deviates from the line of perfect equality, the more unequally income is distributed in the country. Thus, measuring the area between the Lorenz curve and the line of perfect equality, and dividing it by the total area under the line of perfect inequality, gives the Gini coefficient for the country. The Gini coefficient can have a value between 0 and 1, the first describing a perfectly equal income distribution and the latter a situation where all income is earned by a single household. (Weil 2009.) The coefficient can also be multiplied with 100 and stated as a number between 0 and 100. Thus, when discussing a reduction of 1 Gini point in a country, it means a decrease of 0,01 in the coefficient. To maintain consistency, this thesis discusses Gini coefficients with values between 0 and 1.

Even though the Gini coefficient is the most common measure used to compare the levels of income inequality between countries, there are some challenges to it. For example, as discussed in chapter 4.3 when assessing the data sources in Cingano (2014), historically the Gini coefficients have been collected infrequently in most countries. Moreover, despite some common guidelines in how the data behind the coefficient should be collected, irregularities have been found in the methods across countries. Overall, Stiglitz (2013) emphasizes, the data necessary for calculating the Gini coefficient are difficult to collect, especially in the poor countries.

Furthermore, the Gini coefficient does not describe the level of inequality in a complete sense. For example, according to the Official Statistics of Finland, the Gini coefficient for Finland in 2013 was 0,276. When compared to other countries, income is relatively evenly distributed in the Finnish society. Meanwhile, the World Bank reports a Gini coefficient of 0,290 for Albania in the year 2012. However, Albania is one of the poorest countries in Europe, with a GDP per capita level at roughly one 10^{th} of that in Finland. Moreover, the latest coefficient from 2010 for Ethiopia, a country with a GDP per capita level approximately one 10^{th} of that in Albania, is reported as 0,336. Should one consider GDP per capita as an incomplete indicator of welfare, the above comparisons are similar using a different measure for well-being, such as the Human Development Index (HDI). The example illustrates, however, that the Gini coefficient does not describe the absolute levels of income or well-being, a feature one should be wise to remember when comparing countries with each other. Furthermore, Stiglitz (2013) argues that if the Gini coefficient would capture the effects of issues such as healthcare costs or the safety net offered by the government after unemployment, i.e. the United States would be considered a whole lot more unequal than their Gini coefficient (0,389 in 2012) suggests.

2.3. The development of income inequality in the OECD area in recent decades

Based on data from the OECD Income Distribution Database (IDD), Cingano (2014) explains that average real disposable household incomes have risen in all OECD countries annually by 1,6% from the middle of 1980's to the beginning of the financial crisis in years 2007-2008. In 75% of the countries the incomes of the top decile grew faster than those of the poorest 10%. This development has led to widening income inequality. The countries where this development seems to have been highest include the English-speaking countries as well as Israel, Germany and Sweden.

When looking at the period after the financial crisis, from 2007 onwards, Cingano (2014) notes that average real household income stagnated or fell in most of the OECD countries. The hardest hit have been Spain, Ireland, Iceland and Greece. In these countries, average annual real household income has been decreasing by more than 3,6%. Moreover, in the countries where these incomes have fallen, the incomes of the poorest decile have fallen more rapidly. Similarly, in about half of those countries where incomes continued to grow, the top 10% did better than the bottom 10% (Cingano 2014, 9). On average, the mean real disposable household income has fallen annually by 1,8% in the bottom decile and by 0,7% in the top decile after 2007. Overall, the data indicates that before the financial crisis, the incomes of the top 10% grew faster than of the bottom decile, while the decrease of the incomes was relatively faster for the latter after year 2007.

According to the figures from the OECD IDD, the development pre-crisis in Finland has been similar to the trends described above; from 1986 to 2008, average annual increase in disposable income for total population was 1,7% from which the bottom decile accounted for 1,2% while the share of the top decile was 2,5%. Interestingly, the development seems to have continued positive in Finland after year 2008. The calculations in Cingano (2014) show an average annual increase of 1,2%, with 1,5% and 1,0% shares for bottom and top deciles, respectively. These figures are slightly larger than the data provided by the Official Statistics of Finland, who have reported an average annual increase of disposable income of around 0,8% between years 2008 and 2012.

These developments confirm a trend among the OECD countries towards higher income inequality in the long run. Based on the OECD IDD, currently the average income of the top 10% among all OECD countries is about 9,5 times higher than of the bottom decile, whereas the same ratio was 7 to 1 in the 1980's. (Cingano 2014.) This calculation, widely reported in the public statements of the OECD, is based on an indicator called "S90/S10", and seems to be an average of years 2007, 2010 and 2011. In the OECD iLibrary, this indicator is defined as the gap between the average incomes of the richest and poorest 10% of the population, based on equivalised disposable income. In a more general note, this indicator can also be called "Decile dispersion ratio", and it can be adapted to measure the differences between any two portions of the income distribution. It is worth noticing, that calculating a similar ratio based on the OECD data on total income share provided in Cingano (2014) annex A1.2, the ratio between the top 10% and bottom 10% is around 8,41. Even though the difference between these two S90/S10 ratios is not substantial, it implies that there is a difference in which income figures to use and one should be careful when interpreting and comparing the figures between different countries, studies and data sets. Also, as Cingano (2014) recognizes too, another considerable issue is that the ratios provided in his research vary between OECD countries vastly. For example, in Finland the ratio is reported to be around 5,6 to 1, which is much lower than the average. Meanwhile, Portugal, United States and Mexico reach ratios around 10 to 1, 15,8 to 1 and 28,6 to 1, respectively. Once again, the data varies a little between different sources; calculating an S90/S10 average for years 2007, 2010 and 2011 based on the data from the Official Statistics of Finland, the ratio for Finland has been around 6,6 to 1. In relative terms this is quite a bit larger than reported in Cingano (2014).

Cingano (2014) further explains that by using the Gini coefficient to measure income inequality, a more comprehensive view can be formed about the direction and the pace of this development. After 1985, the Gini coefficient has increased in 17 out of the 22 OECD countries for which long time series are reported to have been available in the OECD IDD. In Finland, this development has been relatively faster than on average, with an increase of slightly over 5 Gini points. It is noteworthy, that in absolute terms, Finland is still among the most equal countries in the world in terms of income distribution, with a Gini coefficient of 0,276 in 2013. This fact might in part explain the relative speed of this development.

The only countries where the coefficient is reported to have slightly fallen after 1985 are Greece and Turkey. Other countries where the development has been relatively fast include Sweden, New Zealand and the United States. In the Netherlands, Belgium and France, the Gini coefficients are reported to have remained roughly at the same levels as they were in 1985. (Cingano 2014.) However, the earliest entry for Gini coefficient in France in the OECD IDD time series seems to be for 1996 and for Belgium as late as 2004. The differences between the data provided in the OECD IDD and the figure analyzed in Cingano (2014), also reported in the public statement of the OECD on December 2014, expresses the argumentation in Cingano (2014) in rather a questionable light. After all, the OECD IDD is provided as the only source for the figure in the research. In annex 3 however, Cingano (2014) specifies that the data of OECD IDD is complemented with the Luxembourg Income Study (LIS) data set to compensate for the missing values for inequality in the OECD IDD. The compatibility and significance of these data sets are not discussed in the research of Cingano (2014), but will be assessed in chapter 4.3 in this thesis.

Nevertheless, it can be concluded from figure 3 that on average, the level of income inequality has increased in the OECD countries from the early 1990's to the present while the largest variation has occurred during the 1990's. During years 2000-2010, the average Gini coefficient varied only a little and ended the decade in a similar level to year 2000. After 2010 however, the Gini coefficients of the OECD countries on average seem to be on the rise again.

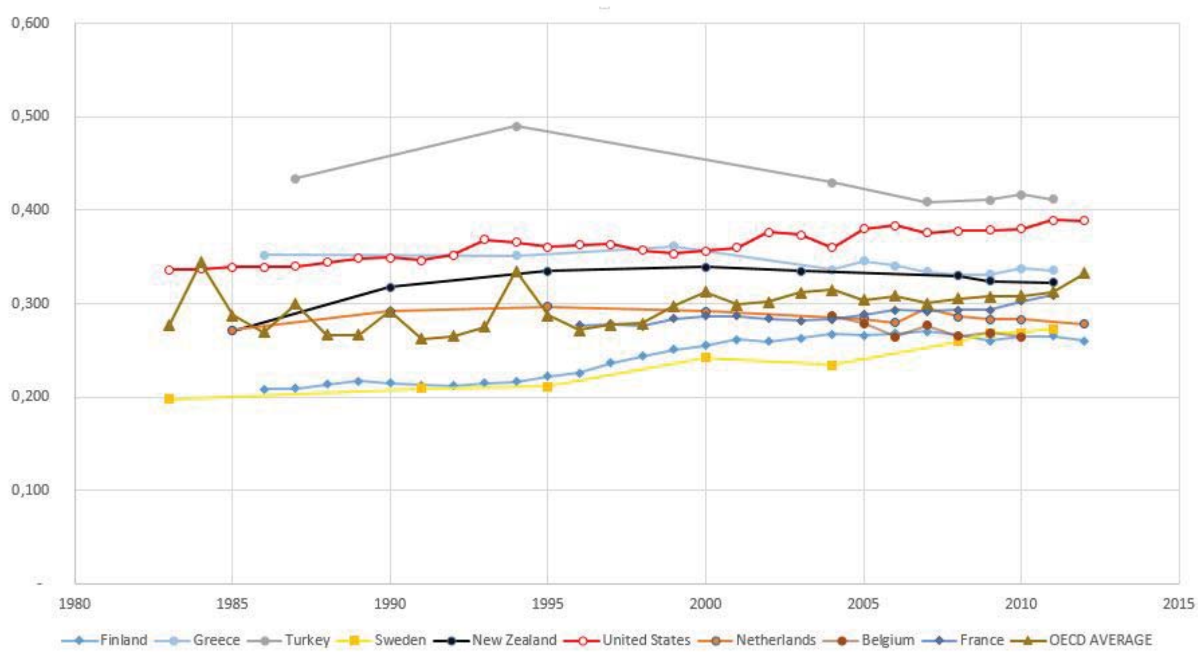

Figure 3: The development of the Gini coefficient in selected OECD countries 1983-2012 (Source: OECD Income distribution database.)

Figure 3 illustrates the data given in the OECD IDD for the countries discussed above. In absolute terms, the lowest levels of the Gini coefficient are found in Finland, Sweden, Belgium and the Netherlands. The latest coefficients for all of these four countries are under 0,3. The latter two have been developing towards a more equal share of income in the recent years, whereas in Sweden, income inequality has been on the rise. In Finland, the last notation in the OECD IDD of the Gini coefficient is from year 2012, when it was at the same level as in year 2001. After 2000, there was first a modest increase followed by a similar decrease after 2007. The highest absolute levels of the coefficient among the represented 9 countries are found in the United States and Turkey, where the most recent values of the Gini coefficients are 0,389 and 0,412, respectively. On average in the OECD countries, the Gini coefficient has been at almost the same level throughout the 21st century, at a value just above 0,3. However, the accelerating speed in the recent years has brought the coefficient up to 0,333 by the end of 2012. Among all OECD countries, the highest Gini coefficients at around 0,5 are found in Latin America, namely Chile and Mexico. The lowest coefficients are found in the Nordic countries, all with values under 0,28.

The long-term development in Finland differs from the rather stationary period of the 21st century. There was a modest increase from 0,209 in 1986 to 0,217 in 1994 after which the speed accelerated until reaching 0,261 in 2001, which is in fact the same level as in 2012. The most notable increase has occurred between 1994 and 2001, a period of strong economic development. In late 1993, the Finnish economy started to recover from a forceful depression. According to the Official Statistics of Finland, the annual increase in the volume of Finland's GDP varied between 2,6% and 6,3% in years 1994-2001. Thus, during this period in Finland, net income inequality increased quite rapidly along with strong economic growth.

2.3.1 Suggested explanations for the development

Weil (2009) introduces three arguments to help explain the development of income inequality in the United States from the 1950's onwards. Despite the fact that Weil's focus is on the United States, he notes that a similar rise in income inequality has been observed in most other advanced economies as well. Therefore, it seems safe to say that these possible explanations can be applied to analyze some of the development in the OECD on average as well.

The first possible explanation is technological development. This argument is based on an idea that technological progress occurs in discrete waves, all concentrated around a so-called general-purpose technology. The most recent of the general-purpose technologies is the semiconductor which has led to a revolution in information technology and is thus considered widely the main source of the speedup in economic growth in the United States on the second half of the 20th century. The development of the information technology complemented the educated workers' skills and this way has contributed to an increase in income inequality. Should this argument be valid, the effects of the current technological revolution inducing income inequality ought to be expected to disappear at some point. (Weil 2009, 386-387.)

Another possible explanation behind the increase in income inequality is linked to increases in international trade. The opening to trade has raised the rate of return to qualities abundant in a given country but scarce in the world as a whole. Since education is more plentiful in a developed country compared to the rest of the world, opening trade tends to raise the return to education and therefore inequality. (Weil 2009, 387.)

The third argument presented by Weil (2009) is the rise of what the author calls a “Superstar” dynamic. This refers to a phenomenon in many occupations, where people with the absolute highest levels of some qualities earn much more than the people with slightly lower level of the same qualities. This development has been clearly visible in many areas, such as sports, entertainment and finance, to name a few. This widely observed system emphasizes a rise in the return to certain qualities and thus increases income inequality. (Weil 2009, 387.)

3. The augmented Solow growth model

The augmented Solow growth model, the cornerstone for the regression model in Cingano (2014), is based on the original Solow model. This chapter introduces these growth models and their empirical specifications. In order to maintain consistency in notations throughout this chapter, the basic Solow model is introduced using some of the creators of the augmented Solow model as the main reference.

3.1. The Solow model

The augmented Solow model is based on a basic neoclassical growth theory presented by Robert Solow in 1956. The cornerstone of the model is a production function

(1) $$Y = F(K, AL),$$

where Y is output, K is capital, L is labor, and A represents the level of technology. The term AL can be interpreted as labor measured in efficiency units combining both the amount of labor and its productivity determined by the level of available technology. (Mankiw, Phelps & Romer 1995, 276.)

Labor is expected to grow with speed n and technology at rate g; denoting $L(t)$ and $A(t)$ as the amount of labor and level of technology at the point of time t, their growth rates are determined by

(2a) $$L(t) = L(0)e^{nt}$$

and

(2b) $$A(t) = A(0)e^{gt}.$$ (Mankiw, Romer & Weil 1992, 409.)

When the production function is assumed to have constant returns to scale, it can be represented as output per efficient unit of labor related to the amount of capital per efficient unit of labor

(3) $$y = f(k),$$

where $y = \frac{Y}{AL}$, $k = \frac{K}{AL}$ and $f(k) = F(k, 1)$. (Mankiw, Phelps & Romer 1995, 276.)

Moreover, let δ and s represent the rates of capital depreciation and savings, respectively. Part of each instant's output is consumed and the rest is saved and invested (Solow 1956, 66). The model takes s, n, g and δ as exogenous (Mankiw, Phelps & Romer 1995, 276). In this basic model, growth arises from the accumulation of capital, and the stock of capital per efficient unit of labor develops according to

(4) $$\dot{k} = sf(k) - (n + g + \delta)\mathrm{k},$$

where $\dot{k} = \frac{\partial k}{\partial t}$. When the production function meets certain assumptions, and is therefore considered well behaved, the economy approaches a steady state defined by $\dot{k} = 0$ over time. (Mankiw, Phelps & Romer 1995, 276.) In addition to the abovementioned qualities, the production function must meet at least the following conditions:

(5a) $$f(0) = 0$$

(5b) $$f'(k) > 0$$

(5c) $$f''(k) < 0,$$

which state that the marginal product of capital is increasing and concave. Furthermore, to ensure that for smaller levels of capital per effective unit of labor, the marginal product of capital is larger and fundamentally decreasing as the stock of capital increases, it must be that:

(5d) $$\lim_{k \to 0} f'(k) = \infty$$

and

(5e) $$\lim_{k \to \infty} f'(k) = 0.$$

With k^* noting a steady state value, the condition of equation (4) becomes

(6) $$sf(k^*) = (n + g + \ \delta)k^*.$$

In the steady state, output per efficient unit of labor is constant, $y^* = f(k^*)$, output per person grows at rate g, and total output at rate $(n + g)$. (Mankiw, Phelps & Romer 1995, 276.) Commonly, the term income is also used instead of output when discussing the Solow model, its empirical specifications and the models derived from it.

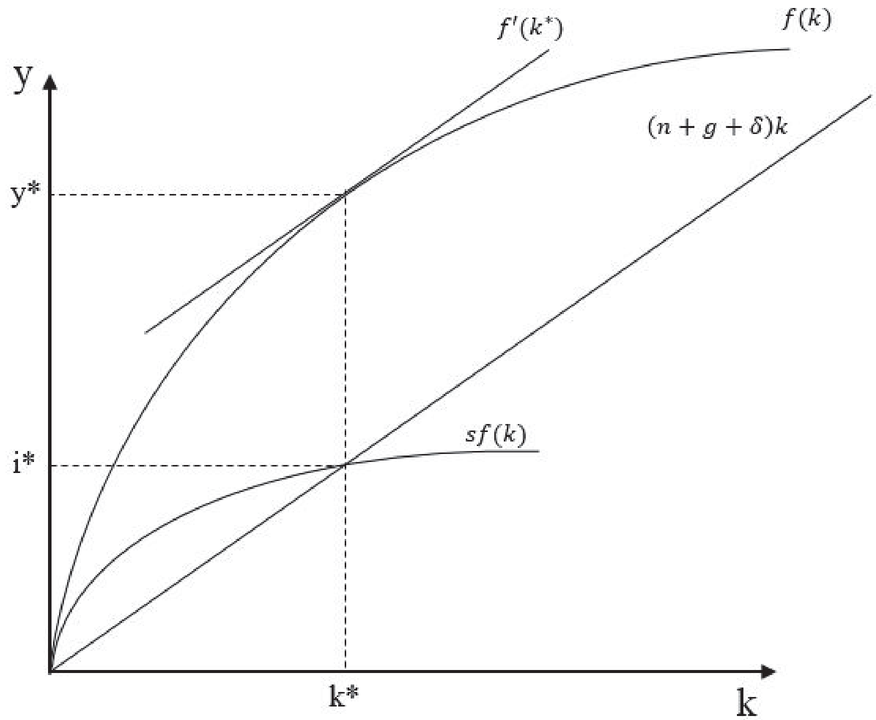

Figure 4: The Solow diagram per effective unit of labor
(Source: Adapted from Romer 2006.)

Adapted from Romer (2006), figure 4 explains the steady state properties of the Solow model with efficient labor units discussed above. Moreover, it illustrates the “golden-rule” level of the capital stock, where $f'(k^*) = n + g + \delta$. The steady state level of capital is denoted by k^*, whereas y^* represents the steady state level of output and i^* the steady state level of investment. Therefore, the difference between y^* and i^* measures the level of consumption in the steady state. Thus, in the steady state, a marginal change in s has no effect on consumption in the long run. Among balanced growth paths, consumption is at its maximum possible level. (Romer 2006.)

3.1.1. Empirical specification

Assuming a Cobb-Douglas form, the production function at time t can be written as

$$Y(t) = K(t)^{\alpha}[A(t)L(t)]^{1-\alpha}, \tag{7}$$

where α represents the capital's share in income and $0 < \alpha < 1$. The evolution of k is then determined by

$$\dot{k}(t) = sy(t) - (n + g + \delta)k(t) \tag{8a}$$

$$\dot{k}(t) = sk(t)^{\alpha} - (n + g + \delta)k(t), \tag{8b}$$

and the steady state value becoming

$$sk^{*\alpha} = (n + g + \delta)k^{*}, \tag{9a}$$

$$k^{*} = \left[\frac{s}{(n+g+\delta)}\right]^{\frac{1}{(1-\alpha)}}, \tag{9b}$$

implying that in the steady state, capital per effective unit of labor is positively related to the saving rate and negatively to population growth rate. (Mankiw, Romer & Weil 1992, 409-410.)

Inserting equation (9b) in to the production function (7), noting conditions (2a) and (2b), and taking logarithms, the steady state income per capita is given by

$$ln\left[\frac{Y(t)}{L(t)}\right] = lnA(0) + gt + \frac{\alpha}{1-\alpha}\ln(s) - \frac{\alpha}{1-\alpha}\ln(n + g + \delta). \tag{10}$$

(Mankiw, Romer & Weil 1992, 410.)

Because the model assumes that factors are paid their marginal products, it predicts not only the signs but also the magnitudes of the coefficients on saving and population growth (Mankiw, Romer & Weil 1992, 410).

When testing empirically the Solow model's predictions on whether real income can be expected to be higher in countries with higher saving rates and lower in countries with higher levels of $(n + g + \delta)$, Mankiw et al. (1992) assume that g and δ are constant across countries. As discussed later in chapter 3.3, especially the assumption of a constant rate of technology growth across countries can be considered rather a debatable simplification and is criticized in some empirical growth literature.

Nevertheless, Mankiw et al. (1992) continue by explaining that besides the level of technology, the term $A(0)$ reflects defining qualities such as institutions, resource endowments and climate that differ across countries. Therefore, a specification is made, $lnA(0) = a + \epsilon$, where a is a constant and ϵ reflects a country-specific shock. Equation (10) is now written as

(11) $$ln\left[\frac{Y(t)}{L(t)}\right] = a + gt + \frac{\alpha}{1-\alpha}\ln(s) - \frac{\alpha}{1-\alpha}\ln(n+g+\delta) + \epsilon.$$

Furthermore, s and n are assumed to be independent of ϵ. (Mankiw, Romer & Weil 1992, 410-411.)

3.2. The Augmented Solow model

The ordinary Solow model does not take accumulation of human capital into account as a source in the process of growth. Including human capital in the model can alter both the theoretical modeling and the empirical analysis of economic growth. To show how ignoring human capital affects the physical capital investment and population growth, Mankiw et al. (1992) expand the model and re-write it as

(12) $$Y(t) = K(t)^{\alpha}H(t)^{\beta}[A(t)L(t)]^{1-\alpha-\beta},$$

where the additional term $H(t)$ is the stock of human capital at point of time t, and β represents the human capital's share of income. The stocks of human and physical capital, and thus the whole economy, then evolve according to

(13a) $$\dot{h}(t) = s_h y(t) - (n+g+\delta)h(t),$$

(13b) $$\dot{k}(t) = s_k y(t) - (n+g+\delta)k(t),$$

where $y = \frac{Y}{AL}$, $k = \frac{K}{AL}$ and $h = \frac{H}{AL}$. In addition, the terms s_h and s_k represent the fractions of income invested in human and physical capital, respectively. It is assumed that the same production function applies to both human and physical capital as well as consumption, so one unit of consumption can be transferred without cost to one unit of human or physical capital. Furthermore, it is assumed that $\alpha + \beta < 1$, so there are decreasing returns to all capital. (Mankiw, Romer & Weil 1992, 415-416.)

Equations (13a) and (13b) further suggest that the economy converges towards a steady state defined by:

(14a) $$k^{*} = \left[\frac{s_k^{1-\beta} s_h^{\beta}}{n+g+\delta}\right]^{\frac{1}{(1-\alpha-\beta)}}$$

and

(14b) $$h^* = \left[\frac{s_k^{\alpha} s_h^{1-\alpha}}{n+g+\delta}\right]^{\frac{1}{(1-\alpha-\beta)}}.$$ (Mankiw, Romer & Weil 1992, 417.)

Similarly as above with equation (10), inserting (14a) and (14b) in to the production function (12) and taking logarithms, the steady state income per capita is given by

(15) $$ln\left[\frac{Y(t)}{L(t)}\right] = \ln A(0) + gt - \frac{\alpha+\beta}{1-\alpha-\beta}\ln(n+g+\delta) + \frac{\alpha}{1-\alpha-\beta}\ln(s_k) + \frac{\beta}{1-\alpha-\beta}\ln(s_h).$$

Equation (15) thus illustrates how income per capita is affected by the accumulation of human and physical capital as well as population growth. In an empirical analysis based on equation (15), Mankiw et al. (1992) find that these three variables in the model explain almost 80 percent of the cross-country variation in income per capita with two out of their three data samples. (Mankiw, Romer & Weil 1992, 417-421.)

Compared to the empirical results received estimating equation (11), the new specification leads the authors to two distinctive predictions. Firstly, high population growth lowers income per capita because the amounts of human and physical capital needs to be spread more thinly over the population. Secondly, the presence of human capital accumulation increases the impact of physical capital accumulation on income. This is because the coefficient $\frac{\alpha}{1-\alpha-\beta}$ on $\ln(s_k)$ is greater than $\frac{\alpha}{1-\alpha}$, regardless of whether the term $\ln(s_h)$ is independent of the other explanatory variables or not. Since higher saving leads to higher income, the steady state level of human capital will become higher, even if the share of income devoted to its accumulation remains unchanged. (Mankiw, Romer & Weil 1992, 417-418.)

Alternatively, the role of human capital in determining income per capita in the model can be expressed by combining equations (15) and (14b). This will yield an equation for income per capita as a function of investment rate in physical capital, population growth rate and the level of human capital (h^*):

(16) $$ln\left[\frac{Y(t)}{L(t)}\right] = \ln A(0) + gt - \frac{\alpha}{1-\alpha}\ln(n+g+\delta) + \frac{\alpha}{1-\alpha}\ln(s_k) + \frac{\beta}{1-\alpha}\ln(h^*).$$

Compared to equation (10), this specification takes the level of human capital into account, whereas in equation (10) it was considered as a part of the error term. The level of human capital should be expected to correlate positively with the saving rate and negatively with the population growth rate since it is influenced by both of them. Thus, the new specification should account for the possible omitted variable bias present in the original Solow model. The available data ultimately determines whether the augmented Solow model ought to be tested based on equation (15) or equation (16). (Mankiw, Romer & Weil 1992, 418.)

The Solow model predicts that countries converge towards different steady states determined by the accumulation of human and physical capital and population growth. Therefore, the model predicts convergence only after controlling these determinants, a feature the authors call "conditional convergence". (Mankiw, Romer & Weil 1992, 422.) Moreover, the augmented Solow model makes quantitative predictions about the speed of convergence to a country's steady state. Similarly as in equation (15), y^* denotes the steady state level of income per effective worker. Furthermore, let $y(t)$ be the actual value at a point of time t. The speed of convergence is given by approximating around the steady state:

(17a) $$\frac{\partial \ln(y(t))}{\partial t} = \lambda[\ln(y^*) - \ln(y(t))],$$

where λ is the convergence rate determined by

(17b) $\lambda = (n + g + \delta)(1 - \alpha - \beta)$. (Mankiw, Romer & Weil 1992, 422.)

For example, assuming that $\alpha = \beta = \frac{1}{3}$ and $n + g + \delta$ = 0,06, would result in a convergence rate of $\lambda = 0{,}02$. Applying this result with the "rule of 70" implies that the economy reaches halfway to its steady state in approximately 35 years. Should the conditions in the original Solow model hold and $\beta = 0$, the convergence rate λ would become 0,04 resulting in a speed of convergence twice as fast. (Mankiw, Romer & Weil 1992, 423.)

Moreover, denoting $y(0)$ as income per effective worker at some initial date, equation (17a) implies that

(18) $$\ln(y(t)) = (1 - e^{-\lambda t})\ln(y^*) + e^{-\lambda t}\ln(y(0)).$$

Subtracting $\ln(y(0))$ from both sides, the condition for the growth of income becomes:

(19) $$\ln(y(t)) - \ln(y(0)) = (1 - e^{-\lambda t})\ln(y^*) - (1 - e^{-\lambda t})\ln(y(0)).$$

Finally, substituting for y^* from equation (15):

(20) $$\ln(y(t)) - \ln(y(0)) = (1 - e^{-\lambda t})\frac{\alpha}{1-\alpha-\beta}\ln(s_k) + (1 - e^{-\lambda t})\frac{\beta}{1-\alpha-\beta}\ln(s_h) - (1 - e^{-\lambda t})\frac{\alpha+\beta}{1-\alpha-\beta}\ln(n + g + \delta) - (1 - e^{-\lambda t})\ln(y(0)).$$

Thus, the growth of income is a function of the initial level of income and the determinants of the ultimate steady state in the Solow model. (Mankiw, Romer & Weil 1992, 423.) Some empirical growth literature based on this model have found past growth to be a surprisingly weak predictor of future growth. However, it is expected to become more accurate slowly over time. (Durlauf, Johnson & Temple 2005.)

The results of regressions based on equation (20), such as Cingano (2014), should be interpreted differently from those based on equations (15) and (16). While the latter two are valid only if countries are in their steady states, or if the deviations are random, equation (20) explicitly takes into account the dynamics related to the countries being out of their steady states. Yet in doing so, a new problem arises. If countries have different initial levels of technology $A(0)$, and thus permanent differences in their production functions, the values for the levels of technology will enter as part of the error term in the regression and correlate positively with initial income. Variation in $A(0)$ would thus affect the coefficient of initial income with a downward bias towards zero. Therefore, permanent differences in production functions between countries will lead to differences in initial incomes that are uncorrelated with subsequent growth rates. This would in turn lead to biased results against finding convergence. (Mankiw, Romer & Weil 1992, 424.)

3.3. Discussion on the augmented Solow model

In a very thorough article, Durlauf, Johnson and Temple (2005) discuss the role of growth econometrics in studying the countless phenomena involved in economic growth and describe the fundamental challenges related to growth regressions. Since empirical growth analyses are often built on the human capital augmented Solow model by Mankiw et al. (1992), discussion related to this model is also central in the research.

Durlauf et al. (2005) recognize the pioneering nature of the augmented Solow model by Mankiw et al. (1992), commonly also cited as simply MRW. However, Durlauf et al. (2005) make interesting observations related to the adaptations of the model to include additional explanatory variables, such as income inequality in Cingano (2014). The additional variables might be considered as allowing for predictable heterogeneity in the steady state growth rate, that is the growth rate of technology, gt, and the initial level of technology $A(0)$. It does not, however, identify whether the additional controls are correlated with one or the other. This might result in dismissing the idea that the additional controls offer further explanatory value in estimating growth over the Solow growth regressors. However, it is argued that these controls might still sometimes function as proxies for predicting differences in the efficiency growth rather than the initial level of technology, thus resulting in possibilities to analyze different technological growth rates between countries. Temple (1999) argues, that while useful in theory, assuming technological progress to be constant across countries in the long-run is not a justifiable assumption in whichever observed sample. This argument can be considered rather essential, considering that in the augmented Solow model, the initial level of technology is also considered to reflect other qualities defined as country specific shocks. Thus, Temple (1999) specifies, the question is not only about measuring technological advances but total factor productivity (TFP) growth. This may be affected by such things as instability and war (Temple 1999, 135). Therefore, Durlauf et al. (2005) argue that proper accounting of the term $ln(n_i + g_i + \delta)$ would allow for some progress in identifying whether the additional controls would affect gt or $A(0)$, since the effects in technology growth rate ought to imply a non-linear relationship between the controls and the overall growth rate $y(t)$. However, this nonlinearity may be too subtle to uncover given the relatively small data sets available to growth researchers (Durlauf et al. 2005, 580).

A key feature in the augmented Solow model, the effect that the accumulation of the growth determinants has on the steady state level of income per capita, and the rate of convergence towards it, has also been criticized in some empirical literature. For example, after constructing a new measure for human capital accumulation and using an alternative empirical approach, Klenow and Rodríguez-Clare (1997) conclude that the amount of cross-country variation in income per capita explained by the factor accumulation is substantially smaller than what was found in Mankiw et al. (1992). Moreover, Easterly and Levine (2001) also state that while factor accumulation should not be overlooked in analyzing differences in economic growth and income across countries, TFP accounts for a substantial amount of cross-country differences. Noteworthy is, that along with the term TFP, Easterly and Levine (2001) use the term “residual”, suggesting that in addition to different rates of technology growth, unobserved growth determinants might play a key part in the growth process.

These observations highlight the question on whether assuming a constant growth rate of technology between countries is relevant in growth regressions such as the one in Cingano (2014). While the problem related to the initial level of technology being unobserved can be dealt with the use of panel data, the linear form of all growth regressions based on the augmented Solow model cannot account for differences in the growth rates of technology.

Furthermore, in his comments to Klenow and Rodríguez-Clare (1997), Mankiw notes what he considers the weakest link in their original MRW empirical analysis, as well as in most empirical literature on economic growth in general; correlation does not imply causation. (Klenow & Rodríguez-Clare 1997, 104.) In addition, as discussed in Durlauf et al. (2005), it is noteworthy that the augmented Solow growth model is indeed a closed economy model, leaving out aspects of interdependence that are surely important in growth processes.

Nevertheless, equation (20) is the starting point for the empirical analysis in Cingano (2014) concerning the effect of income inequality on economic growth in the OECD countries in 1970-2010.

4. On measuring the effects of income inequality on growth

This chapter assesses the model, methods and data used in the research of Cingano (2014) in detail. Discussion regarding all of these aspects is included throughout the chapter.

4.1. The model in Cingano (2014)

The growth model in Cingano (2014) is derived from the augmented Solow growth model. Contrary to the empirical specification for the augmented Solow model presented in chapter 3, namely equations (19) and (20), the specification in Cingano (2014) is of form:

$$\ln\big(y(t)\big) - \ln\big(y(t-s)\big) = \left(1-e^{-\lambda t}\right)\frac{\alpha}{1-\alpha-\beta}\ln(s_k) + \left(1-e^{-\lambda t}\right)\frac{\beta}{1-\alpha-\beta}\ln(h^*) - \left(1-e^{-\lambda t}\right)\frac{\alpha+\beta}{1-\alpha-\beta}\ln(n+g+\delta) - \left(1-e^{-\lambda t}\right)\ln\big(y(t-s)\big), \tag{21}$$

where $(t-s)$ represents a period of 5 years and all other variables are similar to the augmented Solow model. As described in the technical annex, this baseline specification does not account for the term $(n+g+\delta)$ representing cumulating population growth, technological progress and capital depreciation. This simplification is done for specific reasons. Population growth rate is not expected to vary a lot within countries, capital depreciation is assumed constant and technological progress is considered unobserved. Also, the sample size would become too limited without this specification and thus it helps in maximizing the degrees of freedom in the regression. (Cingano 2014, 46.) This raises questions about whether the sample size is then too small, since panel estimation requires a large amount of observations. Furthermore, the assumptions on constant rates of technological progress and population growth across countries are often considered overly simplified, neglecting key features and dynamics in explaining economic growth.

The distinctive difference between this model and the MRW empirical specification is that Cingano seems to have replaced the variable of investment in human capital $\ln(s_h)$ with the level of human capital $\ln(h^*)$. However, as presented with equation (16), the coefficients ought to be different when estimating growth of income per capita using the level of human capital.

In equation (16), the coefficient for $\ln(h^*)$ is defined as $\frac{\beta}{1-\alpha}$, whereas in Cingano (2014) it is $\frac{\beta}{1-\alpha-\beta}$, which is similar to equations (15) and (20), both using $\ln(s_h)$ as the variable. There exists a somewhat similar difference in the model of Cingano with the term $\ln(s_k)$ representing the investment in physical capital. The coefficient in equation (16) for this term is $\frac{\alpha}{1-\alpha}$ while Cingano (2014) uses a coefficient of $\frac{\alpha}{1-\alpha-\beta}$. Overall, it seems that the analysis in Cingano (2014) combines one variable of equation (16) otherwise using equations (15) and (20) with all their characteristics.

These differences in the coefficients can be considered likely to affect the results of the analysis. For example, assuming $\alpha = \beta = \frac{1}{3}$, Cingano (2014) suggests that the coefficient for $\ln(s_k)$ is $\left(1 - e^{-\lambda t}\right)$, while the original model would suggest a coefficient of half this size. Measuring the difference between the coefficients for $\ln(h^*)$ is not that straightforward, due to the mixing of the parts of the model explained above. However, it can be said that the original model would seem to provide smaller coefficients for the variables explaining physical and human capital than the model in Cingano (2014). This could in turn affect the results in explaining the role of human and physical capital in subsequent growth.

More dramatically, in the technical annex 3, Cingano (2014) writes the term before all the variables as $(1 - \mathrm{e})^{-\lambda \mathrm{t}}$. This differs crucially from the expression in the original model specified as $\left(1 - \mathrm{e}^{-\lambda \mathrm{t}}\right)$. However, as explained in section 4.4.1 when discussing the long-term implications of the results in Cingano (2014), it seems that the latter form is used in the calculations in Cingano (2014) and is thus also used in equation (21). This kind of a distinctive vagueness in mathematical notations, though an unintended technicality, plays a part in diminishing the credibility of Cingano (2014).

4.1.1. Empirical specification

The empirical equation in the first part of the analysis in Cingano (2014) estimates growth as a linear function of initial inequality, income as well as human and physical capital. Cingano (2014) explains that the model is derived from the augmented Solow growth model and is similar to most empirical analyses of growth determinants. The regression equation is built on equation (21) with added explanatory variables and is estimated using panel data. In general, the regression equation is of form:

$$lny_{i,t} - lny_{i,t-s} = \alpha lny_{i,t-s} + \beta X_{i,t-s} + \gamma lneq_{i,t-s} + \mu_i + \mu_t + \epsilon_{i,t}. \tag{22}$$

The footnote i represents a country and lny is the logarithm (ln) of real GDP per capita (y). The time interval $t - s$ is 5 years, so the dependent variable estimates the growth of a country on a 5 year period. On the right-hand side of equation (22), $y_{i,t-s}$ is added as a standard control for convergence and vector X consists of a minimum set of controls for human and physical capital. The variable eq is a summary measure for inequality, usually the Gini coefficient. Variables μ_i and μ_t are added to control for country and time fixed effects. These include omitted variable bias not changing over time and global shocks possibly affecting aggregate growth in any period but not recognized by the explanatory variables. Finally, ϵ is the error term. (Cingano 2014.)

Durlauf et al. (2005) describe the benefits of using panel data estimation methods in growth regressions in a concise manner. The number of countries is rather small, and perhaps not altogether comparable in a statistical sense. This results in limited amount of available data and imprecise estimates in growth regressions. Thus, a natural response is to use the within-country variation along with the cross-country variation to multiply the number of observations. However, it is also mentioned that proper care should be implemented when interpreting the estimates, especially based on models with fixed effects.

A more specific form of the regression equation as well as a more detailed description of included variables is given in the technical annex of Cingano (2014). The baseline equation is given as

$$lny_{i,t} - lny_{i,t-s} = \alpha lny_{i,t-s} + \beta_1 {h^*}_{i,t-s} + \beta_2 s_{k_{i,t-s}} + \gamma lneq_{i,t-s} + \mu_i + \mu_t + \epsilon_{i,t}. \tag{23}$$

Coefficients β_1 and β_2 are assigned for variables h^* and s_k, which are introduced compared to the general model. As the augmented Solow model suggests, these two variables represent the level of human capital and the investment in physical capital. The level of human capital is measured in schooling years of the working age population. (Cingano 2014.)

It is worth noticing that in Cingano (2014), the level of human capital is used to explain growth but not in the specific form specified by Mankiw et al. (1992) with equation (16). Moreover, a variable for income inequality is simply inserted into the model and, as will be discussed in section 5, it is found as the only explanatory variable with statistical significance in the model. Furthermore, as discussed in Durlauf et al. (2005), past growth might not be particularly good in predicting future growth.

In equation (23), the error term is changed to account for period t, as expressed in the general form, instead of $t - s$ specified in the technical annex in Cingano (2014). Admittedly, Cingano (2014) explains that in order to reduce the concerns of reverse causality, the relevant explanatory variables are measured at the beginning of the growth spell. Also, since the model is based on assuming conditional convergence, the growth equations presented above are expected to contain some dynamics in lagged output. (Cingano 2014, 14-15.) However, it seems unreasonable to expect the error term to be one of these lagged relevant explanatory variables on purpose while omitting the error term of the period t.

4.2. System GMM estimator

Cingano (2014) notes that the empirical growth models usually assume conditional convergence and are expected to contain some dynamics in lagged output. Therefore, equations (22) and (23) can be expressed as a dynamic panel data model:

$$lny_{i,t} = (1+\alpha)lny_{i,t-s} + \beta_1 h^*{}_{i,t-s} + \beta_2 s_{h_{i,t-s}} + \gamma lneq_{i,t-s} + \mu_i + \mu_t + \epsilon_{i,t}. \tag{24}$$

Cingano (2014) explains that estimating this model with a standard panel data approach such as Least Square Dummy Variable estimator would likely yield biased estimates due to a correlation between $y_{i,t-s}$ and the error term caused by i.e. applying a within transformation or taking first differences. Moreover, this would lead to biased estimates of all coefficients of the independent variables that are correlated with $y_{i,t-s}$. The problem caused by the presence of a lagged dependent variable $y_{i,t-s}$ is called the Nickell-bias. It can arise in a dynamic panel data regression where the time span is rather short (small T) but there are large amount of observations (large N). The mean of the lagged dependent variable $\mathrm{y}_{\mathrm{i,t-s}}$ contains observations from the first observation through (t-1) explaining the change in $\mathrm{y}_{\mathrm{i,t}}$. Moreover, the mean error conceptually subtracted from each $\epsilon_{\mathrm{i,t}}$ contains simultaneous values of the error term for the whole time period. The correlation resulting from these connections creates a bias in the estimate of the coefficient of $\mathrm{y}_{\mathrm{i,t-s}}$ that cannot be reduced by increasing the number of individual units. Furthermore, this bias is not caused by an autocorrelated error process and can arise even if the error process is independent and identically distributed. (Nickell 1981.)

Roodman (2009) describes that the system Generalized Method of Moments (system GMM) approach used in Cingano (2014) is based on an estimation technique called difference GMM, also first-difference GMM, developed by Arellano and Bond in 1991. The difference GMM estimation starts by transforming all regressors, usually by differencing. Further specified by Cingano (2014), lagged values of the explanatory variables are used as instruments to explain their changes when applying the first-difference estimator. The absence of serial correlation in the error term is required and it can be tested with the Arellano-Bond test of autocorrelation in the residuals. However, using the difference GMM estimator is problematic when estimating the effect of income inequality on growth. This is because variables such as inequality are commonly very stable within a country and taking first differences would simply eliminate most of the variation in the data. This would imply that the lagged levels of the explanatory variables would be weak instruments for the variables in differences. (Cingano 2014.)

All the results in the first empirical analysis in Cingano (2014) are based on the system GMM estimator exploiting variation over time both between countries as well as within a single country. It builds on the first-difference estimator, combining first-differenced equations and another set of equations applied in the levels where the lagged first differences of the explanatory variables are used as instruments. This allows the introduction of more instruments and can dramatically improve efficiency (Roodman 2009, 86). Moreover, Cingano (2014) explains that the GMM approach exploits a set of internal instruments built from previous observations of instrumented variables, such as inequality. This allows testing for the validity of these instruments, including Arellano-Bond tests for autocorrelation in the residuals and Hansen tests for joint validity of all the instruments. Neither serial correlation nor joint validity of instruments is found to cause issues with the regression.

Furthermore, it is assumed that the deviations of the initial observations from their steady states should not be correlated with the fixed effects specific for a country. As suggested by Roodman (2009), this requirement is tested regularly in the research with a difference-in-Hansen test. In addition, Roodman (2009) explains that too many instruments can cause a problem with the system GMM estimator. Cingano (2014) notes that is taken into account and therefore the number of instruments is reported in the research. It is worth noticing however, that Roodman (2009) also emphasizes that system GMM works only under arguably special circumstances.

Perhaps, the lesson to be drawn is that internal instruments, though attractive as a response to endogeneity, have serious limitations (Roodman 2009, 156).

Cingano explains that using system GMM results in the largest source of variation in inequality across countries, simultaneously accounting for other potentially relevant explanatory factors specific for a single country. While this might be technically true, it introduces a question whether variation of income inequality across countries truly explains the differences in the growth rates of other countries. Admittedly, as explained by Cingano (2014), many possible effects of the determinants of income inequality on economic growth are not expected to materialize until after a long time, such as a change in the educational system in a country, and thus would imply that cross-country variation might help to identify some of these effects in the long run. However, does maximizing the possible variation across countries necessarily reveal the desired effect of income inequality on growth or does it simply make this relation seem more important than it is? As described in the fifth chapter, none of the traditional growth determinants are found important in explaining growth in Cingano (2014). Could exploiting maximal variation in the inequality indicators be one possible reason for this? After all, the results seem to be extremely sensitive to the data, countries and time periods that are included in the analysis. Moreover, as shown in chapter 4.3 addressing the different data sources, the data on income inequality used in Cingano (2014) seem to be rather scarce.

Furthermore, how can all the determinants be identified in order to make sure there are no unobserved factors leading to a biased estimate and misinterpretation of the results? While it is arguably impossible to take into account all the different determinants behind economic growth, exploiting this maximal variation on purpose raises a question whether the desired outcome can be found like this but not otherwise. After all, as Cingano (2014) also notes, no consensus on the sign and strength of the relationship between income inequality and economic growth can be found based on previous empirical studies, an issue discussed in more detail in chapter 6.

4.3. Data review

Cingano (2014) exploits several different data sources in the research. The most notable sources and their applications are described in this section. Furthermore, discussion regarding the characteristics and compatibility of the different data sets are included. Since the empirical analysis and results of Cingano (2014) are assessed as two different empirical sections in this thesis, the assessment of the data sets is constructed accordingly. The first part of Cingano (2014) refers to the empirical analysis about the effects and magnitude of income inequality on growth. The second part examines how an individual’s parental educational background might affect his or her accumulation of human capital.

4.3.1. The first empirical section

4.3.1.1. OECD Annual National Accounts

Cingano (2014) specifies that the figures used in measuring output and physical capital are obtained from the OECD Annual National Accounts statistics. In general, these figures can be considered highly trustworthy.

4.3.1.2. Barro & Lee (2013)

Cingano (2014) uses the latest release of the Barro & Lee data set to measure the average years of schooling for the working age population (15-64 years) as the stock of human capital. Barro & Lee (2013) explain that this panel data set on educational attainment is derived from 1950 to 2010 and the data are disaggregated by sex and by 5-year age intervals. Moreover, Barro & Lee (2013) suggest that these estimates of educational achievements provide a reasonable proxy for the stock of human capital for a broad group of countries. The data set includes all 34 OECD countries, though Cingano (2014) mentions that data for 31 countries are used in the research. It is not specified which countries are possibly left out.

4.3.1.3. Luxembourg Income Study (LIS)

A complementary source for inequality indicators in the first part of growth regressions in Cingano (2014) is the Luxembourg Income Study (LIS) data set. The inequality indicators in LIS are standardized and based on equivalised household income, so that total income received by household is adjusted for household size with an equivalence scale. This equivalence scale is obtained by dividing unadjusted household income by the square root of the household members. For example, Official Statistics of Finland provides LIS and OECD data concerning Finnish household income on a regular basis. Cingano (2014) explains that information from the LIS is integrated with the OECD IDD in order to account for missing inequality indicators especially in the earlier periods of the time span in the research. While the information from the LIS does complement OECD IDD, most values for Gini coefficients used are from the latter database. The integration of these data sources is assessed separately later in this chapter.

4.3.1.4. OECD Income Distribution Database (OECD IDD)

The main source of inequality indicators in the first empirical part of Cingano (2014), most notably the Gini coefficients, are obtained from the OECD IDD. Cingano (2014) describes that over time OECD IDD has become a high quality data source. Similarly to the LIS, the inequality indicators are based on equivalised household income. Cingano (2014) explains that the income data refer to cash income excluding imputed components such as home production and imputed rents. Furthermore, figures for public transfers and household taxes are included. Hence, the data allows to distinguish the difference between market and net income. Even though the OECD IDD provides this measure of the scale of redistributive policies by containing information of income pre and post taxes and transfers, it does not take redistribution through public services into account.

It is noteworthy that the data for the Gini coefficients in OECD IDD do not cover the period 1970-2010 very thoroughly. In fact, the first year the data can be obtained is 1974. Moreover, there are substantial differences in the availability of the data between different countries. Overall, there are 363 Gini coefficients for the 34 OECD countries during 1974-2010. This amount accounts for around 26% of the potential data.

4.3.1.5. Integration of OECD IDD and LIS

Reconstructing the integrated data on income inequality from LIS and OECD IDD reveals that adding the values of the Gini coefficients missing from the OECD IDD results in a total number of 457 values of the potential amount of 1394. Thus, the data only accounts for around 32,8%

of the possible values. The inclusion of the missing values from the LIS adds 94 values accounting for around 20,6% of the total amount of the Gini coefficients while approximately 79,4% are from the OECD IDD.

There are a total of 209 values for Gini coefficients in the LIS. Since 94 of them are not included in the OECD IDD and thus integrated, it can be concluded that around 45% of the relevant data in the LIS is in use. Out of the 115 values included in both data sets, 11 are equal on a one Gini point level. While the majority of the 104 remaining values do not differ very significantly between the data sets, it is evident that there are some differences in how the coefficients are measured between these two sources.

Even after combining the data sets, the Gini coefficients are extremely strongly concentrated on the more recent years. For example, there are only 19 values for Gini coefficients for period 1970-1979, covering for only about 5,6% of the possible values. Between 1980 and 1989, the data includes 70 Gini coefficients with about 20,6% coverage. Moreover, for period 1990-1999 there exists 122 Gini coefficients covering for around 35,9% of the potential data. Comparing these numbers to the 246 values and approximately 63,8% coverage for period 2000-2009, it seems evident that the inequality data, especially in the earlier periods, might be insufficient to analyze the effects of income inequality on growth in a reliable manner.

The heterogeneous nature of the income inequality data is also clearly shown by examining the differences of the amount of data between countries. The range of the number of Gini coefficients vary from 3 values for Chile to 38 values for Canada. The mode and the median for the sample is 13 and the average is approximately 14,5.

4.3.2. The second empirical section

4.3.2.1. OECD Programme for the International Assessment of Adult Competencies

The data source in the second section of the empirical analysis in Cingano (2014) is an adult skills survey conducted by the OECD Programme for the International Assessment of Adult Competencies (PIAAC). Participants in the first round of this survey consisted of 23 OECD countries and Russia, and the survey took place between 2008 and 2013. A second round is currently underway and expected to be finished in 2016. The first results were reported on October 8th 2013.

The survey is reported to measure key cognitive and workplace skills. Cingano (2014) explains that the survey consists of a wide variety of questions regarding i.e. demographic characteristics, working history and skill proficiency measured with test scores in literacy, numeracy and problem solving in technology-rich environments. Moreover, the survey provides educational and occupational achievements for both the individuals taking the survey as well as information about their parents.

The most notable difference in PIAAC is that it is micro-level data allowing for a different approach in the analysis and possibly much more detailed and reliable results. There is a substantial amount of observations used in the empirical analysis compared to the regressions in the first section in Cingano (2014). For example, most of the analyses exploiting PIAAC survey consist of around 65 000 observations, whereas there are 90-127 observations reported in the first section of the empirical analyses in Cingano (2014).

4.4. General challenges in growth econometrics linked to the research

Durlauf et al. (2005) describe that one major challenge with growth questions is to identify empirically significant determinants of growth amidst a large range of potential factors relative to the number of observations. Moreover, seeking to communicate support for particular growth determinants, individual researchers are typically criticized to stress a single or a small set of models, and then draw conclusions as if that model had generated the data. Furthermore, these standard inference procedures based on a single model are described to likely result in grossly overstating the precision of the estimates since the process ignores the uncertainty surrounding the validity of the model itself. Thus, it is concluded that model uncertainty is a fundamental problem facing growth researchers.

Though a general notation, this description seems extremely befitting when considering the model used in Cingano (2014), where the Mankiw et al. (1992) augmentation of the Solow growth model is complemented with variables measuring income inequality. While the research does provide further understanding on the topic of income inequality and how it might affect growth, it seems that overly specific conclusions especially about the strength and even direction of the possible effects cannot be justifiably made based on it.

Durlauf et al. (2005) continue by assessing the weakness of the available data as another fundamental problem in growth empirics. This limitation is described problematic regardless of which statistical techniques are applied in the analysis. The natural reason for this is the small number of countries in the world resulting in little variation in the data, but it also has to do with limiting the possible amount of testing for model validity. As an example, tests for measurement error and parameter heterogeneity are mentioned. Overall, Durlauf et al. (2005) conclude that the complex nature of the growth process combined with the scarcity of the available data suggest that scientific standards of proof seem unattainable in the field of growth econometrics. Perhaps the best this literature can hope for is to constrain what can legitimately be claimed (Durlauf, Johnson & Temple 2005, 575). This argument is further strengthened when related to researches with a very limited set of data. As pointed out, this seems to be the question with the data in Cingano (2014). Regardless of these notations, the findings in Cingano (2014) are expressed in an extremely specific manner, reporting a strong negative effect of increasing income inequality on subsequent economic growth.

5. Discussion on the findings in Cingano (2014)

In the first part of his analysis, Cingano (2014) discovers that net income inequality has a negative impact on subsequent economic growth. Net income inequality is measured with the Gini coefficient and the total amount of redistribution is obtained by the difference between market and net income inequality. (Cingano 2014, 16.) The second empirical section suggests that reduced investments in human capital by the bottom income deciles is the channel through which income inequality affects growth negatively. In this chapter, the results reported in Cingano (2014) are assessed in detail.

5.1. First empirical section

In the baseline regression, when growth depends on merely lagged values of net inequality and GDP per capita (initial income), Cingano (2014) finds that reducing net inequality by 1 Gini point would result in an increase of 0,774 percentage points in the economic growth after five years. Linear development is expected in Cingano (2104), thus the abovementioned result is reported to imply about 0,15 percentage points increase in growth per year. In addition, the level of initial income (y_{t-s}) is also found to affect growth negatively but the effect is smaller, reported with a value of -0,136 percentage points in the five year period. Similarly, this would imply that lower initial levels of income would result in a higher growth rate, a prediction that follows from adapting the augmented Solow model and its prediction of conditional convergence in the regression model. Both net inequality and initial income are found to be significant on a 5% level in the first baseline regression. The p-values for M2 and Hansen statistics are 0,722 and 0,847, respectively. While the actual hypotheses are left unstated, the p-values would suggest weak evidence against the null hypothesis, that income inequality affects subsequent growth, and thus improve the credibility of the regression. In the first regression, there are 127 observations from 31 countries with 27 instruments in use.

Including the growth determinants human and physical capital in to the analysis leads to less significant results. While the direction and strength of the effects of net inequality and initial income are still similar, only net income inequality is found to be statistically significant on a 5% level. Moreover, neither human nor physical capital are found statistically significant. These results for significance levels of the explanatory variables remain unchanged throughout the complete research. Cingano (2014) notes that the insignificance of the two growth determinants is not uncommon and does not change when alternative measures or specifications are used. This seems like an interesting notation, considering it is human capital accumulation that is suggested to be the channel through which income inequality affects growth negatively later in Cingano (2014). However, as discussed in a more general manner in Durlauf et al. (2005), this might be related to the highly stable nature, or a tendency to trend in one direction, of these two variables over time. Moreover, it is noted that explaining volatile variation, such as growth at short time periods, will typically be difficult using predictors that show little variation over time. Durlauf et al. (2005) conclude that this problem has led a number of panel data studies suggesting that a given variable is insignificant when a more appropriate interpretation would be that its effect cannot be identified with the data at hand.

Furthermore, the fact that human and physical capital are found constantly insignificant in the analysis raises questions on whether the model is then explaining growth very well. Traditionally, these growth determinants are considered highly significant when explaining growth. However, in Cingano (2014), only income inequality seems to matter.

As suggested by Roodman (2009), the augmented regression model is tested with three different instrumental variable matrices in order to account for the problem of too many instruments. The coefficients of the variables stay almost unchanged when altering the instrumental variable matrix. The coefficient of physical capital varies relatively much, however, it was not found statistically significant in the first place. The p-value for the M2 test statistic remains high but for Hansen statistic it is significantly lower when the instrumental variable matrix is collapsed.

It seems that reducing the number of instruments also affects the coefficient of net inequality. The coefficient of net inequality decreases from -0,774 to -0,800 when human and physical capital are introduced to the regression. Using the same model but reducing the number of instruments to 26 from 31, the coefficient changes to -0,809. This change is very small but further collapsing the instrumental variable matrix to 16 instruments changes the coefficient to -1,003. According to this model, a decrease of 1 Gini point would result in an increase of 1 percentage point in GDP per capita in five years. Noteworthy is also, that as the number of instruments are decreased, a second lag for net inequality variable is dropped. Thus, the largest coefficients for net inequality are obtained using one lag of this variable as an instrument, a condition used for all other variables throughout the research.

In order to test whether increased market income inequality would induce voters to choose a high level of taxation, Cingano (2014) runs a regression where gross inequality is the explanatory variable instead of net inequality. However, while the coefficient remains negative (-0,640), it is not found to be statistically significant, thus poorly explaining this so called "endogenous fiscal policy" theorem.

5.1.1. Long-run implications

Cingano (2014) further explains that interpreting the estimated coefficients using the augmented Solow model allows to recover long-run implied effects of changes in inequality as the economy converges to the new steady state. Applying the estimates of the coefficients in the first regression model where human and physical capital are not taken into account, it is concluded that the model implies approximately 0,1 percentage point increase in annual average growth resulting from one Gini point reduction in inequality. Moreover, it is explained that this would mean on average a 3% cumulative increase in GDP at the end of a 25 year period. (Cingano 2014, 17-18.)

These results are obtained applying the Solow model. However, in addition to the fact that the predicted effects are estimated using the most basic regression model including merely net inequality as an explanatory variable, some of the results seem controversial when applying the original model. Cingano (2014) explains that the coefficient $\hat{\alpha}$, estimated for lagged output in equation (24) with a value of -0,136, allows to recover the speed of convergence on equation (21) in the following manner:

(25a) $$\hat{\lambda} = \frac{-\ln(1-\hat{\alpha})}{s},$$

where s=5. According to Cingano (2014), this would yield 0,029. However, it seems that

(25b) $$\hat{\lambda} = \frac{-\ln(1-(-0{,}136))}{5} = \frac{-\ln(1{,}136)}{5} \approx -0{,}0255.$$

This result is substantially different from the convergence rate 0,029 provided in Cingano (2014) and would actually mean that there would be no convergence in this model. While this result would deteriorate the basis of the research, it seems more likely that the calculations in Cingano (2014) are based on

(25c) $$\hat{\lambda} = \frac{-\ln(1-0{,}136)}{5} \approx 0{,}0292.$$

While equation (25c) seems to be the calculation behind the whole analysis, it is not compatible with equation (25a) specified in the technical annex in Cingano (2014).

Nevertheless, the coefficient estimated for inequality, $\hat{\gamma} = -0{,}774$, is explained to allow for computing the change in the steady state level of output:

(26a) $$\widehat{\Delta lny}^{*} = -\left(\frac{\hat{\gamma}}{\hat{\alpha}}\right) * \Delta eq,$$

where Δ denotes a periodical change in time and $\Delta eq = -0{,}01$ represents a decrease of 1 Gini point. According to this analysis, the steady state level of per capita GDP would increase by around 5,7% due to a decrease of one Gini point:

(26b) $$\widehat{\Delta lny}^{*} = -1 * \left(\frac{-0{,}774}{-0{,}136}\right) * (-0{,}01) \approx 0{,}0569.$$ (Cingano 2014, 44.)

In the technical annex, Cingano expresses equation (19) as:

(27) $$\ln y(t) - \ln y(t-s) = (1-e)^{-\lambda t}[\ln(y^{*}) - \ln y(t-s)].$$ (Cingano 2014, 43.)

Cingano (2014) further explains that the long-run implications of inequality on growth are obtained by combining the results of (25c), (26b) and the differential of equation (27). Unfortunately, this expression of equation (27) leads to dramatic problems due to a difference in the multiplier on the right-hand side compared to the original specification denoted with equation (19). In the original model, the term is expressed $(1 - e^{-\lambda t})$ whereas in Cingano (2014) it is noted $(1 - e)^{-\lambda t}$. For example, using values $\lambda = 0{,}029$ and $t = 20$, the original model would yield a coefficient of around 0,44 while the expression in Cingano (2014) would not result in a real number. Thus, it must be assumed that similar to the expression of the speed of convergence, equation (27) in Cingano (2014) is mistaken but the calculations are in fact executed with the proper specification, which should be written as:

(28) $$\ln y(t) - \ln y(t-s) = \left(1 - e^{-\lambda t}\right)[\ln(y^{*}) - \ln y(t-s)].$$

The differential $\frac{\partial lny(t)}{\partial t}$ can thus be noted as a function of lny^{*}:

(29) $$\Delta lny(t) = \left(1 - e^{-\lambda t}\right) * (\Delta lny^{*}).$$

Applying the numerical results obtained with equations (25c) and (26b) and noting $t = 25$, Cingano (2014) deducts that the long-run implication is a cumulative loss in growth of around 3% after 25 years on average.

As described above, when discussing the estimates of the long-run effects of income inequality on growth, the uncertainty in the mathematical notations in Cingano (2014) is prominent and continuous. Therefore it must be noted that these results ought to be examined with caution and the specific conclusions provided in Cingano (2014) should be considered with care.

5.1.1.1. Country-level results

Derived in a similar fashion, a graph visualizing the long-run implications separately for 19 countries is reported. Income inequality is observed mostly in 1985-2005 and its effects are estimated on the cumulative growth rate of GDP per capita measured over the period 1990-2010. Among these 19 countries, Spain, France and Ireland are reported to have benefitted from income inequality. All of the remaining 16 countries would have achieved more growth with a more equal distribution of disposable income according to Cingano (2014). In New Zealand and Mexico, this effect is reported to be the highest with a cumulative loss in growth of more than 10 percentage points in both of them. Finland, Norway and the United Kingdom are presented to have suffered from almost 10 percentage point cumulative loss in growth, while this effect is suggested to have been around 5 points for i.e. Sweden, Germany, Italy, Japan and the United States.

Interestingly, it seems that four countries, Finland, Sweden, New Zealand and the UK, have simultaneously experienced some of the largest actual economic growth as well as the some of the largest increases in inequality during this period. Either this notation is not in line with the findings in Cingano (2014) about inequality severely hurting economic growth, or would suggest that these four countries would have outperformed the other OECD countries by a rather substantial margin in terms of relative GDP growth, and ultimately competitiveness, during this period.

In an intriguing blog comment on Cingano (2014), Eric Crampton points out that the reforms in New Zealand's educational system during this period have likely affected the lower income cohorts' access to education, and notes that none of these changes are accounted for in the research. Similarly in Finland, while the access to education has remained similar within different income groups in the society, there have been substantial structural reforms and changes in the economy and also in education during 1985-2010. For example, as suggested by Lansley (2012) and Stiglitz (2013) to have been a driver for increased inequality in the UK and the US, the substantial development of the financial sector due to banking deregulation in the 1980's could have affected the observed increases in inequality in Finland between 1994 and 2001 as well. Moreover, discussion about the division of elementary and upper secondary schools into good and bad ones has been lively throughout the 21st century. While this kind of a division does not discriminate students in Finland based on their economic background per se, they might, for example, be located in a way to address students with different backgrounds differently.

In addition to the abovementioned shortcomings in transparency and controversy in calculations, the whole analysis of the long-term implications is rather questionable with expected linearity of growth, expressing results as percentage points in loss of cumulative growth. Most notably however, the problems arising from the simplifications in the growth model can also be considered severe and likely to result in biased estimates. As discussed previously, these problems in the model vary from inserting a measure for inequality in a growth model and finding it to be the only variable of explanatory significance to expecting a constant or unobserved rate of technological progress and population growth across countries. Moreover, these simplifications concern the complete first part of the empirical analysis in the research.

5.1.2. Redistribution

Cingano (2014) continues by arguing that should inequality have a negative effect on long-term economic growth, the main direct policy tool to reduce income inequality would be redistribution via taxes and benefits. On the other hand, these measures might also have a negative direct effect on growth. Originally presented by Okun (1975), an analogy of a leaky bucket is introduced as an example of these negative direct effects. According to this theory, when a government transfers income from the rich to the poor, some of it disappears in the process, thus referring to money being carried in leaky bucket. Therefore, high level of taxation and redistribution could imply a waste of resources and generate inefficiencies. (Cingano 2014.)

If this is the case, the specification should account for the fact that reaching a given level of disposable income inequality would entail a stronger drag on growth in countries featuring higher market inequality (Cingano 2014, 19). Including both net and gross inequality in a regression results in the lowest value (-1,257) of the coefficient in net inequality. In this specification, the estimate attempts to reflect the effects of changes in inequality caused by redistribution. The estimate indicates that reducing net inequality would result in increasing growth by the largest margin. The estimate on the coefficient of market inequality remains statistically insignificant, leading Cingano (2014) to conclude that the amount of redistribution necessary to achieve a given level of net inequality has no negative direct effects on growth. (Cingano 2014.) However, any specifications about the discussed levels of redistribution and market or net inequality are not mentioned in the research.

When a variable measuring redistribution as the difference between lagged gross and net inequality is introduced to the regression model, while simultaneously controlling for net inequality, it is concluded that the extent of redistribution in a country has no significant effect on growth. Cingano (2014) notes that this variable remains rather small in magnitude and statistically insignificant also when used as the only independent variable. This leads Cingano (2014) to a conclusion that overall, inequality in disposable income is detrimental for growth while redistribution is neutral at worst.

Contrary to this conclusion, in relative terms the coefficient for the variable measuring redistribution actually does change rather a lot concerning both the direction and the strength. In the regression where net income inequality is controlled, the value for the redistribution coefficient is 0,064. When redistribution is used as the only independent variable, the coefficient changes to negative with a value of -0,365. Moreover, the estimated effect is small and statistically insignificant in absolute terms. Thus, it remains arguable whether conclusions about the effect of redistribution can justifiably be made based on this model. Admittedly, the model does not imply redistribution to have direct negative effects on growth either. However, as Cingano (2014) also notes, the results are based on a partial and relatively crude measure of redistribution; different redistributive tools are not measured independently to account for the different effects they might have on efficiency and growth.

5.1.3. Bottom and top inequality

The first part of the empirical analysis in Cingano (2014) is further specified in order to analyze the effects of income inequality on growth in different parts of the income distribution. Voitchovsky (2005) explains that net income inequality might be associated positively with growth in the top end of the income distribution while simultaneously affecting growth negatively lower down the distribution. Therefore, the Gini coefficient is replaced in the analysis with measures for top and bottom inequality. These measures are obtained by noting

(30a) $$BI = \frac{\bar{Y}}{\bar{y}_n}, \text{ for } n < 5,$$

and

(30b) $$TI = \frac{\bar{y}_n}{\bar{Y}}, \text{ for } n > 7,$$

where $\bar{Y}$ represents the average net income and $\bar{y}_n$ denotes the mean net income of the n^{th} decile in a country. (Cingano 2014.) For example, net inequality concerning the 3rd decile is measured as a ratio of the average net income and the average income in the 3rd decile. Moreover, net inequality for the 9th decile is measured as the ratio between the average net income of that decile and the total average.

Based on a set of regressions, Cingano (2014) suggests that reducing income inequality in the bottom of the distribution has a greater positive effect on subsequent growth than focusing in lowering inequality at the top end. Intuitively this sounds reasonable; an economy could grow faster when increasing the total number of people in the middle and top income deciles. However, it is rather difficult to think of how the growth rate of an economy would increase due to, for example, the richer people moving abroad, an occurrence also decreasing income disparities. Unfortunately, the validity of this conclusion is rather arguable. To be specific, in the technical annex, Cingano (2014) notes that since the income data for most countries are drawn from household surveys, the data might suffer from under-reporting especially at the top and bottom of the distribution. Thus, Cingano (2014) explains that the underlying data does not allow to measure the upper end of the distribution accurately. In the end, none of the results concerning top inequality are found significant in the research.

Not specifying as to which coefficients of the regression analysis are in question, Cingano (2014) rather vaguely argues that the results imply that reducing bottom inequality by half a standard deviation would increase average annual growth by nearly 0,3 percentage points, and in 25 years by a cumulative gain of over 7 percent. In addition to the controversial analogy and calculations behind these figures reducing the credibility of the analysis discussed above, the only hint of the amount of necessary reduction in inequality is detailed as dropping the level of bottom inequality in the UK to the level of France, or the United States to the level of Japan or Australia. No figures are provided to evaluate the validity of these conclusions.

Nonetheless, when bottom inequality is included as the only explanatory variable, the estimated coefficient concerning inequality at the lowest income decile gets value -0,015 and is found statistically significant on a 5% level. The interpretation for this coefficient is the following; an increasing disparity of one unit between the average income and the average income in the bottom 10% of the population, leads to a 0,015 percentage point decrease in growth in the subsequent five year period. However, the unit by which the disparities between income groups are measured is not specified more than in equations (30a) and (30b), so it leaves a doubt over how the coefficient should be interpreted. Moreover, how much in actual terms would it be necessary for the difference between the income groups to increase in order to experience this change in growth?

For example, assume that in country A at the first period, $\bar{Y}(1) = 20000€$ and $\bar{y}_1(1) = 5000€$, so the indicator for bottom inequality is given by $BI(1) = \frac{20000}{5000} = 4$. After five years, the mean income has increased by 2% while the average income in the 1st decile has only increased by 1%. Thus, the figures have changed to $\bar{Y}(2) = 20400€$ and $\bar{y}_1(2) = 5050€$, so $BI(2) = \frac{20400}{5050} \approx 4{,}04$. The change in the indicator for bottom inequality is thus 0,04. Should the change in disparity of one unit be measured similarly as a change in Gini points, the model implies a decrease in growth of $-0{,}06$ percentage points.

Moreover, let Δ represent the difference of 5 years in time. In this scenario, the difference in the development of the incomes has been substantially larger, with $\Delta\bar{Y} = 2000€$, $\Delta\bar{y}_1 = 0$ and $\Delta BI = 0{,}4$. The increase in the average income has thus been 10% while the average income in the 1st decile has not changed. Based on the estimate in Cingano (2014), this would result in a decrease in growth of 0,6 percentage points. Using this analogy the other way around, a similar increase in growth would require that $\Delta\bar{y}_1 \approx 555$ while $\Delta\bar{Y} = 0$, implying over 10% increase in income for the bottom decile while the mean income remains unchanged. However, these kind of a paces for the changes in disparities are enormous for a five year period.

Moreover, what do these changes in country A explain about the situation and the growth rate in country B?

The coefficient decreases with a steady pace through the 2nd decile to the 4th reaching -0,189 for the latter income group. While the p-values of the test statistics for all 4 regressions are rather high, the significance level of the estimated coefficient drops to 10%. Cingano (2014) explains that the decrease in the value of the estimated coefficient on bottom inequality is almost completely offset by a change in the standard deviation of the corresponding coefficient. Thus, Cingano (2014) concludes that the magnitude of the effect of income inequality on growth is remarkably similar in all four income groups. Contrary to the conclusions in Cingano (2014), it is difficult to evaluate the magnitude of the estimated effects due to the challenges in interpreting the coefficients and their validity both within and across countries. On a more fundamental note, it is difficult to comprehend how 93 observations of 30 countries could explain very sufficiently these effects, considering that the time period is 1970-2010. On average, this is about 3 observations per country over 4 decades.

Moving onwards, Cingano (2014) reports another set of regressions where indicators for both bottom and top inequality, measured for the 8th decile, are included as explanatory variables. Including top inequality seems to result in more robust results for the coefficients concerning the bottom deciles. The estimated coefficients for top inequality also imply a negative effect on growth, however, none of the results for top inequality are statistically significant throughout the research. When the 1st and 8th deciles are included, the coefficient for bottom inequality is -0,032 with a 10% significance level. In a model with 2nd and 8th deciles, the coefficient decreases to -0,083 with a 1% significance level. This level remains the same in the model with the 3rd and 8th deciles while the estimated coefficient decreases to -0,132. Finally, with the 4th and 8th deciles, the coefficient is -0,198 with a 5% significance level. These decreases in the coefficient seem to be once more somewhat offset by the changes in the standard deviation but not as largely as in the previous regressions.

Interestingly, the analysis suggests that the largest positive effect of decreasing income inequality on growth would come from reducing inequality in the 4th income decile. One explanation for this feature could be related to the differences in the effects that increased income would initiate in the different income groups. For example, concerning the lowest income group, increases in income are more likely to be directly used in consumption necessary for the daily life, such as food, clothes and transportation. Meanwhile in the 4th income decile, increases in income might be directed in consumption that are likely to have a more substantial and far-reaching effect for the economy as a whole, for example by providing a possibility to purchase a house. Therefore, it could be reasonable to expect that decreasing income inequality in the 4th income decile might have the largest effect on growth. However, as discussed in section 2, redistributing from the median wage earner to the 4th decile would hardly provide incentives to work hard as an average wage earner, and might thus also result in inefficiencies in the economy.

Combining both top and bottom inequality indicators in the regression seems to provide more reliable results but very small in magnitude. According to these results, reducing inequality in the 2nd, 3rd and 4th decile, while accounting for the inequality in the 8th decile, would result in an increase of growth of somewhere between 0,03 and 0,2 percentage points after five years. Thus, it seems unreasonable to expect vast long-run results either, especially without substantial changes in the levels of income inequality between these income groups.

In addition, two more regressions are reported, where top inequality in the 9th and 10th deciles are the explanatory variables. While the p-values for the M2 and Hansen statistics remain rather high in the last two regressions, Cingano (2014) notes that the income data used might not capture the top of the income distribution accurately, thus explaining the insignificant results. This further highlights the fact that the p-values of these statistics do not unambiguously prove the robustness of the model and its results.

Even though the coefficients for bottom inequality indicate that these models add further explanatory value of the effects of inequality in different income groups to economic growth, the problems discussed previously are still present in the research. In general, it is rather questionable whether these kind of possible effects can be measured by running cross-country regressions. Moreover, adding variables for income inequality in the augmented Solow model leads to results where none of the growth determinants usually considered important are found significant anymore.

Given the quality of the available data on income equality, these estimates are even less reliable. More specifically, the coefficients for top inequality are statistically insignificant throughout the research and bottom inequality is the only significant explanatory variable. In addition, the number of observations seem too little concerning the time period and the number of countries. These observations of the suggested shortcomings in Cingano (2014) are not meant to propose that the research has no value in explaining the possible effects of income inequality on growth.

However, in light of the discussion above, it seems that measuring both the causal relationship and the magnitude of these effects in a reliable manner remains unverified.

5.2. Second empirical section – accumulation of human capital as a suggested channel

Albeit not finding human capital to have a positive effect on economic growth, or to be statistically significant in explaining it, Cingano (2014) argues that human capital accumulation is a key channel through which bottom inequality affects negatively on subsequent economic growth. Cingano (2014) states that this conclusion is justified by findings in earlier studies concerning positive consequences of education on individual productivity and the positive effect of human capital on aggregate growth. Moreover, previous studies using panel data and GMM techniques have provided similar results not finding a positive effect of human capital on growth. (Cingano 2014, 22.)

According to this view, inequality would be harmful due to raising the relative costs of education of families in the bottom half of the distribution. Combined with imperfect financial markets, these circumstances would lead to underinvestment in education for the bottom income deciles. Cingano (2014) acknowledges the abovementioned contradiction between the results in the first part of the empirical analysis and the suggested channel, explaining that the reason human capital is not shown to contribute positively on growth in the regressions might be caused by a trend in the variable measuring stock of human capital, thus dramatically lowering the precision of the estimate when exploiting within-country variation. As discussed in Durlauf et al. (2005), this is commonly a problem in the variables measuring human capital, such as educational attainment. However, it does also indicate that the given data or the estimation models and methods are not sufficient in explaining the contribution of this determinant on growth. In addition, interestingly some of the reasoning leading to assess this channel is reported to have been based on research suggesting that income inequality has a positive effect on growth.

Using PIAAC survey as the data source, the second part of the empirical analysis in Cingano (2014) examines whether the educational background of the parents might affect an individual's level or quality of educational attainment and working life.

5.2.1. The baseline equation

To estimate whether this link between educational achievements and income inequality depends on parents' educational background, Cingano (2014) exploits individual-level survey data (OECD Adult Skills Survey, PIAAC). As detailed in section 4.3, exploiting the data from PIAAC allows to distinguish the parental educational achievements for an individual, as well as test scores in numeracy and literacy. Cingano (2014) states that the main problem of the survey is the lack of variation over time. To gain more of this desired variation, Cingano (2014) explains that individuals are pooled by 5-year age groups and each group is assigned with a measure of inequality in their country when they were aged between 10 and 14. Thus, outcomes of the educational achievements for individuals born in 1966-70 are linked to inequality measured in 1980. The baseline regression equation is written as:

(31) $$HC_{i,t,c} = \beta_1 PEB_{i,t,c} * lneq_{t,c} + \beta_2 PEB_{i,t,c} + \theta X_{i,t,c} + \mu_t + \mu_c + \epsilon_{i,t,c}.$$

$HC_{i,t,c}$ is a measure of human capital for individual i in a country c. The vector β_2 is described to capture the degree of intergenerational persistence in educational outcomes. Moreover, the vector β_1 is specified to measure whether this persistence varies with the amount of inequality within a country. The variable eq measures inequality on a country-level, usually in Gini points, and the year used for this variable determines the index t in the model. The variable μ_t accounts for common shocks and μ_c for country fixed effects. Variables in matrix X, used as controls in the analysis, consist of other individual characteristics likely to affect educational choices taken at earlier age such as gender, parents' immigration status and language skills. (Cingano 2014.)

The variable PEB reflects the parental educational background for an individual. This variable is a set of three different indicators; low, medium or high. A low PEB is assigned to an individual whose neither parent has attained upper secondary education. Medium PEB is in question when at least one parent has achieved secondary and post-secondary education. Furthermore, a high PEB is assigned when at least one parent has attained tertiary education. (Cingano 2014.) Definitions for these educational attainments vary across countries due to differences in schooling systems. For example, in Finland upper secondary school can be carried out as either academic or occupational schooling and is usually started at age 16-17. A medium PEB would in Finland be given to an individual whose at least other parent has attended this level of schooling. In addition to traditional universities, tertiary education in Finland includes universities of applied sciences.

5.2.2. Ordered probit model results

Cingano (2014) explains that equation (31) is estimated in separate but complementary ways using different measures for human capital. The first way is estimating an ordered probit model for the highest level of achieved formal education. In this case, human capital can have a low, medium or high value. Low represents lower secondary education, medium is related to upper secondary education and high is assigned to those who have achieved tertiary education. In the estimate, parameters β_1 and β_2 assist in predicting average probability of achieving these educational levels. Cingano (2014) explains that the model is derived from a latent variable model $y^* = X\beta + \epsilon$, with an unobserved and continuous dependent variable y^* measuring the individual propensity to achieve higher education. It is assumed that there are threshold levels α_1 and α_2 that determine observable changes in educational attainment. These levels are interpreted so that:

(32)
$$y = \begin{cases} Low, & if \ \ y^* < \alpha_1 \\ Medium, & if \ \ \alpha_1 < y^* < \alpha_2 \\ High, & if \ y^* > \ \alpha_2. \end{cases}$$

The threshold levels α_1 and α_2 as well as the parameters β_1 and β_2 are estimated by maximum likelihood. (Cingano 2014.)

Cingano (2014) finds that the average predicted probability of tertiary education decreases substantially for an individual with low PEB as inequality increases. When the Gini coefficient is 0,2 the estimated probability is estimated to be around 0,21-0,28 with 95% confidence intervals. With quite a steady pace, the probability decreases to around 0,12-0,15 as the Gini coefficient increases to 0,36. Meanwhile, the predicted probability remains almost the same or increases slightly for individuals with medium and high PEB. These probabilities for individuals with medium and high PEB are estimated to be around 0,26-0,33 and 0,38-0,44 respectively.

Furthermore, congenial results are presented for average probability of achieving lower secondary education or less estimated by PEB and inequality. For an individual with low PEB, this probability is approximated as around 0,18-0,30 with a Gini coefficient of 0,2. This probability is estimated to increase approximately linearly to around 0,31-0,43 when the Gini coefficient increases to 0,36. Again, the probabilities for individuals with medium and high

PEB are expected to decrease slightly or stay put with estimated probabilities of approximately 0,19-0,29 and 0,14-0,21 respectively.

Another application of the ordered probit model allows Cingano (2014) to estimate the average probability of not being employed after entering the labor market for each group of individuals. This estimation is executed by computing the fraction of time spent unemployed over the working life for each individual from the information in the PIAAC survey. Based on this model, Cingano (2014) concludes that individuals with a low PEB are much more likely to end up unemployed with a higher level of inequality than people with a medium or high PEB. When the Gini coefficient is 0,2, individuals with a low PEB are estimated to be unemployed with around 0,07-0,13 probability, whereas this probability increases somewhat linearly to around 0,17-0,22 for this group as the Gini coefficient is increased to 0,36. For individuals with a medium PEB, these estimated probabilities are around 0,07-0,12 for both levels of inequality. The probability is expected to decrease for individuals with a high PEB when inequality increases, with around 0,07-0,11 probability with an 0,2 Gini coefficient falling to around 0,055-0,1 with the 0,36 Gini coefficient.

5.2.3. Linear regression results

Another approach in the second part of empirical analyses in Cingano (2014) is to estimate equation (31) as a linear regression model. In these linear regressions, human capital is measured in either schooling years, or as skill proficiency, using test scores of numeracy and literacy obtained from the PIAAC survey to measure skills.

Cingano (2014) remarks that the test scores of literacy and numeracy as a measure for human capital are potentially better than years of schooling, since these measures allow to interpret the skills obtained from schooling. There are some concerns too, with difficulties to measure as to what extent are these skills acquired while in education and what amount of them are obtained i.e. while working. Furthermore, Cingano (2014) notes that skills in literacy and numeracy acquired in school are likely to depreciate with age. However, it is explained that a previous OECD study on employment found that consequences of training on the job on skills measured by PIAAC survey were not found significant, thus suggesting that the test scores reflect largely those skills obtained while studying. Moreover, should skill depreciation occur at the same rate between countries, the effects would be captured by the time dummies assigned for the age cohorts.

Complementary to the previous findings, Cingano (2014) suggests that higher inequality is negatively and significantly related to years of schooling for individuals with a low PEB. This connection is not found significant concerning medium or high background individuals. The results remain similar in different regressions when the baseline equation is augmented with individual controls, interaction term between PEB and average GDP per capita, country specific trend and controls for interaction between countries and years, respectively. The R-squared values vary between 0,343 and 0,39 in these regressions, and the p-value implies a 1% significance level for the coefficient β_2 in the first three regressions. Cingano (2014) further specifies that the baseline results imply almost half a year decrease in schooling for individuals with low PEB as inequality increases 6 Gini points.

The results are very similar when estimating skill proficiency. According to the baseline regression, the average numeracy scores for individuals with a low PEB are estimated to decrease around six points when inequality is increased with the same amount of Gini points. For example, the gap between numeracy test score results for individuals from low and medium PEB is approximately 10 points when the Gini coefficient is 0,2. This gap increases to around 13 points when inequality is increased with 6 Gini points to 0,26. For low PEB individuals, the decline in points is faster as inequality increases while individuals with medium PEB face a more modest decline in average test score points. The test scores for individuals with a high PEB are found to remain unaffected by changes in inequality. The R-squared value of 0,177 of the baseline regression indicates that the model explains only quite little of the variation in the data. Several regressions are run with different controls and the results remain stunningly similar on most of them. Two regressions stand out with much higher R-squared values of almost 0,7. In these two, the set of controls include problem solving scores as a proxy for ability and education yielding a significantly lower estimate for β_2 than the other regressions with a value of around -0,48. As before, only the estimates concerning individuals with a low PEB are found statistically significant. The regressions with literacy test scores as a dependent variable yield almost identical results.

5.3. Concluding remarks

In the first empirical section, Cingano (2014) finds that net income inequality has a significant decreasing effect on subsequent economic growth. Both short and long-term results, as well as estimates on the different effects of inequality on different parts of the income distribution are provided in detail. Cingano (2014) notes that the most robust effect is found in the bottom of the income distribution and concludes that reducing income inequality at the bottom four deciles would result in increasing economic growth by the largest margin. Redistribution is not found to affect growth negatively but is expected to be neutral at worst.

As discussed throughout this chapter, there are significant doubts over the specific nature in which the results are presented in the first empirical part of Cingano (2014). These problems are related to the growth model, data and the applications of the regression results and their calculations. In Cingano (2014), the growth model is taken as it is expressed originally in Mankiw et al. (1992), but a variable is switched without considering an alternative model built specifically to include that variable, the level of human capital. Also, including a variable for net income inequality leads to results where it is left as the only significant variable explaining economic growth, resulting in neglecting the effects of the basic growth determinants usually considered rather relevant in explaining growth, such as investments and human capital. Furthermore, the analysis expects that some underlying determinants of growth are either unobserved or constant across countries in order to simplify the analysis and to be able to estimate growth linearly. Perhaps most importantly, as noted in empirical growth literature, for example in Klenow and Rodríguez-Clare (1997), the original model is found to be problematic in explaining differences in growth rates between countries. How could it be possible to be able to distinguish what detailed effects income inequality has on growth based on a model that might prove problematic in explaining growth and its differences between countries in a more general manner? In this light, how realistic can we expect that the detailed results provided in Cingano (2014) actually are?

The second part of the empirical analysis in Cingano (2014) assumes that reduced investments in education in the bottom of the income distribution is the reason for the alleged effects estimated in the first section. Constructing different kind of models, and using a detailed micro-level data set, Cingano (2014) finds that when income inequality is higher, individuals whose parents' educational level is relatively lower than the average are likely to have a lower level of education themselves. These individuals are also found to have lower test scores in tests measuring a set of skills expected to be required in the working life. Furthermore, Cingano (2014) estimates a higher probability of ending up unemployed over their working lives for these individuals.

The most obvious problem regarding the second empirical part has to do with the fact that it is built on assumptions that are totally contradictory to the findings in the first part. In fact, when arguing that the channel through which inequality hurts growth is reduced investments in education by the lower income cohorts, Cingano (2014) relies on literature finding a positive effect of inequality on growth. Aside from this contradiction, it seems that the second part provides more reliable and plausible results focusing on measuring the connections between individuals, their characteristics and income inequality. In fact, for example parental educational background and social status have often been considered to affect the intergenerational social mobility in societies significantly [e.g. (Beller & Hout 2006; Causa & Johansson 2010; Stiglitz 2013)].

6. The variety of findings in related literature

The possible links between income inequality and economic development have been studied frequently in economics for a very long time. For example, though the discussion is originated far earlier, Kuznets (1955) constructed a well-known hypothesis arguing that as a country developed, inequality would initially rise and then begin to decrease after reaching a sufficient stage of development. However, attempting to estimate the direction and strength of this relationship in detail is a relatively new field of research starting most notably in the early 1990's. While some researchers apply a different growth model, perhaps the timing of this field of research can also be considered as a response to the construction of the MRW augmented Solow growth model and its empirical specifications in 1992. For around 20 years, different models, methods and data have been applied in order to explain this relationship, however, with rather inconsistent findings among different studies. This chapter discussed some of the findings in the literature and compares their results with the ones in Cingano (2014).

Building their research on an endogenous growth model with overlapping generations, Persson and Tabellini (1994) find a negative effect of income inequality on subsequent economic growth. The data used in the research are rather heterogeneous consisting of 56 countries including democracies and non-democracies. Income inequality is measured as a share of the middle income quintile. An increase in this indicator is thus associated with increased equality. Persson and Tabellini (1994) use OLS regression method to estimate that increases in equality are significantly associated with higher growth rates. The effect is found to be larger than the effects found in Cingano (2014), however it must be noted that the applied data differ between these two researches in such a vast manner, that the results are likely incomparable. Overall, Persson and Tabellini (1994) predict that growth should be inversely related to inequality in a democracy but not necessarily in dictatorships.

After constructing new data sets for inequality and land distribution in 1996, Deininger and Squire (1998) estimate that initial inequality in land distribution is negatively related to long-term growth, and that inequality reduces income growth for the poor but not for the rich. Moreover, Deininger and Squire (1998) do not find much support for the Kuznets hypothesis in their research. The data on income inequality consist of Gini coefficients for 108 countries and information on income distributions for 103 countries. Also relying on OLS regression, Deininger and Squire (1998) find that income inequality is negatively associated with subsequent economic growth; a 9 Gini point decrease would result in about 0,4 percentage point increase in annual economic growth. However, this effect ceases to be significant once regional dummies are included in the analysis. While the direction by which inequality is estimated to affect growth is similar to Cingano (2014), the magnitude of the effects is estimated to be quite a bit smaller.

Adjusting the data set by Deininger and Squire (1996) to achieve better comparability of the data, Li and Zou (1998) exploit a panel data set for 46 countries for time period 1960-1990 and run fixed-effects and random-effects regressions to estimate the effects of income inequality on growth. The data are arranged in five year intervals as in Cingano (2014). Contrary to the findings in the previously assessed studies, Li and Zou (1998) estimate a positive, and on most specifications a significant, effect of inequality on growth for the whole sample. The coefficients for income inequality are consistently higher with the fixed-effects models, estimating an annual increase of around 0,15 percentage points in real GDP per capita with a 1 Gini point increase in inequality, whereas the random-effects estimator suggests a maximum increase of around 0,1 percentage points. Thus, the magnitude of these effects is found very similar as in Cingano (2014), however the direction is estimated to be the opposite.

Also exploiting the unbalanced Deininger and Squire (1996) panel data set, Barro (2000) estimates that the effect of inequality on growth might be negative for values below a certain threshold point (2070$ in 1985 U.S. dollars) and after that would become positive. Barro (2000) notes that this might be explained by more serious constraints in the credit-markets in poorer countries, should these restrictions create a negative effect of inequality on growth. However, the findings in the research are rather inconsistent and insignificant between the different regressions, leading Barro (2000) to conclude that there is little relation between income inequality and growth rates found in the data. Moreover, as noted in also in Cingano (2014), the data used in Barro (2000) consist of information from both developing and developed countries and may capture an average effect, and thus provide misleading results.

Forbes (2000) also applies the Deininger and Squire (1996) data set for measuring income inequality and uses five different estimation methods, including the first-difference GMM, to assess the possible inequality-growth – nexus. Exploiting data for 45 middle and high-income countries, the analysis results in a positive and statistically significant effect of inequality on growth with all estimation techniques. The estimation suggests that an increase of 10 Gini points is correlated with a 1,3 percent increase in average annual growth over the next five years. However, Forbes (2000) notes that the estimates do not directly contradict the often reported negative relationship between inequality and growth due to concentrating on short and medium-term relationships instead of a longer time span. Noteworthy, the shorter time period is also the approach in Li and Zou (1998).

Banerjee and Duflo (2003) approach the question with a completely different angle, abandoning linear regression methods due to lack of support for them in the data. Compared to previous research on the subject, the findings are somewhat different; changes in inequality in any direction are associated with lower short term growth rates in the future. Banerjee and Duflo (2013) find little evidence of inequality itself affecting growth negatively, but overall cast out a warning against the automatic use of linear models in settings where the theory does not necessarily predict a linear relationship. Durlauf et al. (2005) note that one limitation of Banerjee and Duflo (2003) is that the study allows non-linearity for only a subset of growth determinants, such as the Gini coefficient. Durlauf et al. (2005) continue that this assumption is considered to have little theoretical justification, though admittedly more sophisticated than assuming linearity in general. Furthermore, it is concluded in Banerjee and Duflo (2003) that the most compelling evidence on this point needs to come from exploiting micro data.

Tuomas Malinen has addressed the issue in several interlinked studies. With data on a wide range of countries, Malinen (2011, 2012 and 2013) reports a negative and statistically significant effect of income inequality on long-term economic growth. Although the negative effect is dominant, there are some non-linearities found in the relationship with group-related estimation. Malinen (2012) addresses these suspected non-linearities and concludes that there is a long-run equilibrium relationship between income inequality and growth, and this relationship is found negative in the developed economies. All these studies have been executed using panel data on a wide range of countries and a complementary measure for inequality instead of the Gini coefficient. Malinen (2011 and 2013) notes that the Deininger and Squire (1996) data set is likely to contain inconsistencies such that all the results obtained with it are in doubt. Therefore, Malinen uses a measure called EHII2008, which is assumed to be more consistent and the data coverage is also considered clearly extended compared to the Deininger and Squire (1996) data set.

Comparing Malinen's results to the ones obtained in Cingano (2014) is rather ambiguous, since Malinen expresses the results as elasticity of growth with respect to inequality. This value is reported as -0,014 in Malinen (2013), and would at first sight seem like rather a small effect.

However, considering that the elasticity of growth with respect to investments is found to be around 0,028, the effect of inequality can be considered significant in more ways than only in the statistical sense.

Ostry, Berg and Tsangarides (2014) use system GMM estimation approach and attempt to investigate what would happen to the future growth rate of a country of a given income level with different levels of inequality. Moreover, should inequality have a negative effect on growth, the effects of redistribution on growth are of interest in the study as well. With data on 90 countries over the period 1960-2010, Ostry et al. (2014) find that inequality has a statistically significant decreasing effect on medium and long-term growth. For example, while holding the variables for initial income and redistribution constant, increasing inequality by 5 Gini points would result in decreasing real GDP per capita growth on average by 0,5 percentage points in the next five year period. Moreover, income inequality is found to have a statistically significant negative relationship with the duration of growth spells. Ostry et al. (2014) estimate that an increase of one Gini point is associated with a 6 percentage point increase in the risk that the growth spell will end the next year. Furthermore, Ostry et al. (2014) do not find evidence that there would be a trade-off between redistribution and economic growth.

Obtained with the same empirical method, the results are quite similar but slightly smaller in magnitude than the ones in Cingano (2014). Increased income inequality is estimated to reduce future growth and redistribution is not expected to have a negative effect on growth. Ostry et al. (2014) note that, while some policies are associated with Okun's leaky bucket analogy, extreme caution about redistribution is unlikely to be appropriate in many cases. Moreover, governments are suggested to find policies that promote both efficiency and equality. Such policies could be, for example, spending on public capital or education that benefit the poor.

Halter, Oechslin and Zweimüller (2014) apply the first-difference and system GMM estimation methods in their analysis, and conclude that higher income inequality helps growth in the short term but may be harmful in the long run. Moreover, the lagged effect seems to be larger in magnitude, so the total effect is estimated to be negative in the long run. For example, one system GMM regression specification in Halter et al. (2014) yields statistically significant estimates suggesting that in the short term, an increase of 1 Gini point would result in approximately 0,32% increase in growth after 5 years, while the same effect would be -0,57% had the increase in the Gini coefficient occurred 5 years earlier. Halter et al. (2014) suggest that this relationship could be explained by the link that the effects promoting growth arise from purely economic mechanisms, such as convex saving functions and innovation incentives, and therefore become effective quite fast. The effects harmful for growth, however, are more affiliated with such issues as the political process and the change of institutions, or might operate through changes in the educational achievements of the population. Overall, Halter et al. (2014) estimate effects of income inequality on growth far more subtle than what are presented in Cingano (2014).

Halter et al. (2014) also exploit the Deininger and Squire (1996) data set, and complement it with values from the UNU-WIDER World Income Inequality Database for 106 countries during 1965-2005 to estimate these effects. It is concluded that further research will inevitably require longer inequality time series in order to experiment with lagged values of income inequality in a meaningful manner.

This concise literature review illustrates that the findings in the research about income inequality's possible effects on growth vary vastly between each other. Some studies express a strong negative effect, even impact, that income inequality imposes on growth, while a number of studies find the relationship non-existent or positive. Moreover, some studies conclude that the effect is positive in rich while negative in poor countries. In short, as also noted in Cingano (2014), there is no consensus about the effects of income inequality on growth between researchers studying the subject.

There are many reasons for this. One important factor is that regardless of how complicated estimation methods are used, the data seem to be insufficient to reach definitive conclusions about the matter. Alongside with the lack of necessary amount of data, the estimates seem to be extremely sensitive towards which countries and time periods are included as well as which models and methods are applied in the estimation. Moreover, the linear form of the growth models behind many of the analyses are often considered too simplified to explain a process as complicated as growth, let alone how inequality might affect it.

7. Conclusions

Income inequality undoubtedly affects the growth rate of an economy through multiple channels. There exists a vast amount of theories and models explaining these channels, some expressing inequality to have a positive effect on growth while others specify a negative contribution. The positive effects might generate through, for example, accumulation of physical capital, creating incentives for individuals to develop their skills and work hard as well as offering a sufficient amount of initial assets to invest in riskier projects. Meanwhile, the negative effects might be originated, for instance, through lack of sufficient human capital accumulation, inefficiencies created by redistribution through taxation or as a result of sociopolitical unrest originating from income inequality.

Measuring the direction and the strength of these possible effects has been a subject under persistent research in the past 20 years, however, providing virtually as many different results as there are studies on the matter. Part of this disparity can be explained with the dubious nature of growth econometrics in general. As noted by Durlauf et al. (2005), while understanding the wealth of nations is one of the oldest and most important research agendas in growth econometrics, it also seems to be one of the areas where genuine progress is most difficult to achieve. Moreover, the data on inequality are commonly quite persistent within a country, which has led researchers to apply more complicated estimation methods to measure the variation in inequality indicators within and between countries in hopes of gaining further understanding about the effects of inequality on growth. This has led to a wide variety of studies applying a large amount of different growth models and estimation methods.

Federico Cingano tries to tackle this question with a new set of data and arguably one of the most sophisticated estimation methods, the system Generalized Method of Moments. Cingano (2014) builds his estimation on top of the augmented Solow growth model by Mankiw et al. (1992), where the basic Solow growth model is extended to account for human capital and specified in a linear form to enable empirical estimation. Cingano (2014) reports a set of results estimating that income inequality affects growth negatively and significantly. Moreover, it is reported that most OECD countries have been missing out on considerable amounts of economic growth due to increases in income inequality in the last decades, suggesting that addressing the problem of increasing inequality would result in higher growth along with making the societies in the countries fairer. Furthermore, Cingano (2014) proposes that the reason for this estimated effect is reduced investments in education by the people in the lower end of the income distributions. Though officially representing the view of the author, these conclusions have been reported widely in the media as an official OECD position.

Unfortunately, it would seem that there are substantial controversies behind the results in Cingano (2014). The first fundamental problem is related to the growth model behind the analysis and its empirical specification. Admittedly, the MRW augmented Solow model provides a practical and sometimes useful linear specification to estimate growth, however, it has also been pointed out to have its flaws. For example, the technology growth rate, one of the fundamental determinants explaining growth rate of an economy, is expected to be constant across countries in the model. While this can be a justified assumption with long time periods, it can also be considered to be too simplified, affecting the analyses in the shorter term and providing less reliable results. For instance, while the original MRW analysis found the model to explain nearly 80 percent of the cross-country variation of income per capita between countries, Klenow and Rodríguez-Clare (1997) resulted in an explanatory value of about 40 percent with the model.

Moreover, the model explains growth concentrating on the economy as a single sector and is therefore not applicable to analyze the structural problems within an economy. For example, the problems experienced in Finland after 2008 with stagnating growth and high rate of unemployment are connected to the economy’s structural problems, mostly the collapse of the traditional industries. Thus, analyzing the current recession of the Finnish economy with the MRW augmented Solow model is not possible, but would instead require a model taking different sectors of the economy into account. Furthermore, the model arguably overlooks other possible growth determinants, omitting them as unobserved or as a part of the error term. Not all of the controversy of the results in different studies is connected with the simplifications in the model, however, the controversial findings in explaining the differences in growth across countries raise a question whether the model is then suitable in finding the effects of a particular possible growth determinant in the process of growth.

Secondly, after the model-specific simplifications, the original MRW augmented Solow model estimates growth as a function of physical capital, human capital and population growth. Like many researchers in the past, Cingano (2014) adapts the model as given, and simply inserts another assumed growth determinant in the model, income inequality in this case. Suddenly, none of the original growth determinants seem to matter anymore, while income inequality is left as the only variable explaining growth in a significant fashion. The following results can hardly be considered in a meaningful manner, however they are reported as relevant results truly explaining the growth patterns of the OECD economies in detail. Furthermore, strong arguments in favor of unconditionally reducing income inequalities in the OECD countries are expressed based on the results.

Further problems with the model are related to the specifications and conclusions in Cingano (2014). Instead of using the model specified for the level of human capital in the original MRW model, Cingano (2014) uses the specification designed to account for the investment in human capital. Simultaneously, Cingano (2014) exploits measures of the level of human capital, schooling years, in the data. Thus, the variables are used in a model designed for a different set of variables. Furthermore, the conclusions drawn from the model, especially for the long-term implications, are based on controversial reasoning and ambiguous mathematical notations.

Another fundamental problem in the research, and in the whole field of research of inequality affecting economic growth, is the lack of reliable data, especially concerning inequality. As explained in chapter 4.3, the data about inequality are very scarce and in most cases rather heterogeneous. The scarcity of data has led researchers to apply more and more complicated estimation methods in hopes of being able to exploit maximal variation in the data. However, at the same time it raises questions on whether a researcher is artificially highlighting the importance of a single growth determinant expected to have an effect on growth. As the effects of inequality in one country playing a part in the growth rate of another one can justifiably be questioned, the heterogeneous nature of the inequality data between countries furthermore decreases the reliability of these comparisons.

However, other researchers have found somewhat similar results as Cingano (2014) recently. These findings, combined with the theoretical mechanisms assessed in the literature, suggest that there are most likely some channels through which income inequality affects economic growth, and in the case of a developed economy, possibly in a harmful manner. Moreover, it seems reasonable to expect that these effects can be completely different between developing and developed countries, and furthermore, differences are probable within the developed countries as well. Even though the whole field of research is likely to suffer from the uncertainty concerning growth regressions and reliable data, and thus overly specific conclusions should perhaps be best avoided, these possible effects should not be overlooked, even in a country with a relatively equal income distribution like Finland. Perhaps future studies should, however, try to approach the question from another angle, and exploit micro-level data due to the abovementioned difficulties in the current field of research.

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Appendices

Appendix 1. ***A list of OECD member countries***

Australia
Austria
Belgium
Canada
Chile
Czech Republic
Denmark
Estonia
Finland
France
Germany
Greece
Hungary
Iceland
Ireland
Israel
Italy
Japan
Republic of Korea
Luxembourg
Mexico
Netherlands
New Zealand
Norway
Poland
Portugal
Slovak Republic
Slovenia
Spain
Sweden
Switzerland
Turkey
United Kingdom
United States

Source: http://www.oecd.org/about/membersandpartners/list-oecd-member-countries.htm

Appendix 2. ***Finnish income distribution data in 2013***

Percentage of households	Percentage of household income	Cumulative percentage of household income
0	0	0
10	3,72	3,72
20	5,45	9,17
30	6,48	15,65
40	7,46	23,11
50	8,42	31,53
60	9,39	40,92
70	10,47	51,39
80	11,81	63,2
90	13,83	77,03
100	22,98	100,01

Due to rounding the shares do not always sum up to 100.

Source: Official Statistics of Finland (OSF): Total statistics on income distribution [e-publication].
Helsinki: Statistics Finland [referred: 9.5.2015].
Access method: http://tilastokeskus.fi/til/tjkt/tau_en.html